Sustainability metrics for agri-food supply chains

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Abstract

Enhancing sustainability in food production requires knowledge about the economic, environmental and social performance of the various stages of agri-food supply chains. An integrated indicator can provide synthetized information about the extent to which food products are sustainably produced and can guide sustainability improvements. The overall objective of this thesis was to perform integrated assessments of relative sustainability performance of (stages of) agri-food supply chains using integrated indicators. To achieve the overall objective this thesis first developed a theoretical framework for benchmarking agri-food supply chains in terms of their relative sustainability performance. Two integrated indicators were proposed, i.e. the Social Profit indicator that integrates sustainability performance indicators using prices and the Technical Inefficiency indicator that uses distance functions. Next, the Social Profit indicator was illustrated for Brazilian soybean meal chains: non-genetically modified (non-GM) and genetically modified (GM) chains. Further, relative sustainability performance (economic and environmental) of specialized potato farms in Germany and the Netherlands was assessed using both the Social Profit indicator and the Technical Inefficiency indicator. Finally, an alternative approach, the Nerlovian social profit Inefficiency indicator, was used for the assessment of relative sustainability performance of coffee farms in Vietnam.

The results of this thesis suggests that the three proposed integrated indicators can be used in different socio-economic and environmental contexts to capture the multi-dimensional nature of relative agri-food supply chain sustainability. Their implementation helps to overcome some of the limitations of the single-issue and composite indicators that are commonly used in sustainability assessments such as incommensurability, subjectivity and comparability. The indicators provide information that can be used by businesses, stakeholders and policy makers to identify opportunities for relative sustainability performance improvements of agri-food supply chains.

Keywords: Total Factor Productivity, Total Price Recovery, technical inefficiency, agri-food supply chain, externality, social profit.

Contents

CHAPTER 1

Introduction

Background

The role of agri-food supply chains in dealing with sustainability

Agri-food supply chains play a critical role in society for meeting food demand of the growing world's population (Yakovleva 2007). Over the next decades the world's population is expected to increase from 6.8 billion in 2008 to 8.3 billion by the 2030, and to 9.2 billion by 2050 (FAO 2009; UNEP, 2009). Current food production should increase by 70 to 100% by 2050 in order to feed the world population (FAO 2009; World Bank 2008). However, expansion and intensification of agriculture and food production put significant pressure on the environment and society (Black et al. 2011; Yakovleva 2007). Land degradation and deforestation, depletion of natural resources such as water and soil and pollution are threatening the integrity of the natural system and the delivery of ecosystem services worldwide (Butchart et al. 2010). Health problems resulting from potentially indiscriminate use of agro-chemicals, the deterioration of labor conditions, especially in tropical countries and, the migration and marginalization of rural communities cause social impacts (Koning and Robbins 2005). Scholars, planners, producers, policy-makers, and other stakeholders have pointed out the need for a global strategy to examine ways to ensure sustainable food production (Donald 2008; Kissinger 2012; Lewandowski and Faaij 2006). This would require changes on all parts of the agri-food supply chain, that is, from input supply chains to agricultural production, processing, packaging and distribution (Donald 2008; Charles et al. 2010).

The concept of sustainability

Sustainable development was placed on the international agenda of national and supra-national governments by the Brundtland Commission Report (World Commission on Environment and Development, 1987) (Daly 1990; Clift 2003), who defined it as the ''development that meets the needs of the present without compromising the ability of future generations to meet their needs'' (WCED 1987). This human-centered definition of sustainable development is in line with Judeo-Christian religious philosophy in which humans are separated from nature and have dominion over it (Jepson 2004).

Although the Brundtland definition is one of the most cited definitions, the concept still lacks a single and internationally accepted interpretation (Dietz and Neumayer 2007).

A diverse set of definitions of sustainable development has developed over time (e.g. Hart 1995; Elkington 1999; Pearce et al. 1988; Repetto 1985; Solow, 1986). Most of the definitions agree upon three pillars of sustainable development: (1) economic, (2) social, and (3) environmental (Málovics et al. 2008). A comprehensive sustainability assessment should therefore be based on these three dimensions of sustainability (Böhringer and Jochem 2007).

In recent years, economists have made progress to operationalize the concept of sustainable development relying on the capital theory approach (Atkinson 2008; Stern 1997). Under this approach, capital is comprised of three main types, each of those representing one of the three dimensions of sustainability. (1) natural capital which includes renewable and non-renewable natural resources, (2) human capital which is constituted by the stock of education, skills, culture, and knowledges, and (3) man-made capital which comprises buildings, tools, and other physical assets, thus, all produced goods (Ruta and Hamilton 2007). The question whether the three different types of capital can be substituted by one another is the central point of two diverging views on sustainable development, i.e. the weak sustainability and the strong sustainability (Stern 1997). Weak sustainability, on the one hand, assumes that the elasticity of substitution between the three types of capital is one, implying that man-made capital can replace any component of the natural capital and social capital (Stern 1997). For example the rents from the depletion of natural resources can be re-invested in manufactured capital (Hartwick 1977). Under this perspective, development can be considered to be sustainable if it ensures a non-decreasing total capital stock (the sum of all three types of capital) (Pearce and Atkinson 1993). The strong sustainability perspective is less permissive (Málovics et al. 2008). This perspective states that natural capital can only to a certain degree be substituted by man-made capital. This is the case when substitution of the natural capital stock by man-made capital involves irreversible losses, e.g. the species extinction (Hussen 2000). Equally, it states that there are 'critical' components of natural capital that provide irreplaceable life-support functions for humans as well for the resilience of ecological systems and thus, cannot be substituted (Barbier et al. 1994; Ekins et al. 2003; van der Bergh 2007). Those forms of critical natural capital include water, genetic materials, stratospheric ozone layer and conservation of landscapes for other human welfare values (aesthetic, spiritual, etc.) (Ekins et al. 2003). Under the strong sustainability perspective, development can be considered to be sustainable if it ensures that each individual stock of capital is maintained over time (Costanza and Daly 1992).

At the agri-food supply chain level, sustainability can be drawn similar to the reasoning above (Figge and Hahn 2004). Contributions to sustainability can be judged according to the economic, environmental, and social performance of the agri-food supply chain taking into account the interconnectedness of different stages along the chain. Based on the strong sustainability perspective, the agri-food supply chain would be considered to be performing sustainably only if a minimum performance at each stage of the chain and on each dimension of sustainability is achieved (Figge and Hahn 2004). On the other hand, following a weak sustainability view, an agri-food supply chain would be considered to be performing sustainably if a good accumulated performance (i.e. the sum of the economic, environmental and social performance) is achieved at the end of the chain. This implies that a good performance in any stage of the chain can compensate a low performance in another stage, e.g. good accumulated performance in the processing stage can compensate low performance in agricultural production. Equally, this entails that good performance in relation to a given dimension of sustainability can compensate a decrease in performance in another dimension at any or the same stage of the chain, e.g. good economic performance at the processing stage can compensate the environmental deterioration at the agricultural stage. This brings full flexibility in the tradeoffs and perfect substitution between the three dimensions of sustainability and between the performance within the stages along the agri-food supply chain. In a weak sustainability view, assessing the performance of an agri-food supply chain requires aggregating the performance of each stage and each dimension of sustainability into a common metric.

Problem statement

To support the development of sustainable agri-food supply chains, it is essential to increase the knowledge of the economic, environmental and social performance of the various stages along the chains (Kissinger 2012). In recent years, the debate has centered on how chains (or firms) can be monitored and assessed in terms of their sustainability performance (Atkinson 2000). Sustainability assessments have followed an absolute approach and a relative approach (Málovics et al. 2008). The difference between the two approaches depends on deciding the point of reference from which to determine whether the performance of a chain can be considered sustainable (Faber et al. 2005). Using an absolute approach, chains (firms) are expected to be assessed against an idealized end state, which implies that it is known what sustainability means in order to discriminate between what is and what is not sustainable (Faber et al. 2005). Nevertheless, given that our knowledge is limited with regard to the extent to which substitution between the different types of capital is possible (it depends on hardly controllable ecological threshold and, social contexts that determine the degree of substitutability between the three types of capital), this approach, which is closer to the strong sustainability perspective, has a limited applicability (Callens and Tyteca 1999). Due to these limitations, in this dissertation a different approach is used, that is, measuring sustainability performance in relative terms from a weak sustainability perspective. The sustainability performance of chains can be assessed by comparing similar chains (firms) that are placed in similar contexts in terms of their performance (Callens and Tyteca 1999). This assessment can result in the formulation of adequate corrective action, regulations, and incentives that can contribute to sustainability (Callens and Tyteca 1999; Faber et al. 2005).

Implementation of this approach requires the use of a sustainability framework and the use of performance indicators that provide synthetized information about the extent to which food products are sustainably produced (Meul et al. 2008; Van Passel et al. 2007), taking into account the multi-dimensional nature of sustainability and the interconnectedness of the stages along the chains. A growing number of frameworks and indicators to measure sustainability have been developed, e.g. Global Report Initiative, International Organization for Standardization ISO 14031, World Business Council for Sustainable Development (WBCSD), and Centre for Waste Reduction Technologies (CWRT) (Veleva and Ellenbecker 2001). Given that these frameworks generally comprise a particular number of performance indicators that cover each of the three dimensions of sustainability, the use of these frameworks for an integrated sustainability assessment continues to present operational problems (Gómez-Limón and Sanchez-Fernandez 2010). The greatest difficulty involves combining the indicators that are used to evaluate the performance on the three dimensions of sustainability into a single integrated sustainability measure that is convenient for communicating synthetized information to decision makers, producers and consumers (OECD 2002). For example, to answer the question of whether a chain (firm) is contributing more/less to sustainability than another chain (firm) requires making complicated tradeoffs between sustainability issues with different dimensions such as kilograms of CO_2 emissions and hours of child labor. Such tradeoffs, however, are normally not in the mind sets of people (Gómez-Limón and Sanchez-Fernandez 2010). To solve this limitation, composite indicators/indexes of sustainability that combine performance indicators of the different dimensions of sustainability into a single integrated measure of sustainability have gained acceptance (OECD 2002; Singh et al. 2012). However, so far these composite indicators/indexes have three main limitations: (1) the aggregation of performance indicators is in most cases based on subjective assessments, introducing an undesirable subjectivity (e.g. Composite sustainable development index, Compass Index of Sustainability (CIS), Sustainability Performance Index (SPI), Composite Sustainability Performance Index, Dow Jones sustainability group indices (DJSGI), Bovespa Corporate Sustainability Index). (2) when aggregation is undertaken following an objective approach, some composite indicators/indexes fail to incorporate social implications of production (e.g. Eco-points, COMPLIMENT - environment performance index for industries, Eco-compass, ecological footprint and eco-efficiency indices). (3) finally, regardless of the large number of available composite indicators/indexes for companies, there is no formal framework for benchmarking the sustainability of agri-food supply chains (Yakovleva et al. 2011). Thus, although several composite indicators/indexes have been proposed, they have limited usefulness for policy makers in supporting decisions about the implementation of policies and strategies that enhance sustainability of agri-food supply chains. Providing valuable information can help producers in identifying areas of intervention and sustainability improvement, based on reduced economic, environmental and social impacts (Andrews and Carroll 2001, Gómez-Limón and Sanchez-Fernandez 2010).

Objective

The overall objective of this thesis is to perform integrated assessments of relative sustainability performance of (stages of) agri-food supply chains.

The general objective of this thesis is met by addressing the following specific objectives:

1. To develop a framework for the integrated analysis of the relative sustainability performance of agri-food supply chains.
2. To assess the relative sustainability performance of the Brazilian non-genetically modified (non-GM) and genetically modified (GM) soybean meal chains.
3. To assess the relative sustainability performance of specialized potato farms in the Netherlands and Germany.
4. To assess the relative sustainability performance of coffee farms in Vietnam and, to evaluate the impact of socio-economic characteristics and management practices on relative sustainability.

Outline of the thesis

This thesis is divided into six chapters. A general introduction (**Chapter 1**), four research chapters that elaborate on the aforementioned specific objectives (**Chapter 2-5**) and a general discussion (**Chapter 6**). The structure of the dissertation is presented in Figure 1.1.

Chapter 2 develops a framework based on the micro-economic theory of production as the basis to measure the relative sustainability performance of agri-food supply chains. The framework includes the definition and characterization of an agri-food supply chain in terms of outputs, inputs and externalities (which reflect the sustainability issues) and, an approach to operationalize sustainability in relative terms. Depending on the aggregation method used to combine outputs, inputs and externalities, two integrated indicators to measure relative sustainability were proposed, i.e. the Social Profit (or Adjusted Profit) indicator and the Technical Inefficiency indicator. The Social Profit indicator uses prices to aggregate variables whereas the Technical Inefficiency indicator uses distance functions (Figure 1.1). Even though the operationalization of sustainability is further developed throughout the subsequent chapters, this theoretical framework forms the conceptual basis for the remainder of this thesis.

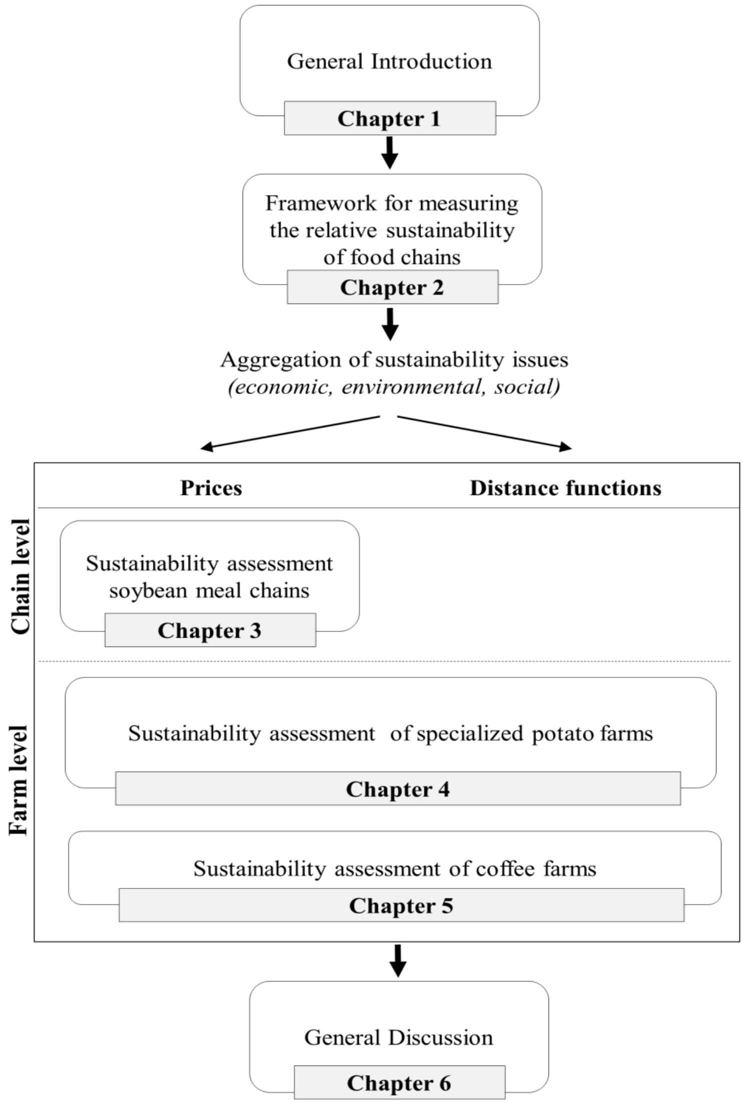

Figure 1.1 Structure of the dissertation

Chapter 3 assesses the relative sustainability performance of the Brazilian non-GM and GM soybean meal production chains using the Social Profit (or Adjusted Profit) indicator. Based on the outcomes and on the sources of variation along these two chains, potential areas on which the sustainability performance of each chain can be improved are determined.

Chapter 4 assesses the relative economic and environmental performance of specialized potato farms in the Netherlands and Germany using two integrated indicators, i.e. Social Profit and Technical Inefficiency. Based on the outcome of the two indicators, potential areas for performance improvement are identified. In addition, the advantages and limitations of each indicator in terms of their usefulness to measure the economic and environmental performance of farm systems are discussed.

Chapter 5 assesses the relative sustainability performance of coffee farms in Vietnam by using an alternative distance-function based indicator, the Nerlovian Social Profit Inefficiency indicator. Even though this indicator uses prices for each output, input and externality, the aggregation is implicitly undertaken using distance functions. Also, this Chapter analyses the impact of a series of external factors that influence on the estimated relative sustainability performance. Based on the outcomes potential areas where the relative sustainability performance of coffee farms can be improved are identified.

Chapter 6 discusses the overall results of the four research chapters in a wider context. The discussion includes critical reflections with regard to the methodologies, data issues and policy and business implications. Finally, the chapter provides the overall conclusions and gives insights into directions for future research.

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CHAPTER 2

Total Factor Productivity: A framework for measuring agri-food supply chain performance towards sustainability

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Abstract

Sustainable agricultural commodities should be favoured in international trade negotiations to meet the growing demand for food in a context of environmental conservation, population growth and globalization. There is a need for a metric that allows for the differentiation of traded agricultural commodities according to how sustainably they were produced. In this context, this paper develops two single metrics based on a Total Factor Productivity indexing approach, for benchmarking products in terms of their sustainability performance. Both metrics are adjusted to internalize the social and environmental externalities of food production, and to account for the sustainability effects of stages along agri-food supply chains. Key aspects, such as data availability, the selection of variables, and the selection of sustainability standards and targets, are discussed.

Keywords: Total Factor Productivity; sustainability performance; agri-food supply chain; externalities.

Introduction

Over the last decades, scholars, planners, producers, policy-makers, and other stakeholders have pointed out the need of finding possible pathways and developments for sustainable food production (Donald 2008). This challenge requires changes in the way food is produced in line with the increasing societal concerns and growing awareness over the social, environmental and food safety/health costs associated with the processes of food production (Ilbery and Maye 2004). Changes should go beyond agricultural production to include the rest of the agri-food supply chain, that is, from agricultural production to processing, packaging, distribution and consumption (Donald 2008; Charles et al. 2010). Therefore, actors throughout the chain can potentially play an important role in promoting sustainability (Sundqvist et al. 2005). In this context, the whole agri-food supply chain provides a suitable framework from which to examine and improve sustainability in food production (Cobb et al. 1999).

Agri-food supply chains account for a significant share of production and consumption, and have significant effects on economic growth, social welfare, development and the natural system (Yakovleva 2007). Because of the world's increasing population, food production is projected to increase to meet the growing demand for food (FAO 2003). This will entail putting significant pressure on land, marine and water resources, as well as society and the economy (Black et al. 2011; Yakovleva 2007). Consequently, the environmental and socio-economic costs associated with the externalities of the intensification of food production are also increasing dramatically (Jackson et al. 2007). Pollution of soil and water has been augmented, biodiversity in agricultural systems and the surrounding ecosystems has been reduced, natural resources have been overexploited (Butchart et al. 2010; Dirzo and Raven 2003), impacts on human health have increased, and ethical issues have arisen (Yakovleva 2007). For this reason, concerns have been raised about whether production is consistent with sustainability (Ilbery and Maye 2004). This has pushed agricultural food production onto the national and international political and research agenda, with the aim of improving the efficiency and sustainability of product lifecycles from cradle to grave (Dorward 2013). Clear attempts at increasing sustainability include the introduction of certification schemes, encouraging the implementation of better production practices, and highlighting the economic, environmental and social impacts of the product (Lines 2005; Sundkvist et al. 2005).

However, the proliferation of certification schemes, and the lack of international accepted standards, have reduced transparency and increased confusion among both producers and consumers (Gerbens-Leenes et al. 2003). Different certification schemes are used for different feed stocks, criteria, and regions (Sawyer et al. 2008) and some of them are in competition with each other. At the most basic level, the multiplicity of certification schemes is costly for producers and poses a barrier for international trade (Lines 2005; Sawyer et al. 2008). Meeting certification standards requires an investment on the part of producers, especially in developing countries (Lines 2005). Given the compliance cost of the majority of standards, producers will only aim to meet the standards if there is an expectation of value (Lines 2005). This value may entail access to a market, or implementing a price premium that would incentive producers to engage in sustainable production (Edwards and Laurance 2012).

On the other hand, importers face a problem in terms of generating credibility regarding to the sustainability of the product (Sundkvist et al. 2005). Some schemes certify against prescriptive standards, and thus are not often based on evidence of reduced social and environmental impacts resulting from certified commodity production (Lines 2005). As a consequence, there are increasing concerns about the sustainability of certified production, which increases the insecurity consumers feel towards imported agricultural commodities (Sundkvist et al. 2005). All these issues constitute a major obstacle in international trade negotiations on sustainability issues (Lines 2005). Given that importers of agricultural commodities meet a significant portion of food demand in many nations (Hooker 1999; Kissinger 2012), it is clear that there is a need for a scientifically validated accepted metric to provide reliable and well-synthetized information about the extent to which agricultural commodities are sustainably produced. Although significant efforts to create such a metric have been made, including Ecological Footprint, Material Input Per Service Unit (MIPS), Dow Jones Sustainability Group Indices (DJSGI), Bovespa Corporate Sustainability Index, Life Cycle Index, Eco-Points, Eco-compass, and Environment Performance Index for Industries (Singh et al. 2009; van Passel et al. 2007), some of these metrics have failed to meet scientific criteria (Böhringer and Jochem 2007), and only a few have embraced an integrated approach including the environmental, economic and social dimensions of sustainability from a supply-chain perspective (Singh et al. 2009; van Passel et al. 2007). There is still a need to look at the interconnectedness of different stages along the agri-food supply chain, and the measures which integrate the multi-dimensional nature of sustainability (Boons et al. 2012; Sloan 2010; Yakovleva et al. 2011).

The objective of this paper is to develop an overarching single metric to enable the comparison of the sustainability performance of agri-food supply chains by applying a Total Factor Productivity (TFP) approach. The concept of TFP has been previously used in green growth accounting as an attempt to address sustainability, by considering the use of the environment as a source of growth (Barnett et al. 1994; Tzouvelekas et al. 2007). Two main advantages exist with respect to making use of the TFP approach. First, TFP acknowledges the fact that an agri-food supply chain is primarily a system of production, which is intimately connected to the ecological integrity of the natural capital. Second, TFP measures can be adjusted to internalize social and environmental externalities of agricultural commodity production, such as biodiversity loss, carbon sequestration and emission of pollutants (Mulder 2003), and thus can be related to some measure of overall welfare. To achieve our objective, we start by outlining a methodological framework that defines an agri-food supply chain in terms of output-input variables (including externalities of production), and introduces TFP as an approach for benchmarking of agricultural commodities in terms of its sustainability performance. Afterwards, we introduce two TFP indicators: a price-related productivity measure – the Bennet TFP indicator – and a distance-function-based productivity measure – the Luenberger indicator – which are adjusted to account for the interconnectedness of stages along agri-food supply chains and for the externalities of production. Potential implementation of the Bennet TFP indicator is illustrated through a case study and, implementation of the distance-function-based indicator is illustrated using a numerical example. In the final Section, key aspects of the implementation of both TFP indicators are analysed, including data requirements, selection of variables and indicators, economic valuation of sustainability-related outputs and inputs, and selection of targets and thresholds for production of externalities.

Implementation of the TFP indicators will allow us to differentiate sustainable agricultural commodity production at different locations and in a variety of socio-economic contexts. Thus, this can serve as the basis on which to protect sustainable food production from competition with unsustainable food. Objective information about the extent to which agricultural commodities are sustainably produced can improve the international flow of sustainable agricultural commodities to which the international market remains closed due to costly environmental, social and food safety requirements (Lines 2005), thus ensuring that preferential market access for sustainable commodities are put in place.

Supply chain sustainability performance

Methodological Framework

Two main types of agri-food supply chains can be distinguished: food supply chains for fresh products (such as vegetables, flowers and fruits), and food supply chains for processed food products (including canned food products, dessert products, chilled products, frozen products, etc.) (Aramyan et al. 2006). These chains consist of a finite set of stages such as farming, wholesaling, importing and retailing, which are connected to produce finished outputs to be delivered to the end consumer in an integrated input–output system (Sloan 2010; Zhu 2003). Consider an agri-food supply chain or Decision Making Unit (DMU_k) *k = 1,...,K*, which consists of stages *z = 1,...,Z* (Figure 2.1). Each stage *z* transforms multiple inputs (exogenous inputs) such as capital, labor and materials, into multiple outputs to produce economic goods and services. The exogenous inputs used at each stage are denoted by the vector $x_k^z = (x_{k1}^z, x_{k2}^z, \dots x_{kN}^Z) \in \Re_+^{N^z}$, where $N_k = N^1 + N^2 + \cdots N^Z$, can be written as $x_k = (x_k^1, x_k^2, \dots, x_k^Z)$.

Furthermore, each stage *z* produces good outputs that can be intermediate or final. In many cases, a portion of the outputs from one stage may be reprocessed at another stage to get a more "pure" form of the product. The intermediate outputs can be denoted, so that those produced by stage *z* and delivered to node *i*, *i = 1,...,Z,* by $v_k^{zi} = \left(v_{k1}^{zi}, v_{k2}^{zi}, \dots, v_{kU}^{zi}\right) \in \Re_+^{U^z}$, where total intermediate outputs $U_k = U^1 + U^2 + \cdots U^Z$, can be shown as a $Z * Z$ matrix v_k. For example, returning to Figure 2.1, the total intermediate outputs produced by stage 1 consist of two elements, v_k^{12} and v_k^{1Z}, where the former is the intermediate output used as the input in stage 2, and the latter is the intermediate output used as the input in stage *Z*. The final output production of stage *Z*, and hence those that are in "finished" form and reach the consumer market, is denoted by $y_k^z = (y_{k1}^z, y_{k2}^z, \dots y_{kM}^Z) \in \Re_+^{M^Z}$, where total final output $M_k = M^1 + M^2 + \cdots M^Z$, is denoted by $y_k = (y_k^1, y_k^2, \dots, y_k^Z)$.

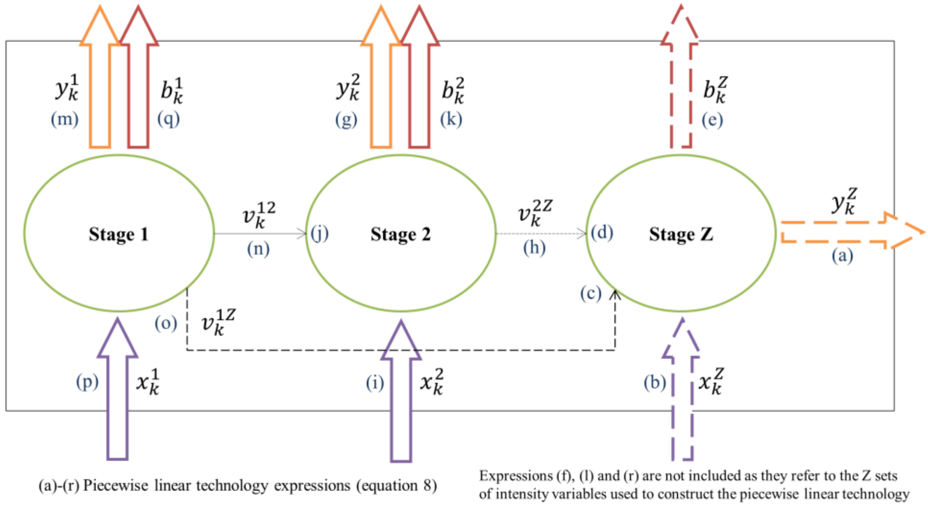

Figure 2.1 Generic schematic representation of an agri-food supply chain.

On the other hand, each stage z produces undesirable factors. These are normally referred to in the literature as bad outputs, and are a set of negative environmental and social externalities that have implications for social welfare. Examples of such externalities are soil erosion, noise, water pollution, air pollution, damage to human health, work dissatisfaction, etc. The production of bad outputs at each stage z is denoted by a vector $b_k^z = \left(b_{k1}^z, b_{k2}^z, \dots b_{kJ}^z\right) \in \Re_+^{J^Z}$, where the overall production of bad outputs $J_k = J^1 + J^2 + \cdots, J^Z$ can be written as $b_k = (b_k^1, b_k^2, \dots, b_k^Z)$.

It should be noted that the methodological framework presented is generic in nature and could be modified so as to include different agri-food supply chain structures (multiple connections between stages) or recycling processes, where some of the final outputs, as well as some of the bad outputs (such as solid waste), can be collected to be reused within the same stage or as part of a different process.

Agri-food supply chain sustainability performance

In line with the framework presented above, an agri-food supply chain likely will perform sustainably if it (i) produces products (good outputs) that generate competitive returns on its capital assets, (ii) produces the lowest possible quantity of negative externalities or bad outputs; taking into account that a zero level of externalities would not be realistic (van der Bergh 2010) and, (iii) uses, as far as possible, a set of inputs that are considered most sustainable. A stage in the agri-food supply chain may make use of an input for which a variety of categories might apply. For example, different sources of energy, such as those derived from natural sources (sun, wind, water, etc.) and from non-renewable energy such as fossil fuels, coal, natural gas and oil, could be used; slaves, children, low-paid workers, or high-quality labor could be employed; land with the existence of legal property rights or illegal tenancy could be exploited; either organic or synthesized fertilizers and pesticides might be used for farming; etc. Thus, agri-food supply chains that substitute undesirable or unsustainable inputs for those perceived to be more sustainable should be considered to be performing more sustainable, since a lower impact (lower quantity of externalities) will be imposed on the environment, society and the economy.

Nevertheless, it should be noted that the use of some inputs might have contradictory influences, depending on the aspects of sustainability and the scale on which it is considered (Callens and Tyteca 1999). For example, energy derived from fossil fuels is generally encouraged to be minimized from an environmental point of view, but if it is the least expensive source of energy it is preferable to maximize its usage from a private economic perspective (Callens and Tyteca 1999). With regard to the spatial scale, the meaning of a sustainable and unsustainable input may vary for individual groups of stakeholders depending on the socio-economic and environmental characteristics of a particular place. For example, the use of child labor is inconceivable in most situations and countries, but it could be argued that in some farming areas it is required for the subsistence of the household, and is a way of transmitting traditional knowledge through generations, so as to maintain the cultural heritage of rural populations. Thus, the boundaries and sustainability goals for the agri-food supply chains under consideration must be defined, and the sustainability goals for the society in question specified.

Total Factor Productivity as a measure of agri-food supply chain sustainability performance

We use a TFP approach for sustainability performance measurement of agri-food supply chains. The general idea behind TFP is to reflect a measure of output per unit of input. The economics literature distinguishes indexes of productivity from indicators of productivity (Diewert 2005). Productivity measures that make use of differences are classified as indicators, whereas measures that make use of ratios are considered as indexes (Diewert 2005). Productivity indicators have an advantage over productivity indexes in that indicators are more general in structure and computationally more convenient when it comes to accounting for the production of good and bad output variables. More importantly, if we wish to additively aggregate the TFP (productivity scores) for each of the stages along the agri-food supply chain, the productivity measures should have an additive, rather than a ratio, form (Färe and Grosskopf 2005).

With respect to a *DMU k*, wherein each comprises *z = 1,...,Z* stages at a certain time period *t*, TFP is defined as the difference between all aggregated good and bad outputs, and all aggregated inputs:

$$TFP_k^t = Q_0(y_k^t, v_k^t, b_k^t) - Q_v(x_k^t, v_k^t), \tag{2.1}$$

The aggregator functions for good and bad outputs and inputs are denoted by $Q_0()$ and $Q_v()$, respectively. The TFP score will reveal the productivity of the *DMU k*, where productivity is taken as performing sustainably or performing unsustainably, as a means to transform inputs throughout the stages into final outputs. The bad outputs are penalties that lower the TFP score. Note the fact, however, that in this framework higher productivity, i.e. higher TFP, is viewed as a necessary, but not sufficient criterion, for a system to be considered as performing relatively sustainable. This means that an agri-food supply chain should comply with a second criterion: a non-decreasing TFP over time (Barnett et al. 1994).

$$TFP_k^{t+1} \geq TFP_k^t, \tag{2.2}$$

Additionally, we might want to compare analogous agri-food supply chains with different sets of outputs, bad outputs and inputs to detect whether some behave in a more appropriate way than others, based on established sustainability goals. We can assess and rank agri-food supply chains in terms of best-worst TFP scores; thereby providing a relative measure of sustainability performance that can be useful to differentiate agricultural commodity production. In this context, for example, the TFP score of DMU_1 in a period t compared with the TFP score of DMU_2 in the same period is estimated as:

$$\widehat{TFP}_{1,2}^{t} = TFP_2^t - TFP_1^t, \tag{2.3}$$

If the TFP score of DMU_2 is greater than that of DMU_1, the consolidated production technology of DMU_2 could be superior to that of DMU_1, its production process may be considered more efficient than that of DMU_1 and/or a lower level of externalities might be produced; thus, DMU_2 would be considered to be performing more sustainably than DMU_1, under the assumption that the negative social and environmental externalities are included as bad outputs.

To enable a consistent comparison approach between the TFP of a chain in two different time periods, expression (2.2), or between analogous chains with different sets of good outputs, bad outputs and inputs, expression (2.3), indexing methodologies, in this case indicators of productivity, are used. The indicators of productivity vary depending on the approach that is used for the aggregation of good outputs, bad outputs and inputs. One approach uses price information as weights, known as the Bennet TFP indicator. An alternative approach uses distance functions that aggregate the different variables based on the technology set and the information of the quantities of good outputs, bad outputs and inputs (Chung et al. 1997), known as the Luenberger indicator (Chambers 1996). Therefore, we focus our discussion on both the price-related indicator – the Bennet TFP indicator – and its counterpart, which is distance-function-based – the Luenberger indicator. A classical pathway to compute both indicators would be to estimate the sustainability performance of an agri-food supply chain without taking into account its internal structure. This would require treating the agri-food supply chain as a "black box," where only the exogenous inputs and the final good and bad outputs consumed and produced at each stage of the chain are considered (Castelli et al. 2010; Chen and Yan 2011). Consequently, all intermediate outputs/inputs would be ignored in the analysis. Although this approach could provide useful information, treating an agri-food supply chain as a "black box" will mean a failure to incorporate the links that exist between stages along the chain, and thus an inability to extract clear evidence of the transformations that the inputs are subject to within the considered stages (Castelli et al. 2010). For example, the chain's overall sustainability performance might be positive even though some stages have large inefficiencies that are compensated by another stage (or stages) (Castelli et al. 2010), thus overrating the real performance of the agri-food supply chain. Consequently, both productivity indicators are developed in such a way that access to the internal structure is feasible.

Bennet Total Factor Productivity (TFP) indicator

The adjusted profit (*AP*) of a *DMU k* in period *t* is defined as the difference between the value of the aggregated final good outputs minus the aggregated inputs and bad outputs:

$$AP_k = p_k{}'y_k - w_k{}'x_k - r_k{}'b_k, \tag{2.4}$$

where *p, r* and *w,* are vectors of (shadow) prices of outputs, inputs and bad outputs that are used to aggregate the different variables (prime indicating the transpose of the vector). The difference in the *AP* between two analogous DMUs can be decomposed into two additive components using the Bennet price and the Bennet quantity indicators: (1) a price component, known as the Total Price Recovery (TPR), which provides the differences in *AP* due to price changes (Miller et al. 1989), and (2) a quantity component, known as the TFP component. Leaving out the TPR component of the *AP* difference, the TFP component provides our measure of relative sustainability performance.

We first compute the TFP component of the partial *AP* difference of a stage *Z* of DMU_2 with the same stage *Z* of DMU_1. In this case the Bennet TFP indicator is defined as:

$$BB_{1,2}^{t,z} = \left[\frac{1}{2}(p'^{Z}_{2} + p'^{Z}_{1})(y^{Z}_{2} - y^{Z}_{1}) - \frac{1}{2}\left(w'^{Z}_{2} + w'^{Z}_{1}\right)(x^{Z}_{2} - x^{Z}_{1}) - \frac{1}{2}\left(r'^{Z}_{2} + r'^{Z}_{1}\right)(b^{Z}_{2} - b^{Z}_{1})\right] \tag{2.5}$$

The Bennet TFP indicator is a price-weighted arithmetic mean of the difference in good outputs, bad outputs and inputs quantities of stage *Z* of DMU_2 relative to stage *Z* of DMU_1 expressed in monetary terms. A positive outcome of the Bennet TFP indicator will indicate that the stage *Z* of DMU_2 performs more sustainably than the stage *Z* of DMU_1. The partial TFP difference can be decomposed into output-specific, input-specific and bad output-specific quantity differences, which allows a variance analysis that provides guidance to determine the sources where the TFP between the stage *Z* of the two chains varies; hence, shedding light on areas for potential sustainability performance improvement.

Due to the additive structure of the Bennet TFP indicator, consolidation of the TFP differences at each stage between the DMUs is very straightforward; the overall TFP difference can be derived simply via the addition of partial TFP scores. Thus, the Bennet TFP indicator reflecting the overall TFP difference between DMU_2 relative to DMU_1 is defined as[1]:

$$\begin{aligned} BB_{1,2}^{t} = \Bigg[&\frac{1}{2}(p'_2 + p'_1)(y_2 - y_1) + \frac{1}{2}(l'_2 + l'_1)\left(\sum_{i=1}^{Z} v_2^{zi} - \sum_{i=1}^{Z} v_1^{zi}\right) \\ &- \frac{1}{2}(w'_2 + w'_1)(x_2 - x_1) - \frac{1}{2}(r'_2 + r'_1)(b_2 - b_1) \\ &- \frac{1}{2}(l'_2 + l'_1)\left(\sum_{i=1}^{Z} v_2^{zi} - \sum_{i=1}^{Z} v_1^{zi}\right)\Bigg] \end{aligned} \tag{2.6}$$

[1] Note that the Bennet indicator can be also used to assess the sustainable performance of an agri-food supply chain between two time periods. Hence, it can be used to assess the second sustainability criterion: non-decreasing TFP over time.

where the vectors l_1 and $l_2 \in \Re_+^U$ are intermediate output prices used to aggregate intermediate output quantities $\sum_{i=1}^{Z} v_1^{zi}$ and $\sum_{i=1}^{Z} v_2^{zi}$ of DMU_1 and DMU_2 respectively. Note that when we aggregate a positive number (such as the intermediate output of a stage z) and a negative number (such as the intermediate output the stage z used as an input in another stage), (1) both are cancelled when they are totalled across all stages, (2) only the final outputs are shown to have positive numbers, and (3) all intermediate outputs cancel out to zero and only exogenous inputs, such as land, labor, and basic raw materials will have negative numbers. By accounting for the interconnections along an agri-food supply chain, and internalizing the social and environmental externalities of food supply chain production, computation of the Bennet TFP indicator reveals the relative sustainability performance of an agri-food supply chain reflected in the form of price signals. Thus, productivity is related to some measure of overall welfare. The DMU_2 will have higher TFP (higher sustainability performance) than DMU_1 if the difference between the production of outputs and the aggregated inputs and bad outputs is larger than the difference in DMU_1. On the contrary, a lower TFP will indicate that the DMU_2 has higher consumption of inputs and production of bad outputs that are not compensated by a higher final good output production and other beneficial social and environmental outputs (Harrington et al. 1994).

Bearing in mind that the outcome of the Bennet indicator only provides information about the relative sustainability performance of one agri-food supply chain against other chains, a hypothetical or benchmark chain representing the best practice in terms of good outputs, bad outputs and inputs within each stage can be developed. The hypothetical chain could include regional, national or/and international targets, with limits set with respect to the production of social and environmental externalities, maximum allowable usage of certain kind of inputs and, when possible, information on social and environmental thresholds. By comparing an agri-food supply chain *DMU k,* against the hypothetical one (used as benchmark), an outcome of the Bennet TFP indicator below zero would indicate that there is room for performance improvement, and, therefore, *DMU k* is not on a sustainable path. On the other hand, if *DMU k* outperforms the hypothetical one, this would indicate that *DMU k* performs well in terms of its sustainability performance.

Sustainability benchmarking of agri-food supply chains using the Bennet TFP indicator: An empirical illustration

To illustrate the usefulness of the Bennet TFP indicator, we draw on Gaitán-Cremaschi et al. (2015). Consider that there are two conventional soybean meal chains either using non-genetically modified (non-GM) seeds or genetically modified (GM) seeds. Each chain consists of two stages[2]. The agricultural stage *z = 1* and the processing and transport to port stage *z = 2*. At stage *z = 1,* five inputs $x_{k1}^{1}, \dots, x_{k5}^{1}$ are used to produce one intermediate output v_{k1}^{12}, i.e. soybeans. At stage *z = 2*, the soybeans that were produced at stage *z = 1* are processed into the final output, soybean meal y_{k1}^{2}. In this process, one input x_{k1}^{2} is used. The soybean meal is transported afterwards to the nearest port to be traded in the international market. Transportation at this stage requires a second input x_{k2}^{2}. The production of soybean meal generates three bad outputs: (1) environmental, farm-worker and consumer toxicity associated to pesticide use b_{k1}^{1}, (2) loss of employment b_{k2}^{1} and, (3) the emission of green-house gases that result from the combustion of fuel b_{k1}^{2}. Both soybean meal chains face their own observable prices for outputs, intermediate outputs/inputs and inputs. Shadow prices of the bad outputs were estimated using the benefit transfer method (see Gaitán-Cremaschi et al. 2015). By using this method, previously computed estimates found in existing studies were adjusted to the Brazilian context to derive the respective shadow prices. Based on the observed data, the quantities and (shadow) prices for the inputs, outputs and bad outputs representing the non-GM and GM soybean meal chains are presented in Table 2.1.

For the Bennet TFP computation using Eq. 2.6 results are illustrated in Figure 2.2.

Figure 2.2 shows that the non-GM soybean meal chain has a higher TFP score (higher sustainability performance) at *z = 1*, i.e. US $12.31, but a lower performance at *z = 2*, i.e. $6.41. Figure 2.2 also shows that the overall sustainability performance of the non-GM soybean meal chain exceeds the GM chain performance by $5.90. The main sources of the higher performance are related to a lower consumption of herbicides, insecticides, and fungicides which are reflected in a lower cost associated to pesticide toxicity.

[2] Note that in the study of Gaitán-Cremaschi et al. (2015) the non-GM and GM soybean meal chains are modelled up to the destination port (Rotterdam Port) and consist of four stages. For the complete and detailed study of the sustainability analysis of the soybean meal chain in Brazil see Gaitán-Cremaschi et al. (2015).

Table 2.1 Quantity and (shadow) price information for the output, input and bad output variables. Data was taken from Gaitán-Cremaschi et al. (2015).

		Non-GM soybean meal chain		GM soybean meal chain	
Stage (z = 1)	Quantity/Price	Quantity	Unit price	Quantity	Unit price
Inputs					
Seed	x_{k1}^{1}/w_{k1}^{1}	17.7	0.8	16.0	1.29
Fertilizers	x_{k2}^{1}/w_{k2}^{1}	68.4	0.6	68.2	0.56
Fungicides	x_{k3}^{1}/w_{k3}^{1}	0.3	46.0	0.3	46.74
Herbicides	x_{k4}^{1}/w_{k4}^{1}	1.0	15.1	1.5	6.46
Insecticides	x_{k5}^{1}/w_{k5}^{1}	0.2	27.2	0.3	33.54
Bad outputs					
Toxicity	b_{k1}^{1}/r_{k1}^{1}	35.1	0.3	50.9	0.26
Loss of employment	b_{k2}^{1}/r_{k2}^{1}	2.4	3.4	3.0	3.40
Stage (z = 2)					
Outputs					
Soybean meal	y_{k1}^{2}/p_{k1}^{2}	1.0	448.7	1.0	420.0
Inputs					
Hexane and electricity	x_{k1}^{2}/w_{k1}^{2}	1.0	58.5	1.0	59.2
Diesel	x_{k2}^{2}/w_{k2}^{2}	217.5	0.07	169.3	0.07
Bad outputs					
CO_2 emissions	b_{k2}^{2}/r_{k2}^{2}	668.1	0.02	520.3	0.02

Due to the fact that the intermediate output of *z = 1* is used as input at *z = 2*, when they are totalled across the chain both are cancelled out to zero. Thus they are not included in the computation.

Nevertheless, the non-GM chain has higher consumption of diesel to transport the product to the Brazilian port. This is reflected in a worse performance in terms of green-house gas emissions. Although the sustainability assessment focuses on the TFP component of the adjusted profit difference between chains, the TPR component of such difference may also provide useful information regarding the preference of consumers, and/or differences in the quality of inputs and outputs (see Gaitán-Cremaschi et al. 2015).

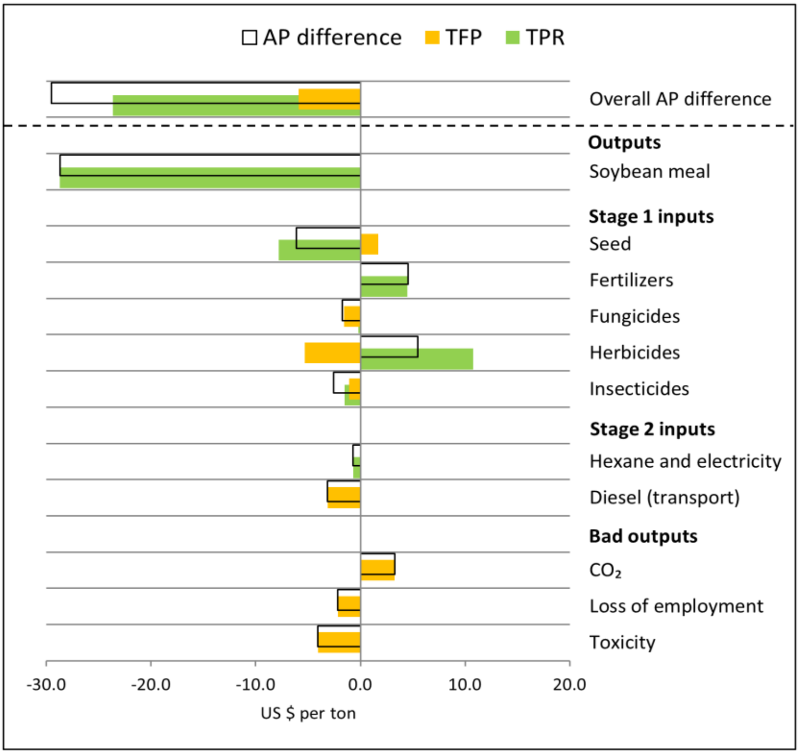

Figure 2.2 TFP and TPR components of the adjusted profit differences between the GM soybean meal chain relative to the non-GM chain in the form of price signals ($). TFP and TPR deviations are illustrated for each output, input and bad output at each chain stage. The higher the deviation of the TFP component, the more sustainable is performing the GM soybean meal chain compared to the GM chain.

Agri-food supply chain performance using a measure of directional distance functions

Consider the stages of the agri-food supply chain (*DMU*) described in Figure 2.1, and assume that there are $k = 1,...K$ analogous DMUs each with different observations for good outputs, bad outputs, exogenous inputs and intermediate outputs/inputs. The network production technology for the set of DMUs is defined as:

$$T = \{(x, y, v, b): x \text{ can produce } y \; and \; b \text{ via the intermidiate outputs } v\}, \tag{2.7}$$

where T consists of $z = 1,...,Z$ sub-technologies $T^1, T,...,T^Z$. As the basis for the sustainability performance measurement (in terms of economic, environmental and social performance), and following Färe and Grosskopf (2005), we impose the weak disposability and null-jointness properties. Weak disposability refers to the idea that a reduction of bad outputs is costly, and therefore states that a reduction in bad outputs is feasible only if good outputs are simultaneously reduced, given a fixed level of inputs. On the other hand, null-jointness states that the production of good outputs (final and intermediate) inevitably implies production of the bad outputs, and thus the only way to avoid producing any bad output is by producing zero good outputs (Färe and Grosskopf 2005). Substitutions might be allowed between some good outputs, bad outputs and inputs, without necessarily affecting the sustainability performance (for instance, substitution may be viable given some sort of technological change). To ensure that the assessment is in line with sustainability, targets for bad outputs, restrictions and substitutions for the use of certain kind of inputs (for example green energy vs. energy derived from fossil fuels) may be included in the construction of the network production frontier. These targets and maximum restrictions will safeguard the fact that the performance of an agri-food supply is consistent with securing a minimum essential level or quality for some components of the environment that can be rarely substituted, or non-substitutable, (such as water, biodiversity, etc.). For example, farming may have specific limits on emissions of specific undesirable outputs, or restrictions on the use of specific inputs such as fertilizers, pesticides, etc. This explicit information on regulatory rules and sustainability criteria can be included as explicit constraints in the model, rendering parts of the efficient boundary of the network production frontier no longer efficient (Figure 2.3). The frontier of the network production technology is considered the best-practice frontier, and can be regarded as an empirical standard of excellent sustainability performance. Thus, a *DMU k* is said to be technically efficient, and thus will be performing more sustainable than other DMUs, if it produces at the network production frontier.

Empirically, the network production frontier defined above can be estimated from good output, bad output and input data through Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA). Although SFA has the advantage that it takes into account measurement errors and random noise, the discussion will focus on DEA, as, compared to SFA, restrictions do not have to be a priori imposed on the functional form representing the technology (Hailu and Veeman 2001b). Furthermore, SFA cannot easily accommodate multiple outputs and inputs, and the regularity conditions such as monotonicity, convexity, and homogeneity of the technology frontier are often not satisfied (Fried et al. 2007). The DEA approach assumes that all relevant good outputs, bad outputs and inputs are observed for all the units of analysis, and thus all possible output-input vectors are contained in the data set (Fried et al. 2007).

Following Färe and Grosskopf (2000), the network production technology T (chain technology), illustrated in Figure 2.1, which consists of *z = 1,...,Z* stages, can be defined in terms of piecewise linear technology as:

$T = \{(x, y, v, b)$:

Stage Z

$$(a)\ y_m^Z \leq \sum_{k=1}^{K} \alpha_k^Z y_{km}^Z,\ \ m = 1, \dots, M^Z; \quad (b)\ \sum_{k=1}^{K} \alpha_k^Z x_{kn}^Z \leq x_n^Z,\ \ n = 1, \dots, N^Z;$$

$$(c)\ \sum_{k=1}^{K} \alpha_k^Z v_{ku}^{1Z} \leq v_u^{1Z},\ \ u = 1, \dots, U^1; \quad (d)\ \sum_{k=1}^{K} \alpha_k^Z v_{ku}^{2Z} \leq v_u^{2Z},\ \ u = 1, \dots, U^2;$$

$$(e)\ \sum_{k=1}^{K} \alpha_k^Z b_{kj}^Z = b_j^Z,\ \ j = 1,2, \dots, J^Z; \quad (f)\ \sum_{k=1}^{K} \alpha_k^Z \geq 0,\ \ k = 1,2, \dots, K;$$

...,

Stage 2

$$(g)\ y_m^2 \leq \sum_{k=1}^{K} \alpha_k^2 y_{km}^2,\ \ m = 1, \dots, M^2; \quad (h)\ v_u^{2Z} \leq \sum_{k=1}^{K} \alpha_k^2 v_{ku}^{2Z},\ \ u = 1, \dots, U^2;$$

$$(i)\ \sum_{k=1}^{K} \alpha_k^2 x_{kn}^2 \leq x_n^2,\ \ n = 1, \dots, N^2; \quad (j)\ \sum_{k=1}^{K} \alpha_k^2 v_{ku}^{12} \leq v_u^{12},\ \ u = 1, \dots, U^1;$$

$$(k)\ \sum_{k=1}^{K} \alpha_k^2 b_{kj}^2 = b_j^2,\ \ j = 1,2, \dots, J^2; \quad (l)\ \sum_{k=1}^{K} \alpha_k^2 \geq 0,\ \ k = 1,2, \dots, K;$$

Stage 1

$$(m)\ y_m^1 \leq \sum_{k=1}^{K} \alpha_k^1 y_{km}^1,\ \ m = 1, \dots, M^1; \quad (n)\ v_u^{12} \leq \sum_{k=1}^{K} \alpha_k^1 v_{ku}^{12},\ \ u = 1, \dots, U^1;$$

$$(o)\ v_u^{1Z} \leq \sum_{k=1}^{K} \alpha_k^1 v_{ku}^{1Z},\ \ u = 1, \dots, U^1; \qquad (p)\ \sum_{k=1}^{K} \alpha_k^1 x_{kn}^1 \leq x_n^1,\ \ n = 1, \dots, N^1;$$

$$(q)\ \sum_{k=1}^{K} \alpha_k^1 b_{kj}^1 = b_j^1,\quad j = 1,2, \dots, J^1; \qquad (r)\ \sum_{k=1}^{K} \alpha_k^1 \geq 0,\ \ k = 1,2, \dots, K\}$$

$$\begin{aligned} &x_{kn}^1 \leq \hat{x}_n^1;\ x_{kn}^2 \leq \hat{x}_n^2; \dots;\ x_{kn}^Z \leq \hat{x}_n^Z; \\ &b_{kj}^1 \leq \hat{b}_j^1;\ b_{kj}^2 \leq \hat{b}_j^2; \dots;\ b_{kj}^Z \leq \hat{b}_j^Z \end{aligned} \tag{2.8}$$

In the network model we can identify the $z = 1,...,Z$ stages with their corresponding sub-technologies. Each of the (a-r) expressions is linked to Figure 2.1. Stage 1, with a sub-technology T^1, consists of expressions (m)-(r). The second stage with a sub-technology T^2 is given by (g)-(l), and the Z stage with a sub-technology T^Z is represented by the expressions (a)-(f). The model has Z sets of non-negative intensity variables $(\alpha^1, \alpha^2, \dots, \alpha^Z)$ that are restricted to sum greater or equal to one, which implies a network technology that exhibits constant returns to scale. The additional constraints $\hat{b}_j^z$ and $\hat{x}_n^z$ refer to targets limiting the production of bad outputs and the use of certain kinds of inputs for each stage of the agri-food supply chain.

Having formalized the network production technology, we can reveal which among the set of agri-food supply chains are closest to, or farthest from, the frontier. In that sense, the next task is to determine how to evaluate the distance of the set of agri-food supply chains towards the frontier. We use the directional distance functions introduced by Chung et al. (1997), which make it possible to measure the distance to the frontier, while searching for the contraction of bad outputs simultaneously with the expansion of good outputs and the reduction of certain kinds of unsustainable inputs. Figure 2.3 represents this graphically; here, a target for bad output production and a maximum allowable usage of an unsustainable input are imposed (the dotted parts of the efficient boundary of the production frontier are no longer efficient). On the left side, the directional vector $(g_{y_m}, -g_{b_j})$ scales the output vector in the direction of expansion of the good output y_m and reduction in the bad output b_j – thus, from point A to point B on the production frontier. This means that *DMU k* produces an excessive amount of the bad output (its production is above the target $(\hat{b}_j)$ to produce its final output), and hence is not performing sustainably.

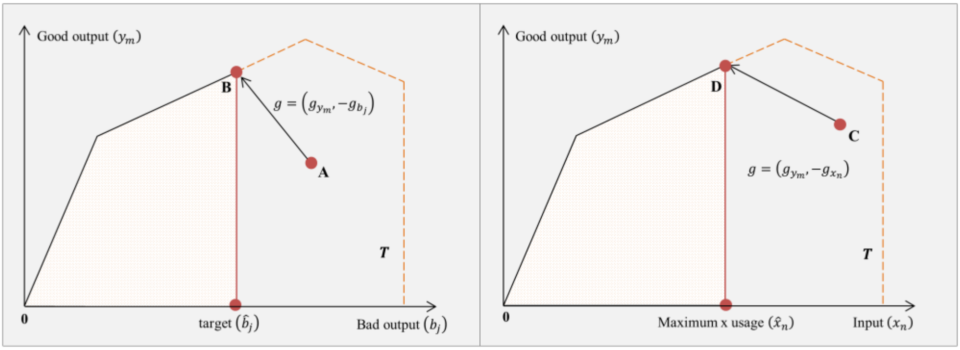

Figure 2.3 Directional distance functions with maximum and minimum restrictions in outputs and inputs.

Similarly, the right side of Figure 2.3 illustrates how the directional vector $\left(g_{y_m}, -g_{x_n}\right)$ projects *DMU k* from point C to point D on the frontier, thereby expanding the final output vector and reducing the input x_n to the maximum allowable quantity ($\hat{x}_n$). In this case, *DMU k* is not performing fully sustainable, as it uses too much of the exogenous input that is considered unsustainable to produce its final outputs. In both cases, the distance of *DMU k* from point A to B, and from point C to D, provides a measure of technical inefficiency that is taken as a relative measure of sustainability performance of the unit of analysis compared with the best performers.

Formally, the directional distance function defined on the network production technology *T* is defined as:

$$\vec{D}_T(x, y, v, b; g) = max\left\{\beta : \left(x - \beta g_{x_n}, y + \beta g_{y_m}, v + \beta g_{v_u}, b - \beta g_{b_j}\right) \in T\right\}, \quad (2.9)$$

where the directional vector $g_{y_m} \in \Re_+^M, \neq 0^M, g_{v_u} \in \Re_+^U, \neq 0^U, g_{x_n} \in \Re_+^N \neq 0^N$ and $g_{b_j} \in \Re_+^J, \neq 0^J$, which has to be chosen by the researcher, will determine the final, intermediate and bad output vector on the network frontier of *T* from which a *DMU* would be evaluated. Taking into account the fact that for some inputs and bad outputs maximum usage restrictions and targets, respectively, will not be available, the directional vector can also be used in such a way that societal preferences with regard to sustainability aspects are accounted for (Kuosmanen and Kortelainen 2004). This will allow the inclusion of trade-offs between economic, environmental and social aspects. For example if it is assumed that biodiversity loss is more important than acidification, the directional vector can be formulated in relative terms (Kuosmanen and Kortelainen 2004); biodiversity loss (b_1) considered at least twice as important as pressure on acidification (b_2). In this case, the directional vector would be defined as $(g_x, g_y, g_v, 2b_1, b_2)$.

The directional distance function defined on the network technology and computed using linear programming techniques is for $DMU_{k'}$ the solution for the maximization problem:

$$\vec{D}_T(x_{k'}, y_{k'}, v_{k'}, b_{k'}; g) = \max \beta$$

$$s.t.$$

Stage Z

$$y^Z_{k'm} + \beta g^Z_{y_m} \leq \sum_{k=1}^{K} \alpha^Z_k y^Z_{km}, \;\; m = 1, \ldots, M^Z, \;\; \sum_{k=1}^{K} \alpha^Z_k x^Z_{kn} \leq x^Z_{k'n} - \beta g^Z_{x_n}, \;\; n = 1, \ldots, N^Z;$$

$$\sum_{k=1}^{K} \alpha^Z_k v^{1Z}_{ku} \leq v^{1Z}_{k'u}, \;\; u = 1, \ldots, U^1; \qquad \sum_{k=1}^{K} \alpha^Z_k v^{2Z}_{ku} \leq v^{2Z}_{k'u}, \;\; u = 1, \ldots, U^2;$$

$$\sum_{k=1}^{K} \alpha^Z_k b^Z_{kj} = b^Z_{k'j} - \beta g^Z_{b_j}, \quad j = 1,2, \ldots, J^Z; \qquad \alpha^Z_k \geq 0, \;\; k = 1,2, \ldots, K;$$

…,

Stage 2

$$y^2_{k'm} + \beta g^2_{y_m} \leq \sum_{k=1}^{K} \alpha^2_k y^2_{km}, \;\; m = 1, \ldots, M^2; \;\; v^{2Z}_{k'u} + \beta g^{2Z}_{v_u} \leq \sum_{k=1}^{K} \alpha^2_k v^{2Z}_{ku}, \;\; u = 1, \ldots, U^2;$$

$$\sum_{k=1}^{K} \alpha^2_k x^2_{kn} \leq x^2_{k'n} - \beta g^2_{x_n}, \;\; n = 1, \ldots, N^2; \qquad \sum_{k=1}^{K} \alpha^2_k v^{12}_{ku} \leq v^{12}_{k'u}, \;\; u = 1, \ldots, U^1;$$

$$\sum_{k=1}^{K} \alpha^2_k b^2_{kj} = b^2_{k'j} - \beta g^2_{b_j}, \quad j = 1,2, \ldots, J^2; \qquad \alpha^2_k \geq 0, \;\; k = 1,2, \ldots, K;$$

Stage 1

$$y^1_{k'm} + \beta g^1_{y_m} \leq \sum_{k=1}^{K} \alpha^1_k y^1_{km}, \;\; m = 1, \ldots, M^1; \quad v^{12}_{k'u} + \beta g v^{12}_u \leq \sum_{k=1}^{K} \alpha^1_k v^{12}_{ku}, \;\; u = 1, \ldots, U^1;$$

$$v_{k'u}^{1Z} + \beta g_{u_v}^{1Z} \leq \sum_{k=1}^{K} \alpha_k^1 v_{ku}^{1Z}, \;\; u = 1, \dots, U^1; \quad \sum_{k=1}^{K} \alpha_k^1 x_{kn}^1 \leq x_{k'n}^1 - \beta g_{x_n}^1, \;\; n = 1, \dots, N^1;$$

$$\sum_{k=1}^{K} \alpha_k^1 b_{kj}^1 = b_{k'j}^1 - \beta g_{b_j}^1, \quad j = 1,2, \dots, J^1; \qquad \alpha_k^1 \geq 0, \;\; k = 1,2, \dots, K;$$

$$x_{k'n}^1 - \beta g_{x_n}^1 \leq \hat{x}_n^1;\; x_{k'n}^2 - \beta g_{x_n}^2 \leq \hat{x}_n^2; \dots;\; x_{k'n}^Z - \beta g_{x_n}^Z \leq \hat{x}_n^Z; \tag{2.10}$$
$$b_{k'j}^1 - \beta g_{b_j}^1 \leq \hat{b}_j^1;\; b_{k'j}^2 - \beta g_{b_j}^2 \leq \hat{b}_j^2; \dots;\; b_{k'j}^Z - \beta g_{b_j}^Z \leq \hat{b}_j^z,$$

The $DMU_{k'}$ is technically efficient and thus it is considered performing more sustainably than other DMUs when $\vec{D}_T(x_{k'}, y_{k'}, v_{k'}, b_{k'}; g)$ is equal to zero (the DMU is operating on the network production frontier). On the other hand, it is considered technically inefficient, thus performing more unsustainable, in the case where a value for $\vec{D}_T(x_{k'}, y_{k'}, v_{k'}, b_{k'}; g)$ is greater than 0.

When we extend the analysis to assess the sustainability performance at country level of analogous agri-food supply chains, we define the Luenberger indicator introduced by Chambers (1996), using the directional distance functions previously presented, as:

$$SL(.) = \frac{1}{2}\{[\vec{D}_{T_B}(x_{kA}, y_{kA}, v_{kA}, b_{kA}; g) - \vec{D}_{T_B}(x_{kB}, y_{kB}, v_{kB}, b_{kB}; g)]$$
$$+[\vec{D}_{T_A}(x_{kA}, y_{kA}, v_{kA}, b_{kA}; g) - \vec{D}_{T_A}(x_{kB}, y_{kB}, v_{kB}, b_{kB}; g)]\}, \tag{2.11}$$

where A and B refer to two different countries, each of which has $k = 1,\dots,K$ observations and a network production technology T_A and T_B respectively. The Luenberger indicator consists of four directional distance functions. Two measure the technical inefficiency of a set of DMUs of countries A and B using their own network production technology $\vec{D}_{T_A}(A)$ and $\vec{D}_{T_B}(B)$, respectively, and two measure the technical inefficiency using mixed countries. Therefore, with the observations of country B with reference to the network production technology calculated for country A, $\vec{D}_{T_A}(B)$, and the network production technology calculated for country B with the observations of country A, $\vec{D}_{T_B}(A)$ (Figure 2.4). This means that if there are no variations in the technical efficiency between the observations of the two countries there will be no differences in the performance of the agri-food supply chains, $SL(.) = 0$. On the other hand, in case $SL(.) > 0$ or $SL(.) < 0$, the indicator points out that the agri-food supply chains of country B are performing better (worse) than those of country A. Note that the Luenberger indicator is also used to assess the sustainable performance of an agri-food supply chain between two time periods. Hence, it is used to assess the second sustainability criterion: non-decreasing TFP over time.

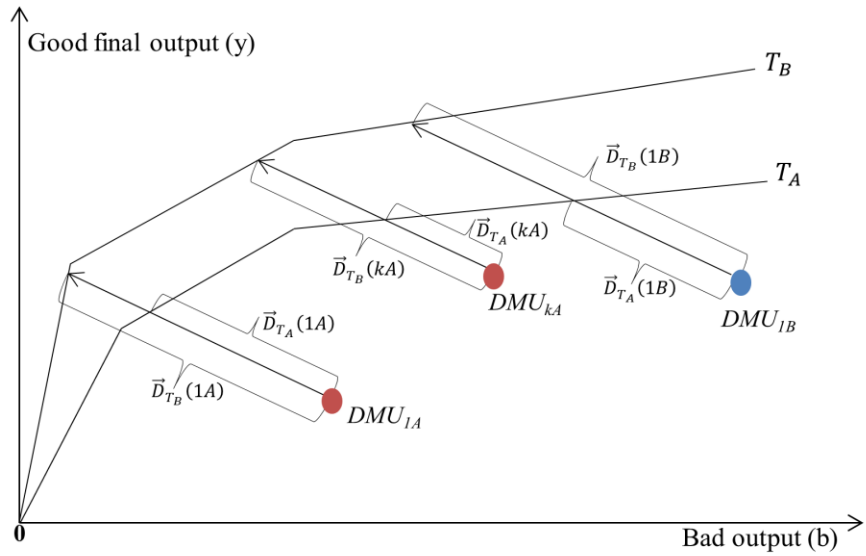

Figure 2.4 Luenberger indicator for pairwise comparison of agri-food supply chains in different countries.

In this case, the Luenberger indicator would consist of four directional distance functions. Two that will measure the technical inefficiency of a set of DMUs in period t and, the same set of DMUs in period $t+1$, and two that will measure the technical inefficiency using mixed periods. Thus, the observations in period t in relation to the network production technology calculated for period $t+1$, and the DMUs in period $t+1$ with reference to the network production technology of period t. In case the Luenberger indicator for *DMU k* is greater than zero it will indicate that the *DMU* has non-decreasing TFP over the two periods and therefore it is performing sustainably.

Sustainability benchmarking of agri-food supply chains using the directional distance function: A numerical example

Application of the directional distance function approach requires the same type of quantity data for good outputs, inputs and externalities as presented for the Bennet TFP computation. Nevertheless, quantity data for a large set of DMUs is required. Consequently, in this subsection only a numerical example that uses constructed data is provided.

Consider a simple example, where there are four agri-food supply chains DMU_1-DMU_4 which each consists of two stages: $z = 1$ and $z = 2$. At stage $z = 1$ one input x_{k1}^{1} is used to produce an intermediate output v_{k1}^{12}. At stage $z = 2$ the intermediate output produced at stage $z = 1$ is used as input to produce one final good output y_{k1}^{2}. As side effects of production, one bad output (the same bad output) is produced at each stage, i.e. b_{k1}^{1} and b_{k1}^{2}. The quantities of the network structure appear in Table 2.2.

Table 2.2 Quantity information for the output, bad output and input variables – network structure.

Network Structure					
Stage (z = 1)		DMU_1	DMU_2	DMU_3	DMU_4
Intermediate output	v_{k1}^{12}	2.5	2.5	4.0	1.0
Input	x_{k1}^{1}	4.0	4.0	4.0	4.0
Bad output	b_{k1}^{1}	1.0	2.5	4.0	3.0
Stage (z = 2)		DMU_1	DMU_2	DMU_3	DMU_4
Final output	y_{k1}^{2}	4.0	9.0	2.0	1.5
Intermediate input	v_{k1}^{12}	2.5	2.5	4.0	1.0
Bad output	b_{k1}^{2}	1.0	4.0	2.0	3.0

An optional approach would be to consider the agri-food supply chain (*DMU*) as a black box structure. Hence, ignoring the intermediate outputs/inputs and only considering the good outputs, inputs and the sum of bad outputs generated in both stages. The quantities of the variables in this case appear in Table 2.3.

Table 2.3 Quantity information for the output, bad output and input variables – black box structure.

Black box structure [a]					
		DMU₁	*DMU₂*	*DMU₃*	*DMU₄*
Output	y_{k1}^{2}	4.0	9.0	2.0	1.5
Input	v_{k1}^{12}	4.0	4.0	4.0	4.0
Bad output	b_{k1}^{2}	2.0	6.5	6.0	6.0

a. the production of bad outputs at both stages were added together

To evaluate the performance of the DMU_S for both the network structure and the black box structure we applied Eq. 2.10[3] imposing constant returns to scale. We assumed the directional vector to be $(g_y, g_x, g_b) = (1, -1, -1)$. Hence, we credited the simultaneous expansion of final outputs and the contraction of inputs and bad outputs (see results in Table 2.4).

Table 2.4 Technical inefficiency scores.

	DMU_1	DMU_2	DMU_3	DMU_4
Black box	-	-	2.2	2.3
Network structure (z1+z2)	-	-	-	1.7

Directional vector for good outputs = 1, inputs = 1 and bad outputs = 1

The assessment for the black box technology results in 2.2 for DMU_3 and 2.3 for DMU_4, which means that DMU_3 *and* DMU_4 are technically inefficient as they could increase their outputs and decrease their inputs and bad outputs simultaneously by 2.2 and 2.3 units respectively. This assessment is illustrated by means of an isoquant map (Figure 2.5).

[3] In this example the equality for the bad outputs in Eq. 2.10 does not hold, because bad outputs are treated as free disposable inputs.

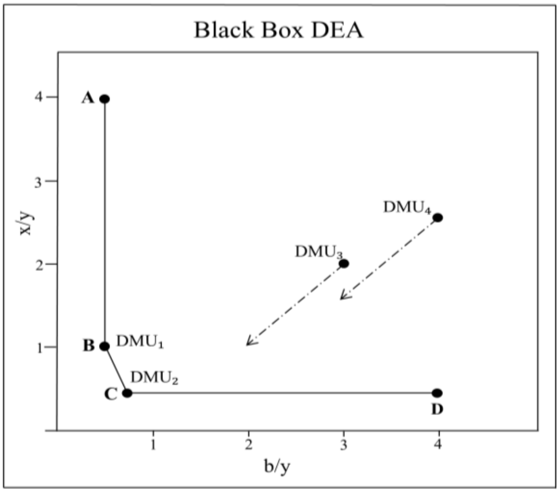

Figure 2.5 Performance assessment in a black box structure.

Given that the black box technology exhibits constant returns to scale, we divided the quantity of good outputs, inputs and bad outputs by the good output. Hence, the horizontal axis represents the quantity of the input divided the good output and the vertical axis represents the quantity of the bad output divided by the quantity of the good output. Points ABCD represent the efficient frontier of the production possibility set. The broken arrows represent the directional vectors which places technical inefficient DMUs, i.e. DMU_3 and DMU_4, on the efficient frontier by expanding good outputs and contracting inputs and bad outputs simultaneously.

By incorporating the links between the stage $z = 1$ and stage $z = 2$, thus modelling explicitly the transformation process of intermediate outputs/inputs within the considered stages, results give 1.7 units for DMU_4. It means that considering the linkages between stages the only technical inefficient DMU is DMU_4. DMU_4 could increase by 1.7 units its final output production while at the same time it could reduce both bad outputs and inputs by 1.7 units. In the network structure assessment the DMU_3 resulted to be technically efficient, therefore performing on the frontier. This assessment is illustrated by means of isoquant maps for each stage of the network structure (Figure 2.6).

Given that the network technology exhibits constant returns to scale, at stage $z = 1$ the intermediate output, input and bad output were divided by the intermediate output. At stage $z = 2$, the good output, intermediate input and bad output were divided by the quantity of the good output. Points ABCD represent the efficient frontier of the production possibility set and the broken arrows the directional vector. The directional vector scale technical inefficient DMUs, that are DMU_2 and DMU_4 at stage $z = 1$, and DMU_3 and DMU_4 at stage $z = 2$ on the efficient frontier. The only technical inefficient observation at both stages is DMU_4.

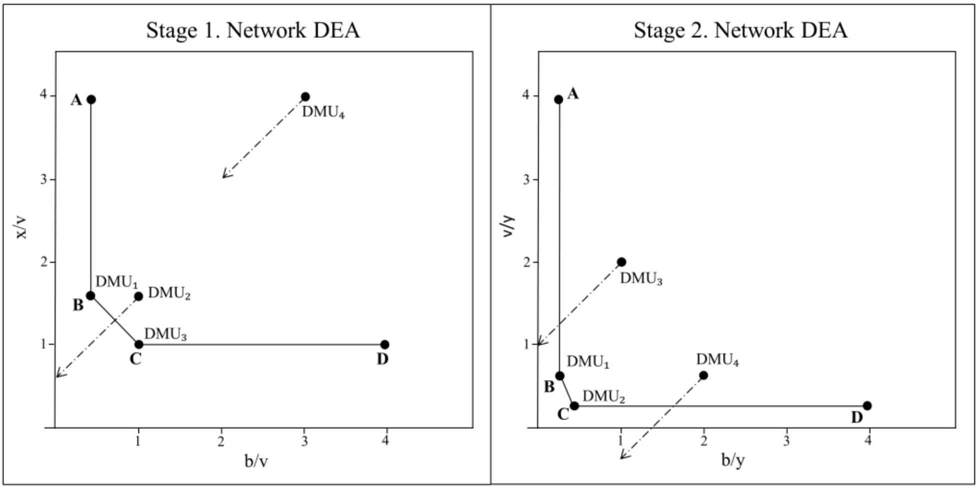

Figure 2.6 Performance assessment in a network structure.

Implementation issues

Selection of output (good and bad)-input variables

As a first point, prior to selecting the output-input variables, comparison of a set of agri-food supply chains requires them to be homogenous, which in practice might not be the case. Even though the set of DMUs under consideration could produce the same product, differences in their internal structure may exist, implying variations in the stages along the chains. Consequently, either the aggregation or disaggregation of stages might be necessary to make the DMUs comparable with regard to the types of output-input variables and the number of stages that would be considered. Once agri-food supply chains have been homogenized, the selection of output-input variables for each stage of the chain should be conducted. The selection of variables, especially those related to bad output production, should be based on the issues and aspects of sustainability that are of established concern for expert communities and in relation to society's well-being (such as global warming, energy, innovation, human rights, equity, etc.), which in turn are linked to the economic, environmental and social dimension of sustainability. These can be identified from regional, national and/or international food sustainability debates, which includes the opinions and perceptions of a variety of stakeholders including policy makers, academics, the production sector, and society as a whole (Michalopoulos et al. 2013). Once these aspects have been identified, a standard set of indicators sufficient to provide reliable information about the sustainability performance of any food system have to be selected. Nevertheless, depending on the level of analysis, supplemental indicators for evaluating production-specific impacts can be used, as suggested by Veleva and Ellenbecker (2001). Indicators should comply with at least three main criteria: relevance, scientific quality and data management.

As a starting point, the Global Reporting Initiative (GRI) guidelines that were created to internationally harmonize global standards for measuring sustainability (Sloan 2010) can be used. However, given that the GRI lacks indicators for some sustainability aspects, such as soil, land use, animal welfare and cultural landscape, the list can be augmented with indicator sets developed by international organizations such as the OECD, ISO, EMAS, Lowell Centre for Sustainable Production, FAO, among others, and from a number of scientific publications on agri-food supply chain sustainability. It should be noted that, when possible, the aggregation of single indicators into sub-indexes should be undertaken (OECD 2002). For example, when several pollutants have similar effects, a single sub-index can be constructed – such as an index of greenhouse gas emission. The aggregation of single indicators will make it possible to convey single messages about complex issues in a synthetized manner, thus reducing information overload for environmental and social managers, and for policy decision-making (OECD 2002). The final set of indicators and sub-indexes should be broad enough to provide relevant information about the economic, environmental and social performance of any agri-food supply chain, thereby accounting for the multi-dimensional nature of sustainability (Yakovleva et al. 2011).

Data requirements

The Bennet TFP indicator has the advantage of demanding few observations, i.e. it can be applied as long as two or more observations/time periods can be compared). This is, in fact, a benefit with respect to the policy decision-making process in data-poor situations, where information about different environmental and social variables is lacking (Hailu and Veeman 2001a). Application of the Bennet TFP indicator, however, requires derivation of shadow prices for those variables for which economic prices do not exist. Although in practice this is a difficult task, shadow prices for non-marketed output-input variables can be estimated through standard economic valuation methods. These methods involve elicitation of the Willingness to Pay (WTP) for improvements to aspects of the environment or society and, conversely, Willingness to Accept (WTA) compensation for some degradation and sustainability losses (Farber et al. 2002). Methods to estimate WTP or WTA can be classified into three main categories: *stated preference methods*, *revealed preference methods* and *benefit transfer methods* (Kuosmanen and Kortelainen 2004). Stated preference methods are employed through the construction of hypothetical markets to assess the WTP or WTA (de Groot 2006). Well-known examples are the contingent valuation method and the choice experiment method. Revealed preference methods are used where conventional or proxy market prices exist for the non-marketed good and services. Examples of these methods are replacement cost, travel cost, avoided cost and hedonic pricing (de Groot 2006). Finally, the benefit transfer method uses values borrowed from existing studies (Mburu et al. 2005).

Estimating shadow prices using stated and revealed preference methods would be costly and impractical. Thus, we propose making use of the benefit transfer method, which assumes a relationship between ecosystem services in geographical areas with similar characteristics (Wilson and Hoehn 2006). Shadow prices estimated in existing studies can thus be transferred and used to estimate shadow prices in similar socio-economic and environmental contexts under analysis (Mburu et al. 2005). However, it is important to be frank regarding the nature of this task. Market prices theoretically exist, however, in some cases they are distorted due to market failures or governmental interference such as tariffs, taxation, subsidizing and regulation (Kuosmanen et al. 2004). For commodities that currently incur external costs (and/or benefits), it is clear that their precise calculation is often impossible. Nevertheless, economic calculations are used simply to raise awareness of the social benefits and costs associated with agri-food supply chains, which in turn can be used to differentiate agricultural commodities that are produced under better economic, environmental and social practices. Furthermore, considering that the estimation of shadow prices is context specific, these prices would also reflect the relative regional importance of external costs or external benefits valued at social prices (Mburu et al. 2005). Thus, the implicit regional weights that communities assign to each aspect related to sustainability would be considered during trade negotiations of agricultural commodities.

In contrast, conducting the sustainability performance analysis by making use of directional distance functions would allow readily integrating multiple outputs, including environmental and social externalities and other social outputs, without requiring price information (Färe and Primont 2003). Nevertheless, other problems related to the dimensionality of the DEA formulation should be addressed. A large number of output-input variables will affect the DEA results, implying higher probability of fully technical efficient DMUs (Dyson et al. 2001). Thus, care must be taken regarding the number of variables selected and the number of observations for which the sustainability performance analysis is conducted (Fried et al. 2007, p. 320). Two widely adopted rules of thumb are to let the number of DMUs be higher than twice the number of outputs multiplied by the number of inputs (Dyson et al. 2001), bearing in mind that, whenever possible, the aim is to have as large a set of DMUs as possible (Fried et al. 2007, p. 321; Madlener et al. 2009). Aggregation of single indicators into sub-indexes, as previously proposed, will make it possible to reduce the number of variables and the problems related to the dimensionality of the DEA formulation.

Setting maximum restrictions for input–output variables

Based on concepts such as sustainable reference values, carrying capacity or critical load, targets and restrictions (maximum restrictions) for the use of certain inputs, and for the production of bad outputs, should be established (Moldan et al. 2012). Nevertheless, it should be noted that these targets and restrictions are often not agreed upon based on scientific evidence, but rather are set through political processes and compromises reached through national or international negotiations (Moldan et al. 2012). Consequently, they rarely reflect pure sustainability considerations (Moldan et al. 2012). Thus, selection of the maximum restrictions to be included in the Bennet TFP indicator (construction of the hypothetical *DMU*), as well as in the Luenberger indicator (construction of the network production technology frontier), should be derived, where possible, from scientific literature, environmental and public standards, and expert judgments (Moldan et al. 2012). Although the imposition of such maximum restrictions will not necessarily reflect the performance required to achieve sustainability, it will provide a benchmark on which to assess those agri-food supply chains that are doing best in terms of reaching common economic, environmental and social goals, and therefore are on the path to sustainability.

Relative importance of sustainability aspects

Different aspects, such as climate change, equity, profitability, etc., as well as indicators to measure the sustainability performance might vary in importance for individual groups of stakeholders. The relative importance of bad output variables in the Bennet indicator will be expressed in the shadow prices attached. A higher shadow value (higher expected cost valued at social prices) will implicitly reveal that the bad output is considered as having more importance for sustainability. On the other hand, the relative importance of bad outputs in the performance assessment using directional distance functions is expressed through incorporating weights in the selection of the directional vectors (Madlener et al. 2009). Typically, a large number of stakeholders are involved or affected by the sustainability performance of agri-food supply chains, and therefore there are different points of view about the relative importance of bad output variables in relation to different sustainability aspects, especially those for which high risk and uncertainty are involved, such as biodiversity or land use change. Thus, as long as the risk and uncertainty are made explicit, and the selection of weighting factors is based on the consensus of different groups of stakeholders (in different regions and time periods), the incorporation of weights within the assessment can provide a useful basis on which to ensure that bad output variables that are of particular relevance to society are given higher priority (Becker 2004).

Conclusions

Based on the TFP approach this manuscript has introduced two potential metrics for uniform measurement of the sustainability performance of agri-food supply chains.

The metrics, either the Bennet TFP indicator or the Luenberger indicator, are sufficiently flexible to allow aggregation of different sustainability issues taking into account the interconnectedness of different stages along agri-food supply chains, and the multi-dimensional nature of sustainability. Consequently, they could be used by governments and others, e.g. farmers, retailers, companies, to compare the sustainability level of various agricultural commodities that are produced at different locations and in a variety of socio-economic contexts; thereby providing a consistent approach for benchmarking of chains in terms of its sustainability performance. The construction of both metrics, however, involves making choices regarding the number and types of variables, the targets and restrictions, the prices for non-marketed outputs and inputs, and the weighting methodologies for assessing the relative importance of economic, environmental and social aspects, which could be subject to political and social dispute. This might raise the criticism that the metrics are subjective in nature. However, we argue that both of the metrics are useful to integrate and summarize the sustainability performance of agri-food supply chains into a single metric, which cannot be captured using isolated indicators; thus, the indicators support the policy decision-making process. As long as data is available regarding the main sustainability aspects and a combination of uncertainty and sensitivity analysis is undertaken, providing quantitative information will allow uniform agri-food supply chain comparability, which could be the basis of certification schemes, international harmonization and corporate sustainability reporting. Additionally, application of the TFP indicators can help to frame policy discussions on sustainability issues related to the trade of agricultural commodities, by providing reliable information about the extent to which commodities are sustainably produced. In turn, this will make it possible to impose trade preferences for sustainable commodities, and set an incentive to switch production towards better environmental and social practices along agri-food supply chains (Lines 2005).

Acknowledgments

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CHAPTER 3

Benchmarking the sustainability performance of the Brazilian non-GM and GM soybean meal chains: An indicator-based approach

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Abstract

A commonly accepted approach for measuring the sustainability of agricultural products is the first step towards treating traded products differentially according to their sustainability. If we were able to measure sustainability, business stakeholders could optimize food production chains, consumers could demand products based on reduced environmental and social impacts, and policy makers could intervene to meet the growing demand for food in a context of environmental conservation, population growth, and globalization. We proposed to measure profit adjusted for the negative externalities of production as a promising single metric for benchmarking products in terms of their relative sustainability. The adjusted profit differences between different products are then assessed by means of the Bennet Total Factor Productivity (TFP) indicator and the Total Price Recovery (TPR) indicator to highlight areas for potential sustainability improvement. To illustrate the usefulness of the indicator-based approach, we assessed the relative sustainability of two Brazilian conventional soybean meal chains, non-genetically modified (non-GM) and genetically modified (GM) chains. Based on the results, we indicated potential areas for sustainability improvement. Sustainability issues included in the assessment were profitability, global warming potential, eutrophication potential, environmental toxicity, farmworker toxicity, consumer toxicity, deforestation, and loss of employment. Results showed that the non-GM soybean meal chain is more sustainable than the GM chain. However, both chains require joint efforts to address their economic, environmental, and social deficiencies. These efforts should focus on providing technical and high quality assistance to reduce biocide use, and improving transportation. The analysis in this study could be extended by undertaking a comparative assessment of the sustainability performance of major soybean meal producers, i.e. United States, Argentina, China, and Brazil. The approach proved to be a promising benchmarking tool for agricultural trade flows. It allows an integrated assessment of the dimensions of sustainability along food chains that is sufficiently flexible to compare the sustainability level of various biomass stocks that are produced in different locations and in a variety of environmental and socio-economic contexts. Nevertheless, it requires consensus on which components of sustainability are to be assessed.

Keywords: Sustainability performance, TFP, TPR, soybean meal chain, externality.

Introduction

Soybeans are one of the main raw materials in the world (Jaguaribe Pontes et al. 2009). Brazil is the second largest soybean producer, following the United States, with a production of 74.8 million tons from 24 million hectares in 2011 (IBGE 2013). In Brazil, soybeans are predominantly produced in conventional farming systems, either using non-genetically modified (non-GM) seeds, i.e. the non-GM system, or genetically modified (GM) seeds, i.e. the GM system. The GM system is different from its non-GM equivalent only insofar as the gene that confers degradation of the herbicide glyphosate by the soy plant (MAGP and IICA 2012). This means that the GM soy plant is resistant to the herbicide glyphosate whereas its non-GM equivalent is not. In the GM system, glyphosate can be applied after the crop has emerged to remove weeds without causing crop damage (MAGP and IICA 2012; Meyer and Cederberg 2012). In contrast, the non-GM system requires the use of a variety of selective herbicides and/or non-chemical methods such as mechanical measures (Meyer and Cederberg 2010). For both types of farming systems, the harvested soybeans are crushed into two main products, soy oil and soybean meal. The soybean products are then transported, traded, and sold to manufacturers in different industries. Soybeans are used for human consumption, as an input in integrated supply chains for livestock production, and in the production of many by-products, such as paints and greases (Jaguaribe Pontes et al. 2009; The Dutch Soy Coalition 2008; WWF 2003). The main trade destinations for soybean products are the European countries and China (Ortega et al. 2004).

Soybean production and its associated industry have brought widespread economic benefits and wealth to Brazil. The agricultural sector contributes up to 27% of Brazilian GDP (Aprosoja 2014). Nevertheless, the rapid growth of the soy industry has raised concerns about environmental and social sustainability, due to the negative externalities of production, i.e. the external costs that are borne by society (Ortega et al. 2004; Willaarts et al. 2013). Soybean production is associated with environmental costs, such as deforestation, pollution of water bodies and soil, and costs associated with the transportation of soybeans and their derived products. Potential deforestation of the Brazilian biomes, such as the Amazon, the Cerrado, and the Mata Atlântica, can lead to the loss of ecosystem functions and services (WWF 2003). Pollution of water bodies and soil is mainly caused by the large quantities of pesticides and fertilizers used in soybean production (Pimentel et al. 2009; Willaarts et al. 2013). Soybeans and their derived products are often transported large distance from farms to the crushing units and then on to the importing countries. Transportation of soybeans requires large quantities of fossil fuel combustion, which contributes to the depletion of non-renewable energy sources and climate change. In addition to environmental costs, social costs are also relevant. Soybean plantations are not labor intensive, with an average of one farmworker per 167 ha of soybeans; for large plantations this is reduced to one per 200 ha (Fearnside 2001). This has resulted in farmworkers migrating to urban areas and the subsequent depopulation of the countryside (Fearnside 2001; The Dutch Soy Coalition 2008; WWF 2003). For example, in the North of Paraná, labor intensive crops, such as coffee, were replaced by soybean cultivation, which resulted in a reduction in agricultural employment (WWF 2003).

The soybean products derived from non-GM and GM soybeans differ in terms of the economic, environmental, and social sustainability performance throughout the production chain. It is expected that stakeholders, i.e. business stakeholders, consumers, and policy makers, would want to treat traded non-GM and GM soybean products differently according to how sustainably they were produced. Certification schemes are currently used for such differentiation (Sundkvist et al. 2005). These schemes typically cover life cycle issues of a product and often, although in some cases not explicitly stated, use life cycle assessment (LCA) methods. The labels and standards used in these schemes, however, are not commonly accepted (Gaitán-Cremaschi et al. 2014). The current schemes have two main limitations, which are inherent in the use of LCA methods: (i) social and economic implications of food production are often left aside, and (ii) the outcomes of the environmental impacts are measured using different units and cannot be aggregated into a single metric. Hence, decision makers can only judge the most sustainable product by using their own weighting factors, which explicitly rely on complicated trade-offs between sustainability issues that are not normally in their mind sets, e.g. kg of carbon dioxide (CO2) versus kg of nitrates, (Gaitán-Cremaschi et al. 2014). Thus, certification schemes and their associated LCA methods have limited usefulness for benchmarking purposes.

Following Gaitán-Cremaschi et al. (2014), this paper proposes an integrated indicator, i.e. Adjusted Profit, that is based on the micro-economic theory of production, for benchmarking products in terms of their sustainability. The Adjusted Profit indicator takes into account the multiple input-output nature of an agricultural supply chain, accounts for the negative externalities of production and provides a single integrated measure of sustainability performance. The approach integrates the multiple outputs (products), inputs (capital, labor, materials, energy, and services), and externalities (e.g. environmental and social impacts such as pollution and loss of employment) along the supply chain into adjusted profits, using a common denominator, money (Barnett et al. 1995). Observed prices can be used for the marketable inputs and outputs, and shadow prices can be attached to the externalities arising from production. Based on the Adjusted Profit indicator, a product is more sustainable than another if its adjusted profit is higher (Gaitán-Cremaschi et al. 2014). To allow a consistent comparison between the adjusted profits of different products, an index number methodology, the Bennet Total Price Recovery (TPR) indicator and the Bennet Total Factor Productivity (TFP) indicator, can be used. Using the Bennet indicators, the variation of total adjusted profit between production chains can be decomposed into variation caused by price differences (the price component reflects differences in TPR) and, variation caused by quantity differences (the quantity component reflects differences in TFP) for each output, input, and externality. The latter has been pointed as a key element of sustainability (Barnes 2002; Barnes and McVittie 2006; Barnett et al. 1995; Ehui and Spencer 1992; Glendining et al. 2009; Lynam and Herdt 1989). Such information is valuable as it highlights areas for potential sustainability improvement. Additionally, it provides information that can be used to rank products in terms of their sustainability. Hence, it gives information that can be used to provide market access preferences to products with the highest adjusted profit or green-tariffs to products with the lowest adjusted profit.

The objective of this study was to assess the relative sustainability performance of the Brazilian non-GM and GM soybean meal production chains using the indicator-based approach, and to determine potential areas for improving sustainability according to the sources of variation along these chains.

Data and Methods

Indicator-based approach

The Brazilian soybean meal chain, for both non-GM and GM, is defined in this study as a set of four life cycle stages, z = 1,2...4, integrated in an input-output system: agricultural (z = 1), processing (z = 2), transport to port (z = 3), and transoceanic transportation (z = 4). The chain is modelled up to the destination port (Rotterdam Port). At each stage, multiple inputs, denoted by vector x, are transformed into multiple outputs, denoted by vector y. As side effects of production, multiple environmental and social externalities are produced, expressed by vector b, such as waste, pollution, poor working conditions, and loss of biodiversity (Figure 3.1). The soybean meal chain has a positive (negative) adjusted profit (AP) if the difference between the aggregated outputs and the aggregated inputs is positive (negative), as the externalities are output penalties that lower the score:

$$AP = p'y - r'b - w'x, \tag{3.1}$$

The multiple outputs, inputs, and externalities are aggregated using vectors of (shadow) prices, p, w, and r, respectively (prime indicating the transpose of the vector).

We assume that there are $k = 1, \ldots, K$ observations for the non-GM soybean meal chain and $m = 1, \ldots, M$ observations for the GM soybean meal chain. To assess the relative sustainability performance, i.e. to compare the adjusted profit within and between both soybean meal chains, the Bennet Total Factor Productivity indicator and the Bennet Total Price Recovery (TPR) indicators are used:

$$\begin{aligned} B_{1,2} = &\left[\frac{1}{2}\left(p'_2 + p'_1\right)(y_2 - y_1)\right] - \left[\frac{1}{2}(w'_2 + w'_1)(x_2 - x_1)\right] - \left[\frac{1}{2}(r'_2 + r'_1)(b_2 - b_1)\right] \\ &+ \left[\frac{1}{2}(y_2 + y_1)\left(p'_2 - p'_1\right)\right] - \left[\frac{1}{2}(x_2 + x_1)(w'_2 - w'_1)\right] - \left[\frac{1}{2}(b_2 + b_1)(r'_2 - r'_1)\right] \end{aligned} \tag{3.2}$$

where the best performer in the data set (in terms of the highest adjusted profit) is denoted as 1 and any other observation, i.e. k or m, is denoted as 2. Computation of the sum of the Bennet indicators reveals in monetary terms the aggregated adjusted profit difference of a particular chain relative to the benchmark. Hence, a lower value of the sum of the Bennet indicators indicates low sustainability performance of the assessed observation relative to the benchmark (note that a positive outcome cannot be obtained as the benchmark is the observation with the highest adjusted profit). The difference in the adjusted profit between the benchmark and any other observation can be decomposed into two parts. A first part that captures differences in (shadow) prices p, w, and r (TPR component – second line of Eq. 3.2) and the second part that reflects differences in the quantities of y, x, and b (TFP component – first line of Eq. 3.2). The latter is associated, among others, with the production technology, and/or the production processes along the production chain (Gaitán-Cremaschi et al. 2014). Due to the additive nature of the Bennet indicators, the differences in the adjusted profit associated with the TFP or TPR components can be evaluated at each stage of the soybean meal chain. This decomposition provides information, which highlights potential areas for sustainability improvement.

Selection of outputs, inputs, and externalities

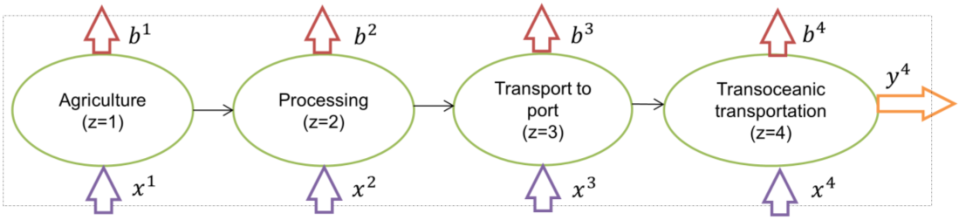
To assess the relative sustainability performance of the non-GM and GM soybean meal chains, the main outputs, inputs, and externalities along the product life cycle were selected. The process of selecting the externalities consisted of three steps. (i) A generic set of sustainability issues, i.e. topics that are of public concern, such as land use, health, energy, biodiversity, profitability, and water, was provided to a group of stakeholders involved in chain sustainability. Stakeholders were asked to assign a score to each of the issues using a five-point Likert scale, where 1 represented “not at all important” and 5 “extremely important” for the given dimension of sustainability, either economic, environmental, or social. The group of stakeholders consisted of eight academic researchers and eleven practitioners (NGO’s, certifying organizations and firms in the agri-food sector). (ii) Once answers were received, the percentage of participants who gave a score of 4 or 5 was calculated for each issue. The issues for which at least 65% of the participants gave a score of 4 or 5 were selected as being of utmost importance (Table 3.1).

Table 3.1 Sustainability issues for the different dimensions of sustainability and percentage of stakeholder respondents who rated the issue as being of utmost importance (scores 4 and 5).

Dimension	Issue	Description	% respondents with a score of 4 or 5[a]
Environmental	Atmosphere	Release of substances that are considered to be pollutant to the environment. Includes air and soil emissions and effluents.	**70**
	Water	Water quality (pollution of water) and quantity (availability) (FAO 2012).	**80**
	Soil	Organic matter, physical structure and chemical quality (FAO 2012).	45
	Biodiversity	Diversity of genes, species and ecosystems (FAO 2012).	**65**
	Material	Use of inputs such as raw materials, associated process materials and semi-manufactured goods along food chains (FAO 2012).	**75**
	Energy	Use of direct and indirect energy.	50
	Land use change	Land shifting from natural land use covers to another land use (FAO 2012).	45
	Landscape	Shaped landscapes as the result of human activities and the natural environment.	15
Economic	Economic performance	Economic impacts of the system, such as profitability, contribution to gross domestic product, imports and exports (GRI 2011).	**95**
	Innovation	Use of knowledge to accelerate the market expansion and performance of the food chain (GRI 2011).	45
	Uncertainty and risk	Micro-economic risk and macro-economic uncertainty (include issues of geopolitical instability, price volatility, labor costs).	55
Social	Labor rights	Employment, training opportunities, occupational health and safety, remuneration and gender equality (GRI 2011).	**90**
	Product responsibility	Issues of health and safety, labelling and marketing (GRI 2011).	**65**
	Human rights	Includes issues such as non-discrimination, gender equality, freedom of association, child labor and indigenous rights (GRI 2011).	55
	Society	Impact on the local communities (development programs, corruption, influence in public policy-making) (GRI 2011).	50

a. Bold numbers indicate that the corresponding issue was selected for the sustainability assessment

A total of seven sustainability issues were selected. Four issues were selected for the dimension of environmental sustainability: *water*, *materials*, *atmosphere*, and *biodiversity*. *Economic performance* was selected for the economic dimension, and *labor practices* and *product responsibility* for the social dimension. (iii) Based on two criteria, data availability and relevance, indicators were defined to measure the performance of the soybean meal chains for each selected issue.



	STAGE z = 1	STAGE z = 2	STAGE z = 3	STAGE z = 4
OUTPUTS (y)				
Soybean meal				y_1^4
INPUTS (x)				
Seeds	x_1^1			
Lime	x_2^1			
Fertilizers	x_3^1			
Herbicides	x_4^1			
Insecticides	x_5^1			
Fungicides	x_6^1			
Other inputs	x_7^1			
Fuel (machinery)	x_8^1			
Labour	x_9^1			
Other expenses	x_{10}^1			
Capital fixed inputs	x_{11}^1			
Diesel (transport)	x_{12}^1			
Hexane and electricity		x_1^2		
Diesel (transport to port)			x_1^3	
Bunker fuel				x_1^4
EXTERNALITIES (b)				
CO2 –eq. emissions (GWP)	b_1^1	b_1^2	b_1^3	b_1^4
P emissions (EP)	b_2^1			
Deforested natural area (DEF)	b_3^1			
Environmental Toxicity (ET)	b_4^1			
Farmer Toxicity (FT)	b_5^1			
Consumer Toxicity(CT)	b_6^1			
Loss of employment (LE)	b_7^1			

Figure 3.1 Schematic representation of the soybean meal chain (note that intermediate outputs are cancelled as they become inputs in the following stage).

The following indicators were chosen: profitability for the issues *materials* and *economic performance*, global warming potential (GWP) for *atmosphere*, eutrophication potential (EP) for the *water* issue, deforestation (DEF) and environmental toxicity (ET) as proxies of *biodiversity*, and farmer toxicity (FT), consumer toxicity (CT), and loss of employment (LE) for *product responsibility*. The selected indicators, in turn, represent the negative externalities arising from soybean meal production. The indicator profitability is associated with conventional outputs y, inputs x, and market prices p and w throughout the soybean meal chain.

A schematic representation of the Brazilian soybean meal chain and the indicator-variables that were included at each life cycle stage is presented in Figure. 3.1.

Data collection

We quantified the outputs, inputs, and externalities for eleven observations for the non-GM soybean meal chain (k=11) and eleven observations for the GM soybean meal chain (m=11). At the agricultural stage, each observation represents average quantities across farms at the municipality level in the year 2011, differentiated between non-GM and GM soybean production in the cases where both farming systems were found. The municipalities cover some of the major soybean production areas and belong to six different states of Brazil (Table 3.2). The variables were quantified for the production of one ton of soybean meal delivered at Rotterdam Port. Given that the soybean meal is co-produced with soybean oil, economic allocation was performed. Hence, each variable was allocated to soybean meal production based on the relative economic value of soybean meal in relation to soybean oil (Middelaar et al. 2011). Consequently, 60% of the outcome of each variable was allocated to the soybean meal production[1].

Once the quantities were collected, the (shadow) prices p, w, and r associated with the variables were derived. Prices were expressed in 2011 US dollars (US $). If it was necessary, prices were inflated to 2011 US dollars using Consumer Price Indices. We computed the adjusted profit for each observation to identify the “best” performer

[1] Average soybean oil price for the year 2011 was US $1023.7 per ton (Soybean meal and oil - monthly price, source: The World Bank 2014a). From one ton of soybeans, 75.8% is processed into soybean meal (ECOINVENT 2007).

from the observed data (in terms of highest adjusted profit) to be used as the benchmarking observation in the Bennet computation. All calculations and data sources are fully detailed in the supplementary material (Annex 3A).

Table 3.2 Characteristics of soybean production in the selected municipalities of Brazil.

Municipality	Farming system	Planted area (ha)[a]	Share of total municipality area (%)	Farms (units)[b]	Production (thousand tons)[a]	State
Anahy	non-GM, GM	5,116.0	64.2	184.0	16.3	Paraná
Andirá	non-GM	11,802.0	30.2	164.0	34.4	Paraná
Arapoti	non-GM	17,933.0	39.5	86.0	58.2	Paraná
Cafelândia	non-GM, GM	22,078.0	70.2	256.0	69.2	Paraná
Marialva	non-GM, GM	23,054.0	52.1	484.0	65.8	Paraná
Londrina	non-GM, GM	40,333.0	39.4	455.0	111.7	Paraná
C. Mourão	non-GM, GM	49,660.0	73.0	318.0	145.6	Paraná
Guarapuava	non-GM, GM	51,452.0	35.8	181.0	159.5	Paraná
Sorriso	non-GM	585,676.0	84.5	367.0	1,831.7	Mato Grosso
C. Novos	non-GM, GM	35,667.0	27.9	141.0	100.6	Sta. Catarina
Araguari	GM	17,100.0	20.6	24.0	54.0	M. Gerais
P. Afonso	non-GM	29,413.0	37.1	25.0	72.2	Tocantins
P. Missões	GM	90,500.0	87.6	663.0	245.4	RGS
Cruz Alta	GM	81,167.0	83.6	343.0	196.8	RGS
Passo Fundo	GM	37,767.0	87.4	413.0	103.6	RGS

Source IBGE (2013)
a. Average values for the period 2006-2011.
b. Data from the Brazilian Agricultural Census 2006.
Campo (C.) Mourão; Campo (C.) Novos; Pedro (P.) Afonso; Palmeira das (P.) Missões ; Rio Grande du Sul (RGS)

Quantification of outputs, inputs, and externalities

Profitability

Profitability was estimated as the difference between the revenue and the cost of producing one ton of soybean meal. Revenues are given by the market price (p) of one ton of non-GM and GM soybean meal at Rotterdam Port. Costs refer to the expenditure on inputs used at each stage of the chain. At the *agricultural stage*, production costs, i.e. variable and fixed costs, were obtained from the Brazilian Agricultural Research Corporation (EMBRAPA). The variable costs cover operating expenditures on seeds, lime, fertilizers, pesticides, other inputs such as adjuvants, fuel, labor, and other expenses such as insurance, taxes, and technical assistance. Fixed costs are related to machinery and infrastructure depreciation. Costs at the *processing stage* include the expenses related to the use of hexane, electricity, and labor, among others. Because quantity and price information for inputs at the processing stage were not accessible, the crush margin, i.e. the difference between the market value of soy oil and soybean meal and the cost of the soybeans, was used to estimate the processing costs. Finally, costs at the *transport to port* stage were estimated as the cost of diesel used in the transportation of soybean meal from the municipalities to the closer exporting port (Rio Grande, Paranaguá, or Santos), and costs at the *transoceanic transportation stages* were estimated as the cost of bunker fuel used in the transportation of soybean meal from the exporting port to Rotterdam Port.

Environmental and social externalities of soybean meal production

The GWP of the greenhouse gases (GHGs) emitted by the observations of the soybean meal chains was expressed in kg of CO_2 equivalents (kg CO_2-eq.). The following GHGs were included: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). At the *agricultural stage,* the inputs considered as having the potential to emit GHGs were seeds, lime, fertilizers, pesticides, and fuel. At the *processing stage,* electricity was the only input considered to emit GHGs, and fuel was the only input for the *transport to port* and *transoceanic transportation* stages. Input-specific emission factors proposed by IPCC (2006) were used.

The EP was calculated based on the difference between the average amount of phosphorous (P) absorbed by the soy plant and the amount of P added through fertilizer at the *agricultural stage*. The EP was expressed in kg of P. As soy plants biologically fix nitrogen in soils, the potential eutrophication due to an excess of this nutrient was considered to be zero (Hungria et al. 2001).

The DEF for each municipality was obtained from the project "Monitoring of Deforestation of the Brazilian Biomes by Satellite, PMDBBS" (IBAMA 2013). It was calculated as the average annual deforestation rate (m^2/year) for two different biomes, Mata Atlántica and Cerrado, over the periods of 2002-2007, 2008-2009, and 2010. In situations where both non-GM and GM farming systems are found in a given municipality, the allocated annual deforestation rate was divided in equal proportions, given that these systems both have a share of about 50% in the total soybean production of Brazil (IBGE 2013).

The ET, FT, and CT were expressed using the Environmental Impact Quotient (EIQ) developed by Kovach et al. (1992). The EIQ method gives a toxicity score for a kg of a specific active pesticide ingredient for three components: the EIQ for the environmental component (EIQe), the EIQ for the farmworker (EIQf) and the EIQ for the consumer (EIQc). To quantify the toxicity of the pesticides, the EIQ scores for the three components were collected for the different active pesticide ingredients used in soybean production. Afterwards, the EIQ scores were added together and were adjusted taking into account the percentage of active ingredient in the commercial products and the usage rate per ton of soybean meal. Higher scores represent higher toxicity. This procedure was performed for each municipality and farming system.

LE was only estimated for the *agricultural stage* and was defined as the difference between the weighted average workload for the different agricultural land uses for each municipality and the workload required for soybean production, both non-GM and GM. The workload was expressed in hours per soybean meal ton and included both family and contracted labor. Agricultural land uses included permanent crops, cattle, horticulture, and temporal crops, such as cotton, sugar cane, tobacco, and cereals.

Table 3.3 summarizes the quantification of the externalities for the non-GM and GM soybean meal chains exporting to the European market, for each selected municipality. Externalities are expressed in units per ton of soybean meal.

Table 3.3 Quantification of the externalities arising from soybean meal production (per ton of soybean meal). Stage 1 = agricultural, stage 2 = processing, stage 3 = transport to port, and stage 4 = transoceanic transportation.

Indicator	GWP				EP	ET	FT	CT	DEF	LE
Unit	kg CO_2-eq.				kg P	EIQ	EIQ	EIQ	m^2	hours
non-GM chain	Stage 1	Stage 2	Stage 3	Stage 4						
Andirá	271.1	20.4	446.0	713.3	0.0	21.2	10.3	4.4	0.0	3.5
Cafelândia	235.1	20.4	627.3	723.8	0.0	21.9	9.4	4.4	0.05	3.9
Marialva	254.1	20.4	473.7	723.8	0.0	23.7	10.9	4.7	0.0	3.2
Arapoti	236.0	20.4	25.5	723.8	2.2	16.3	8.3	4.3	0.9	2.2
Anahy	248.9	20.4	651.6	723.8	0.0	26.2	12.3	5.7	0.0	2.4
Campo Mourão	240.8	20.4	539.4	723.8	0.0	18.4	7.0	3.7	0.0	3.9
Guarapuava	255.8	20.4	303.9	723.8	0.0	21.2	8.0	7.0	2.2	2.2
Londrina	253.6	20.4	450.4	723.8	0.0	23.3	10.6	5.4	0.0	2.9
Campos Novos	269.0	20.4	424.6	723.8	0.3	20.5	10.7	4.6	0.0	1.5
Pedro Afonso	222.8	20.4	1219.0	713.3	1.5	21.2	11.3	4.8	53.8	0.7
Sorriso	226.2	20.4	2187.8	713.3	0.5	14.6	6.6	3.5	14.4	0.0
GM chain										
Cafelândia	233.9	20.4	630.4	723.8	0.0	29.7	7.2	4.2	0.05	4.2
Marialva	249.3	20.4	480.4	723.8	0.0	31.3	7.7	4.5	0.0	3.4
Anahy	249.3	20.4	652.3	723.8	0.0	36.4	10.8	6.0	0.0	2.5
Campo Mourão	248.1	20.4	536.9	723.8	0.0	25.1	5.9	4.0	0.0	4.1
Guarapuava	249.9	20.4	312.4	723.8	0.0	34.8	8.4	7.6	2.2	2.3
Londrina	250.4	20.4	457.1	723.8	0.0	36.0	9.3	5.6	0.0	3.1
Campos Novos	192.9	20.4	430.2	723.8	0.3	34.5	7.8	4.6	0.0	1.6
Araguari	217.8	20.4	684.6	713.3	2.2	39.2	11.8	6.0	13.8	1.0
Palmeira das Missões	212.7	20.4	543.8	748.4	0.0	46.0	14.2	4.9	0.01	5.2
Passo Fundo	270.4	20.4	547.8	748.4	0.0	45.5	13.0	7.2	0.00	5.0
Cruz Alta	294.5	20.4	447.0	748.4	0.0	35.2	10.8	4.4	0.04	1.0
Average non-GM chain	246.7	20.4	668.1	720.9	0.4	20.8	9.6	4.8	6.5	2.4
Average GM chain	242.7	20.4	520.3	729.5	0.2	35.8	9.7	5.4	1.5	3.0

Shadow prices attached to the environmental and social externalities

A number of studies have estimated the costs of releasing CO_2 gases into the atmosphere (see Tol 2008 for an overview). These costs are associated with the impacts of CO_2 on the environment, the economy, and human health. These include parasitic and vector borne diseases, sea-level rise, river runoff and decreased water availability, melting of ice sheets, the loss of ecosystem and its associated biodiversity, and climate instabilities, such as higher incidence of droughts, changes in precipitation patterns, and higher storm frequency (Nordhaus 2007; Pretty et al. 2000; Tol 2005; Tol 2008). To select an appropriate shadow price for CO_2 equivalents, the mean value of estimates found in existing literature sources was computed. As a result, we used a shadow price of USD 0.02 per kg CO_2-eq.

Losses of P from agricultural systems contaminate water and soils, affecting the dynamics and processes of different ecosystems (Csathó et al. 2007). To determine a shadow price for P losses from soybean production, we used the mean value of two estimates, US $1.95 and US $9.51 per kg of P. The first shadow price was calculated by de Bruyn et al. (2010) as the external costs of all the direct impacts attributed to P emissions into the environment. The second estimate was based on the total monetary expenditure by Dutch authorities in the year 2000 in order to reduce P emissions to reach a policy target (Huppes et al 2007). Owing to the fact that both shadow prices are context dependent and are closely related to income levels, i.e. they reflect the willingness to pay for maintaining a certain environmental quality or the willingness to accept compensation for the environmental degradation, the shadow prices were corrected for the Brazilian context using the ratio of the Gross Domestic Product (GDP) per capita of Brazil to the average GDP per capita of the Netherlands. As the purchasing power of a dollar varies between Brazil and the Netherlands, we expressed the GDP in purchasing power parities (PPP) in current international dollars (Int. US $). As a result, we assumed a shadow price of US $1.98 per kg P.

The mean economic value per hectare of the ecosystem services provided by ten biomes around the world was estimated by van der Ploeg et al. (2010). Of the ten biomes, two are related to the Cerrado and Mata Atlântica Brazilian biomes, i.e. the wood/shrub land and the grass/rangeland. The total monetary value per hectare of wood/shrub land was estimated at a median value of US $867.9 per ha. The median value per hectare of grass/rangeland was estimated at US $1.200 per ha[2]. Assuming that the shadow price of deforestation is equivalent to the foregone benefits derived from the provision of such ecosystem services, we calculated our shadow price for deforestation as the average value of the two estimates, which is US $0.10 per m^2.

To select a shadow price for environmental toxicity, farmworker toxicity, and consumer toxicity, we partially used the Pesticide Environmental Accounting (PEA) tool developed by Leach and Mumford (2008). The tool adjusts a set of base values for external costs categories[3] associated with the application of one kg of an average active pesticide ingredient, taking into account the relative toxicity of pesticides expressed by the EIQ scores (Praneetvatakul et al. 2013). Base values for external cost categories were derived by Pretty et al. (2000) and (2001), based on detailed cost studies done in the United Kingdom, the United States, and Germany. Following Leach and Mumford (2008), we first redistributed the base values over the three EIQ model components, i.e., environmental, farmworker, and consumer. Redistributed external costs were afterwards adjusted to the Brazilian context using the ratio of the GDP per capita of Brazil to the average GDP per capita of the UK, the USA, and Germany (Praneetvatakul et al. 2013), expressed in PPP in current Int. US $. In addition, following Praneetvatakul et al. (2013), the farmworker external costs were adjusted by a factor that represents the ratio of Brazil's share of employment in agriculture to the average share of agricultural employment in the UK, the USA, and Germany. This factor scaled the farmworker external costs according to the potential amount of people that could come into direct contact with pesticides in Brazil. The adjusted external costs of the application of one kg of an average active pesticide ingredient (US $9.57 per kg active ingredient) were multiplied by the total quantity of active pesticide ingredients used in the USA in the year 2001 (425 million kg active ingredient)[4] (Pretty et al. 2000). Total external costs for the USA, US $4,066 million, were divided into the three EIQ components according to the external cost share of the average active pesticide ingredient.

[2] Ecosystem services included in the estimation comprised food and raw materials, benefits for air quality, climate regulation, waste treatment, water purification, maintenance of soil fertility and erosion prevention, maintenance of genetic diversity, tourism, recreation, and aesthetic information (see van der Ploeg et al. 2010 for an overview).
[3] Cost categories included: treating contaminated water, monitoring of pesticides, medical costs for treating pesticide poisonings, and costs associated with biodiversity loss (Pretty et al. 2001).
[4] Total kg of active pesticide ingredients used in the USA in the year 2001 (Pretty et al. 2001). Due to data availability, the UK and Germany were not used in this calculation.

The quantities of the most commonly used active pesticide ingredients in the USA were identified and their corresponding EIQ scores were collected (matching the total amount of 425 million kg of active pesticide ingredients). Adding the EIQ scores for the environmental, farmworker, and consumer components and dividing the corresponding total external costs by these amounts, the shadow price of one EIQ for each component was estimated at US $0.02 per EIQe, US $0.4 per EIQf and US $0.3 per EIQc.

With regard to the employment that is lost in agricultural soybean production, the price used in this study was the overall agricultural average wage of US $3.4 per hour.

Table 3.4 summarizes the shadow prices that were calculated from literature sources and reports and adjusted to the Brazilian context.

Table 3.4 Shadow prices of one unit of externalities in soybean meal production.

Externality	Unit	Shadow price 2011 US $
Global Warming Potential (GWP)	kg CO_2-eq	0.02
Eutrophication Potential (EP)	kg PO_4-eq	1.98
Deforestation (DEF)	m^2	0.10
Environmental Toxicity (ET)	EIQe	0.02
Farmer Toxicity (FT)	EIQf	0.42
Consumer Toxicity (CT)	EIQc	0.31
Loss of employment (LE)	Hour	3.40

See the supplementary material for sources and data calculations (Annex 3A)

Adjusted profit of the selected non-GM and GM soybean meal chains in Brazil

Table 3.5 shows the adjusted profit estimated for each of the observations of the non-GM and GM soybean meal chains.

Table 3.5 Adjusted profit for the observations of the non-GM and GM soybean meal systems in Brazil (results in US$ per soybean meal ton). In the column headings, y = vector of outputs, x = vector of inputs, b = vector of externalities, p = vector of prices of outputs, w = vector of prices of inputs, r = vector of (shadow) prices of externalities; thus, $(p'y)$ = value of production, $(w'x)$ = value of inputs, $(r'b)$ = value of externalities, and adjusted profit = $p'y - w'x - r'b$ (consistent with Eq. 3.1).

non GM soybean chain	$(p'y)$	$(w'x)$	$(r'b)$	Adjusted Profit (AP)
Guarapuava[a]	448.7	262.1	42.7	143.9
Campos Novos	448.7	275.9	44.1	128.8
Andirá	448.7	273.3	50.4	125.0
Campo Mourão	448.7	273.1	51.4	124.2
Londrina	448.7	279.7	48.6	120.5
Marialva	448.7	278.4	49.9	120.4
Anahy	448.7	291.8	52.1	104.8
Arapoti	448.7	313.3	39.5	95.9
Cafelândia	448.7	314.0	54.9	79.8
Sorriso	448.7	341.7	76.4	30.6
Pedro Afonso [b]	448.7	368.6	65.9	14.2
GM soybean meal chain				
Guarapuava	420.0	258.1	43.7	118.2
Campos Novos	420.0	277.2	41.9	100.9
Campo Mourão	420.0	274.7	52.2	93.2
Londrina	420.0	284.4	48.9	86.6
Marialva	420.0	287.0	49.4	83.5
Cruz Alta	420.0	296.7	43.6	79.7
Anahy	420.0	295.3	52.2	72.5
Passo Fundo	420.0	304.6	61.0	54.4
Cafelândia	420.0	314.4	54.7	50.9
Araguari	420.0	320.4	53.1	46.5
Palmeira das Missões	420.0	315.4	59.9	44.7
Average non-GM chain	448.7	297.1	52.4	99.3
Average GM chain	420.0	295.0	50.9	73.9

a. highest adjusted profit. b. lowest adjusted profit.

The highest adjusted profit was calculated for the non-GM observation with production in the municipality of Guarapuava, equal to $143.9 per ton of soybean meal. This observation was used as the benchmark observation for the computation of the Bennet TFP and TPR indicators.

Results and discussion

Results in section 'Benchmarking of the soybean meal chains using the Bennet TFP and TPR indicators; aggregated differences in the adjusted profit at each chain stage and in section 'Decomposition of differences in the adjusted profit into the TFP component and the TPR component associated with outputs, inputs, and externalities', provide the outcomes of the Bennet indicators. Differences in the adjusted profit along the chain between the observations and the best performing observation (benchmark) are presented in section 'Benchmarking of the soybean meal chains using the Bennet TFP and TPR indicators; aggregated differences in the adjusted profit at each chain stage'. In section 'Decomposition of differences in the adjusted profit into the TFP component and the TPR component associated with outputs, inputs, and externalities', these differences are further decomposed into those that are related to price differences (TPR component) and those that are associated with quantity differences (TFP component) for each specific output, input, and externalities. Finally, potential areas for improvement of the sustainability performance of the non-GM and GM soybean meal chains are suggested in section 'Potential areas for sustainability performance improvements in soybean meal production'.

Benchmarking of the soybean meal chains using the Bennet TFP and TPR indicators; aggregated differences in the adjusted profit at each chain stage

The differences in the adjusted profit between the best performing observation, i.e. non-GM soybean meal production at Guarapuava, and the remaining 21 observations are presented in Table 3.6 for each life cycle stage of the soybean meal chain and decomposed into the TFP and TPR components. In addition, the average GM soybean meal chain is compared to the average non-GM soybean meal chain using the latter as the benchmark.

Positive values for the sum of the Bennet indicators show that the observation is more sustainable than the benchmark observation, whereas negative values indicate that the observation is less sustainable. Main differences between the non-GM and GM observations and the benchmark are found at the *agricultural stage*, ranging from US$4.0 to US$-90.7 per soybean meal ton (sum of the TPR and TFP component), and at the *transport to port stage* where differences range from US$12.1 to US$-81.6 per soybean meal ton.

Table 3.6 Differences in the adjusted profit (AP) within and between observations of the non-GM and GM soybean meal chains at each life cycle stage, expressed in US $ per soybean meal ton. The AP difference is decomposed into TFP and TPR components (consistent with Eq. 3.2).

Non-GM chain	Agriculture (Stage 1)		Processing (Stage 2)		Transport to port (Stage 3)		Trans. transportation (Stage 4)		Adjusted Profit difference
	TFP	TPR	TFP	TPR	TFP	TPR	TFP	TPR	
Guarapuava[a]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Campos Novos	-12.9	3.0	0.0	0.0	-5.2	0.0	0.0	0.0	-15.2
Andirá	-13.7	0.4	0.0	0.0	-6.2	0.0	0.7	-0.2	-18.9
Campo Mourão	-6.9	-2.6	0.0	0.0	-10.2	0.0	0.0	0.0	-19.8
Londrina	-15.8	-1.4	0.0	0.0	-6.3	0.0	0.0	0.0	-23.5
Marialva	-19.3	3.2	0.0	0.0	-7.4	0.0	0.0	0.0	-23.5
Anahy	-21.2	-2.9	0.0	0.0	-15.1	0.0	0.0	0.0	-39.2
Arapoti	-28.5	-31.6	0.0	0.0	12.1	0.0	0.0	0.0	-48.1
Cafelândia	-18.6	-31.5	0.0	0.0	-14.0	0.0	0.0	0.0	-64.2
Sorriso	-14.1	-18.2	0.0	0.0	-81.6	0.0	0.7	-0.2	-113.4
Pedro Afonso	-56.6	-34.0	0.0	0.0	-39.7	0.0	0.7	-0.2	-129.8
GM chain									
Guarapuava	-3.9	8.0	0.0	-0.7	-0.4	0.0	0.0	-28.7	-25.7
Campos Novos	-8.9	0.8	0.0	-0.7	-5.5	0.0	0.0	-28.7	-43.0
Campo Mourão	-7.3	-4.0	0.0	-0.7	-10.1	0.0	0.0	-28.7	-50.8
Londrina	-17.0	-4.3	0.0	-0.7	-6.6	0.0	0.0	-28.7	-57.4
Marialva	-17.4	-5.9	0.0	-0.7	-7.7	0.0	0.0	-28.7	-60.4
Cruz Alta	-15.3	-11.7	0.0	-0.7	-6.2	0.0	-1.7	-28.7	-64.2
Anahy	-22.2	-4.8	0.0	-0.7	-15.1	0.0	0.0	-28.7	-71.5
Passo Fundo	-49.0	1.1	0.0	-0.7	-10.6	0.0	-1.7	-28.7	-89.5
Cafelândia	-18.4	-31.1	0.0	-0.7	-14.1	0.0	0.0	-28.7	-93.0
Araguari	-37.1	-15.0	0.0	-0.7	-16.5	0.0	0.7	-28.7	-97.5
P. das Missões	-46.0	-11.7	0.0	-0.7	-10.4	0.0	-1.7	-28.7	-99.3
GM chain vs. benchmark= non-GM chain	-6.6	4.9	0.0	-0.7	6.4	0.0	-0.6	-28.7	-25.3

A positive value indicates higher performance relative to the benchmark in terms of TFP and TPR.
a Benchmarking observation

At the *transport to port* stage, differences arise from variation in the distances between the municipalities where agricultural production takes place and the closest Brazilian port. Even though differences in the adjusted profit at this stage are small for most of the observations, large distances for some municipalities entail higher transportation costs and a greater release of GHGs. Both of these costs are partially associated with obsolete transportation (production is transported by trucks) and the lack of well-maintained rural roads and congested routes (Jaguaribe Pontes et al. 2009). The municipalities of Sorriso and Pedro Afonso are an example. Both belong to the states of Mato Grosso and Tocantins, where most non-GM soybean production is found.

The average non-GM soybean meal chain differs from the GM soybean meal chain mainly at the *transoceanic transportation* stage (Table 3.6). At this stage, the average GM chain has a lower adjusted profit of about US$29.3 (sum of the TPR and TFP component) due to the price premium given to the non-GM soybean meal, which is approximately 7% of the soybean meal base price (Embrapa Soja 2012).

Decomposition of differences in the adjusted profit into the TFP component and the TPR component associated with outputs, inputs, and externalities

So far we have presented aggregated differences in the adjusted profit along the chain between the benchmark and the remaining non-GM and GM observations (Table 3.6). To discover the reasons for the aggregate differences, these are decomposed into differences that are related to quantity effects (TFP component) and differences that are related to price effects (TPR component) for each specific output, input, and externality. As an example of this analysis, the Bennet TFP and TPR indicators for the average GM chain compared to the average non-GM chain are computed (Figure 3.2). This analysis can easily be conducted for each of the non-GM and GM observations in comparison to the benchmark (non-GM soybean meal production at Guarapuava).

The decomposition of the aggregate difference in the adjusted profit between the average GM and non-GM soybean meal chains highlights five main differences in TFP and TPR for the inputs, output, and externalities. (1) The GM chain faces a lower price for herbicides and fertilizer, which represents a lower expenditure of US $15.3 per soybean meal ton if compared to the prices faced by the average non-GM chain. On the other hand, a higher price for seeds and insecticides for the GM chain decreases the adjusted profit by approximately US $8.5 per soybean meal ton if compared to the benchmark. (2) The average GM soybean chain has a higher consumption of herbicides, insecticides, and fungicides. This is also reflected in slightly higher environmental, farmworker, and consumer toxicity, i.e. the environmental, farmworker, and consumer toxicity decreases the GM chain's adjusted profit by US $5.2 per soybean meal ton.

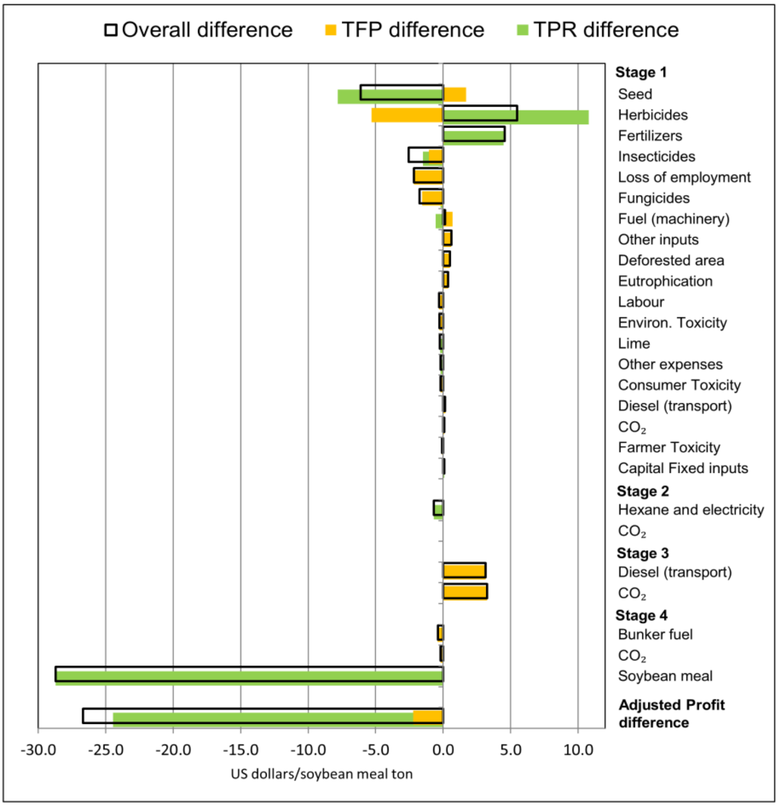


Figure 3.2 Decomposed differences in the adjusted profit between the average GM soybean meal chain and the average non-GM chain. The bars represent the deviations of the average GM chain relative to the benchmark (average non-GM system) in terms of quantities (TFP component) and prices (TPR component) for each output, input, and externality. The higher the deviation, the more sustainable the GM chain is in comparison to its non-GM equivalent (Note the fact that results vary if the Bennet computation is performed using both shadow prices for eutrophication, i.e. US $0.7 per kg P and US $3.3 per kg P. Under the first scenario the adjusted

profit per ton of soybean meal for the average non-GM and GM soybean meal chains would decrease by US$ 0.5 and US$ 0.3. On the other hand, under the second scenario the adjusted profit per ton of soybean meal for the average non-GM and GM soybean meal chains would increase by US $ 0.5 and US $ 0.3 respectively).

(3) The average GM chain consumes less diesel to transport the product to the Brazilian port. Most GM soybean production is found in the southern states of Brazil, which are closer to the ports. This is reflected in a better performance in terms of CO_2-eq. emissions and in lower transportation costs at the *transport to port* stage. Both the TFP and TPR differences imply a higher adjusted profit of the average GM chain of about US $6.4 per soybean meal ton in relation to the non-GM chain. (4) The GM soybean chain has a higher loss of employment at the *agricultural* stage. (5) The GM soybean meal product has a price US$28.7 per ton lower than its non-GM equivalent. The lower price for the GM soybean meal is the main reason for the aggregate difference in the adjusted profit. In case the price premium per ton of non-GM soybean meal was not paid, the price effect would be zero, implying a difference of the adjusted profit between chains of US $3.3 in favor of the GM chain. Nevertheless, it should be noted that the price premium paid per ton of non-GM soybean meal is relevant. Such difference reflects the preference of European consumers for meat from animals not fed with genetically modified crops (Garret et al. 2013), This is related to the fact that the risk and potential impacts of the consumption of food containing genetically-modified material on human health are still unknown (Domingo 2011)."

Focusing on productivity terms, i.e. excluding the adjusted profit differences due to price changes, the average GM chain might be considered less productive than its non-GM equivalent (lower TFP). It produces less output per unit of input (Figure 3.2), i.e. US $2.2 per soybean meal ton in comparison to the average non-GM chain. In addition, the Kovach method used to estimate the toxicity of pesticides does not take into account the long term effects of persistent substances in the environment (van der Werf 1996). Therefore the toxicity of the soybean meal chain may be underestimated, particularly for the GM chain, which has a higher consumption of pesticides, especially the RoundUp herbicide. Long term impacts of increased RoundUp consumption are still relatively unknown, but may include the development of new diseases and tolerant weeds (Bonny 2011).

Although our study suggests that the non-GM soybean meal chain is performing more sustainable than the GM chain (higher adjusted profit), it should be noted that there are other externalities of soybean meal production, which were not included in our study. Negative externalities not addressed in this research include child labor, land concentration, concentration of profits by a small group of stakeholders, illegal land tenure, and loss of genetic agricultural diversity (Franke et al. 2011; Petkova et al. 2011; WWF 2003). Positive externalities not addressed in this research include carbon sequestration by soy plantations, landscape, and employment in the processing sector. Including these externalities will allow a more precise benchmarking of both soybean meal chains in terms of their sustainability.

Potential areas for sustainability performance improvements in soybean meal production

Both chains have areas that show deficiencies in their economic, environmental, and social performance. In the areas where performance can be improved, joint efforts should be put in place by the main actors in the soybean meal chain, such as farmers, governments, the private sector, traders, and non-governmental organizations. The following efforts are proposed for each of the two soybean meal chains.

Most non-GM production is found in Mato Grosso State, mainly in the northern region where the Amazon starts (MAGP and IICA 2012). Soybean production in this area is mainly transported by trucks to Brazilian Ports located in the north, for which the transportation infrastructure is limited and often poorly maintained (Flaskerud 2003; Jaguaribe Pontes et al. 2009). These limitations imply the consumption of a larger quantity of energy resources, leading to higher transportation costs and greater production of GHG emissions than for transgenic beans, which are mainly produced in Rio Grande do Sul State and transported shorter distances to the ports in the south. Salin (2013) concluded that Brazil's competitiveness in the world market largely depends on its transportation infrastructure. Consequently, efforts should therefore focus on providing economic resources for infrastructure projects, such as paving roads and increasing the railways and waterways (Jaguaribe Pontes et al. 2009; Salin 2013). Providing economic resources will not only reduce truck transportation and lead to lower non-GM soybean meal's marketing costs, but will also reduce the associated GHG emissions. Other positive side effects of this intervention might include the reduction in the prices for fertilizers and pesticides that are used in non-GM soybean production at the agricultural stage. Nevertheless, improving the infrastructure matrix in remote areas of Brazil might have indirect negative effects on other sustainability issues, such as biodiversity. Improving access to remote areas and soybean marketing channels, coupled with the reduction in input prices, could encourage the expansion of the soybean area. As a result, increased deforestation could be expected, affecting the provision of the associated ecosystem goods and services (Barona et al. 2010).

Efforts in GM soybean meal production should be focused at the agricultural stage, and aimed at decreasing the application rates and regularity of biocide use. This requires specification of the application rates for biocides, through prior tests and following technical recommendations. A lower consumption of biocides would entail a significant reduction in the agricultural production costs (pesticide use constitutes approximately 28% of the variable costs at the agricultural stage), and lead to a reduction in both GHGs emissions and potential impacts of pesticide use on the environment, the farmworker, and the consumer.

Methodological implications of the indicator-based approach for stakeholders

The assessment presented in this paper can be further complemented by performing a comparative assessment of the sustainability of soybean meal production chains, either non-GM or GM, from the major production countries, i.e. United States, Argentina, China, Paraguay, and Brazil. Such an analysis would provide detailed evidence on the relative competitiveness of each country in the world market and would shed light on the variation between regions and countries in terms of environmental and social sustainability performance. This information can be used to construct possible soybean meal production scenarios in a context of environmental conservation, climate change, and economic performance.

This analysis could also be conducted for other internationally traded products. The sustainability performance of other products, such as sugar, cotton, cereals, and palm oil, which are produced to meet the growing demand for food, feed, and energy (The Dutch Soy Coalition 2008) can also be assessed. If enough data is available, future assessments can establish the relative level of sustainability of products; this information could then be used in the mitigation of sustainability conflicts in trade negotiations. This would require, however, consensus building to define a commonly accepted base level of sustainability. Such a base level of sustainability could consist of a limited number of outputs, inputs, and externalities; just enough to convey information for the decision-making process about the level of sustainability of production chains.

Although the use of the proposed indicator-based approach is justified on the basis of a pragmatic argument, i.e. the aggregation of sustainability issues into a common metric to facilitate the decision-making process, this approach has a limitation that merits special attention. By equating the economic, environmental, and social dimensions of sustainability on the basis of monetary values, we accept that an increase in the sustainability performance of any of the three dimensions can compensate the deterioration of the other(s). In other words, we accept that as long as social welfare is maintained (in terms of positive adjusted profits), sustainability will be achieved. Although this may be the case for some sustainability issues, e.g. the economic profits of soybean production can to some extent be reinvested to improve the structure and fertility of soil, for other issues such as biodiversity loss, this may be not consistent any more with sustainability. Biodiversity provides several benefits for society that can be quantified in monetary terms, but it also provides essential and irreplaceable services for which the shadow price to society would be regarded as infinite (Ayres et al. 1998; Barbier et al. 1994). Therefore it would not be technically and ethically possible to capture these values using monetary metrics on a technical basis (Chan et al. 2012). Consequently, when assessing the sustainability performance of products using a set of economic, environmental, and social indicators, the assessment should be complemented by the identification of key areas that must be maintained at certain quantity and quality levels, e.g. high conservation value areas where agricultural production cannot take place, and by specifying requirements to strictly avoid ethically unacceptable activities, such as child labor and forced labor, as a prerequisite for long-term sustainability.

Conclusions

Our results show that the non-GM soybean meal chain is more sustainable than the GM chain. Quantity differences (TFP component) include a lower use of biocides, i.e. pesticides, fungicides, and herbicides, in the non-GM chain. The main price difference (TPR component) is associated with the price premium paid per ton of non-GM soybean meal, which reflects consumer preference for non-GM products. In contrast, the GM soybean meal chain has a lower emission of GHGs at the transport to port stage due to a lower amount of fossil fuel used in transportation. This is because GM soybean production is mainly found in the southern Brazilian states that are closer to the ports. Our study highlights areas for improving the sustainability of the GM and non-GM chains. Externalities arising from soybean meal production could be reduced by introducing technical assistance in GM soybean production to reduce the application of biocides and by improving the transport infrastructure matrix, especially in remote non-GM soybean production areas of Brazil. These efforts would also reduce production costs. Nevertheless, negative side effects of these interventions, such as increased deforestation, should be taken into consideration.

Although our study focused on the assessment of the relative economic, environmental and social performance of the soybean meal chain, the indicator-based approach has a much wider applicability. It is sufficiently flexible to allow aggregation of different sustainability issues and therefore can be used to analyze the relative sustainability of trade flows at different locations and in a variety of socio-economic contexts. Further development and acceptance of this approach as a benchmarking tool in trade negotiations could assist in the future imposition of trade preferences for sustainable commodities and provide an incentive to switch production towards better economic, environmental, and social practices throughout production chains.

Acknowledgments

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Annex 3A.

Data and the related sources used in the calculation of the adjusted profits: Outputs, inputs and externalities and the related price information

Quantification of conventional outputs and inputs and price information

A summary of the quantities for the outputs and inputs and their associated prices used for the calculation of the Adjusted Profit indicator are found in Table 3A.3. All prices are expressed in 2011 US dollars. The exchange rate used in this study was 1.8 Reals per 1.0 US $ dollar.

Revenue (quantities y and prices p)

- Given that the functional unit is the production of one soybean meal ton at the Rotterdam port, the output quantity y_1^4 was set to one. The price p (CIF price at the Rotterdam port) is US $420.0 per soybean meal ton (The World Bank 2014a). A price premium of 7% applies for the non-GM soybean meal ton (Pashaei Kamali et al. 2014).
- Intermediate outputs of the agricultural stage (z = 1), processing stage (z = 2), and transport to port stage (z = 3) were omitted as they become inputs to the next stage. Thus, they are cancelled when they are totaled across all stages.

Cost (input quantities x and prices w)

Agricultural stage (z = 1)

Costs of soybean production (quantities and prices) for the non-GM and GM farming systems (municipalities) were obtained from the Brazilian Agricultural Research Corporation (EMBRAPA) and represent average input quantities and total input prices across farms at the municipal level in the year 2010/2011 (Hirakuri 2008; 2010a; 2010b; Hirakuri and Lazzarotto 2009a; 2009b). For those inputs for which data was not explicitly available, the following estimations were undertaken:

- Price data (w) for the different inputs ($x_1^1, x_2^1 \dots, x_{12}^1$) was obtained by dividing total input cost by the quantities consumed.

- The quantity of the input "labor" (x_9^1), which is expressed in hours per soybean meal ton, was not available. Thus, it was derived by dividing the total input cost by an assumed hourly wage of US $3.4 per hour (personal communication).
- The quantity of the inputs "other expenses" (x_{10}^1), and "capital fixed costs" (x_{11}^1), was set to one.
- The quantity of the input "diesel transport" (x_{12}^1) was estimated in two steps: (i) the total input cost was divided by the cost of transport (US $ per soybean meal ton and per km) in order to estimate the distance (km) from the farm to the processing unit. (ii) the quantity of diesel consumed (liters per soybean meal ton) was estimated by multiplying the distance (km) times an average consumption of diesel (liters per soybean meal ton and per km).

  Cost of transport: US $0.07 ton per km (derived from Salin 2013).
  Average consumption of diesel: 0.4 liters per km and per ton (IPCC 2006).

- For the municipalities of Pedro Afonso, Sorriso, Araguari and Palmeira das Missões input quantity data was not available. Quantities were derived by dividing the total cost of the different inputs by the average price faced in the other municipalities with the same farming system.

Processing stage (z = 2)

Quantity and price information related to the use of hexane, electricity and labor at the processing stage was not accessible. Hence, the input quantity (x_1^2), was set to one and the crush margin, i.e. the difference between the Free on Board Price (FOB) of the soy oil and the soybean meal and the cost of the soybean meal at the farm gate (soybean price allocated to soybean meal), was used to estimate the processing costs:

- Average soybean meal price (FOB price): US $378.9 per ton (The World Bank 2014a).
- Farm gate soybean meal price: US $284.8 per ton (soybean price at the farm gate allocated to soybean meal).
- Gross benefits processing unit (US $ per soybean meal ton) = Average soybean meal price (FOB price) minus the farm gate soybean meal price: US $94.1 per soymeal ton.

- Given that the crush margin is of about US $34.9 per ton of GM soybean meal and US $35.6 per ton of non-GM soybean meal (derived from The World Bank 2014a), then the gross benefits minus the crush margin is equal to the processing costs. Thus, the processing input costs of the non-GM and GM soybean meal are of about US $58.5 and US $59.2 per soybean meal ton respectively.

Transport to port stage (z = 3)

The quantity of the input "diesel transport to port" (x_1^3), expressed in liters per soybean meal ton, was estimated by multiplying the distance (km) from each municipality to the closer Brazilian Port (Table 3A.1) times an average consumption of diesel (liters per soybean meal ton and per km).

Table 3A.1 Distances from the selected municipalities of Brazil to the closer Brazilian Ports.

Distance municipalities to port (km)	Paranaguá Port	Santos Port	Rio Grande Port
non-GM systems			
Andirá		362.9	
Cafelândia	510.4		
Marialva	385.5		
Arapoti	20.8		
Anahy	530.2		
Campo Mourão	438.9		
Guarapuava	247.3		
Londrina	366.5		
Campos Novos	345.4		
Pedro Afonso			1,780.1
Sorriso		1,780.1	
GM systems			
Cafelândia	512.9		
Marialva	390.9		
Anahy	530.8		
Campo Mourão	436.8		
Guarapuava	254.2		
Londrina	371.9		
Campos Novos	350.1		
Araguari		557.0	
Palmeira das Missões			442.5
Passo Fundo			445.7
Cruz Alta			363.7

The price of the input was calculated as the distance (km) from each municipality to the closer Brazilian Port times the cost of transport (US $ per km and per soybean meal ton).

Cost of transport: US $0.07 ton per km (derived from Salin 2013).
Average consumption of diesel: 0.4 liters per km and per ton (IPCC 2006).

Transoceanic transportation (z=4)

The quantity of the input "bunker fuel" (x_1^4), expressed in liters per soybean meal ton, was estimated by multiplying the average daily fuel requirement of a ship times the number of shipping days from the Brazilian port to the Rotterdam port. The price per liter of bunker fuel was assumed to be the total transportation cost divided by the total quantity of bunker fuel consumed (Table 3A.2).

Table 3A.2 Main data and sources used to calculate the quantity and price of bunker fuel.

Transoceanic transportation	Unit	Paranaguá Port	Santos Port	Rio Grande Port
Quantity of bunker fuel				
Transportation days [a]	day	31.8	31.3	31.4
Bunker fuel [a]	kg/soybean meal ton/day	207.2	207.2	217.0
Bunker fuel consumption	kg/soybean meal ton	6,579.7	6,484.4	6.803.5
Price bunker fuel				
Total transportation cost [a]	US$/soybean meal ton	35.0	34.7	36.1
Bunker fuel price	US$/kg bunker fuel	0.01	0.01	0.01

Derived from: Salin (2012)

Table 3A.3 Summary of quantity and price input data used in the adjusted profit calculation. Data expressed per soybean meal ton.

Data on quantities of outputs (y), inputs (x) and prices (p and w) for the observations of the non-GM soybean meal chain													
		Unit	Andirá	Cafelândia	Marialva	Arapoti	Anahy	C. Mourão	Guarapuava	Londrina	C. Novos	Pedro Afonso	Sorriso
Output quantities (y)	y_1^4	ton	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Input quantities (x)													
Stage 1													
Seed	x_1^1	kg	15.7	13.6	19.0	15.8	17.2	17.2	22.3	18.0	13.6	23.1	18.9
Lime	x_2^1	ton	0.7	0.3	0.5	0.2	0.5	0.5	0.8	0.5	0.6	0.6	0.8
Fertilizer	x_3^1	kg	65.5	60.7	64.3	89.3	61.4	61.4	34.1	64.2	74.2	101.8	75.2
Herbicides	x_4^1	kg	1.0	1.2	0.9	0.9	1.3	0.6	0.7	1.0	1.3	1.5	0.7
Insecticide	x_5^1	kg	0.3	0.3	0.4	0.1	0.3	0.4	0.01	0.3	0.2	0.1	0.1
Fungicide	x_6^1	kg	0.2	0.2	0.3	0.2	0.2	0.2	0.5	0.2	0.3	0.2	0.2
Other inputs	x_7^1	kg	0.1	0.2	0.8	0.8	0.3	0.2	0.5	0.3	0.2	0.2	0.2
Fuel (machinery)	x_8^1	hour	0.8	0.8	0.8	0.7	0.8	0.8	0.7	0.8	0.8	0.9	1.0
Labor	x_9^1	hour	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2	0.8
Other expenses	x_{10}^1	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Capital Fixed costs	x_{11}^1	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Diesel (transport)	x_{12}^1	kg	32.0	34.0	31.6	33.6	30.6	30.7	28.7	31.6	30.8	35.7	41.4
Stage 2													
Hexane, electricity	x_1^2	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Stage 3													
Diesel (transport)	x_1^3	kg	145.2	204.2	154.2	8.3	212.1	175.6	98.9	146.6	138.2	396.8	712.0
Stage 4													
Bunker fuel	x_1^4	kg	6,484	6,580	6,580	6,580	6,580	6,580	6,580	6,580	6,580	6,484	6,484

Table 3A.3 (Continued) Summary of quantity and price input data used in the adjusted profit calculation. Data expressed per soybean meal ton.

Data on prices of outputs (p) and inputs (w) for the observations of the non-GM soybean meal chain													
		Unit	Andirá	Cafelândia	Marialva	Arapoti	Anahy	C. Mourão	Guarapuava	Londrina	C. Novos	Pedro Afonso	Sorriso
Output price (p)	p_1^4	$/ton	448.7	448.7	448.7	448.7	448.7	448.7	448.7	448.7	448.7	448.7	448.7
Input prices (w)													
Stage 1													
Seed	w_1^1	$/kg	0.7	0.9	0.7	1.1	0.7	0.8	1.2	0.7	0.8	0.8	0.8
Lime	w_2^1	$/ton	10.8	15.1	10.8	4.2	9.8	8.0	3.6	10.8	8.5	10.5	10.5
Fertilizer	w_3^1	$/kg	0.5	1.0	0.5	0.9	0.5	0.5	0.5	0.5	0.5	0.9	0.9
Herbicides	w_4^1	$/kg	10.8	16.6	11.4	21.0	13.0	18.9	19.0	15.5	10.4	14.8	14.8
Insecticide	w_5^1	$/kg	23.5	28.0	17.6	37.0	46.3	18.5	32.6	23.5	17.5	27.3	27.3
Fungicide	w_6^1	$/kg	48.2	50.8	50.7	43.1	46.3	47.6	32.0	46.3	46.6	47.4	47.4
Other inputs	w_7^1	$/kg	5.2	4.1	0.9	2.3	4.0	4.5	2.8	2.8	8.1	3.5	3.5
Machinery	w_8^1	$/hour	19.2	17.0	19.2	17.0	19.2	19.2	19.2	19.2	19.2	18.1	18.1
Labor	w_9^1	$/hour	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Other expenses	w_{10}^1	$/unit	50.6	52.1	50.7	52.2	51.0	49.9	50.2	50.8	50.3	54.8	34.8
Capital Fixed costs	w_{11}^1	$/unit	18.8	17.2	18.4	15.7	17.6	17.6	16.4	18.4	17.7	19.7	26.6
Diesel (transport)	w_{12}^1	$/kg	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Stage 2													
Hexane and electricity	w_1^2	$/unit	58.5	58.5	58.5	58.5	58.5	58.5	58.5	58.5	58.5	58.5	58.5
Stage 3													
Diesel (transport)	w_1^3	$/kg	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Stage 4													
Bunker fuel	w_1^4	$/kg	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 3A.3 (Continued) Summary of quantity and price input data used in the adjusted profit calculation. Data expressed per soybean meal ton.

Data on quantities of outputs (y), inputs (x) and prices (p and w) for the observations of the GM soybean meal chain													
		Unit	Cafelândia	Marialva	Anahy	C. Mourão	Guarapuava	Londrina	C. Novos	Araguari	P. Missões	Passo Fundo	Cruz Alta
Output quantities (y)	y_1^4	ton	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Input quantities (x)													
Stage 1													
Seed	x_1^1	kg	14.4	19.4	18.4	13.2	21.0	18.3	12.7	12.9	19.95	13.1	13.1
Lime	x_2^1	ton	0.3	0.5	0.5	0.5	0.8	0.5	0.6	0.3	0.69	0.4	0.7
Fertilizer	x_3^1	kg	64.2	65.5	61.4	63.6	34.1	65.5	76.3	93.4	71.97	81.5	72.8
Herbicides	x_4^1	kg	1.1	1.1	1.7	0.9	1.2	1.3	1.5	1.6	2.28	1.9	1.9
Insecticide	x_5^1	kg	0.3	0.5	0.3	0.4	0.01	0.3	0.2	0.1	0.14	0.5	0.1
Fungicide	x_6^1	kg	0.2	0.3	0.2	0.2	0.5	0.3	0.3	0.3	0.20	0.4	0.2
Other inputs	x_7^1	kg	0.2	0.1	0.2	0.1	0.3	0.1	0.2	0.0	0.21	0.4	0.4
Machinery	x_8^1	hour	0.8	0.7	0.7	0.8	0.6	0.7	0.7	0.9	0.89	0.8	0.8
Labor	x_9^1	hour	1.2	1.2	1.2	1.2	1.2	1.2	1.2	0.9	1.28	1.3	1.3
Other expenses	x_{10}^1	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.00	1.0	1.0
Capital Fixed costs	x_{11}^1	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.00	1.0	1.0
Diesel (transport)	x_{12}^1	kg	33.3	30.1	30.4	31.2	26.9	30.1	29.6	36.7	37.11	32.3	32.3
Stage 2													
Hexane, electricity	x_1^2	n/a	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.00	1.0	1.0
Stage 3													
Diesel (transport)	x_1^3	kg	205.2	156.4	212.3	174.7	101.7	148.8	140.0	222.8	177.0	178.3	145.5
Stage 4													
Bunker fuel	x_1^4	kg	6,580	6,580	6,580	6,580	6,580	6,580	6,580	6,484	6,804	6,804	6,804

Table 3A.3 (Continued) Summary of quantity and price input data used in the adjusted profit calculation. Data expressed per soybean meal ton.

Data on prices of outputs (p) and inputs (w) for the observations of the GM soybean meal chain													
		Unit	Cafelândia	Marialva	Anahy	C. Mourão	Guarapuava	Londrina	C. Novos	Araguari	P. Missões	Passo Fundo	Cruz Alta
Output price (p)	p_1^4	$/ton	420.0	420.0	420.0	420.0	420.0	420.0	420.0	420.0	420.0	420.0	420.0
Input prices (w)													
Stage 1													
Seed	w_1^1	$/kg	1.1	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
Lime	w_2^1	$/ton	15.1	10.8	9.8	8.0	3.6	10.8	8.5	10.6	10.5	11.0	8.5
Fertilizer	w_3^1	$/kg	1.0	0.5	0.5	0.5	0.5	0.5	0.5	0.8	0.6	0.5	0.5
Herbicides	w_4^1	$/kg	10.7	6.3	4.7	6.3	6.3	6.6	4.4	7.0	7.0	6.0	6.0
Insecticide	w_5^1	$/kg	28.0	17.6	47.4	18.5	32.6	23.5	17.5	37.4	37.4	21.8	87.3
Fungicide	w_6^1	$/kg	50.8	51.4	45.7	48.9	32.0	46.3	46.8	49.0	49.0	35.8	58.3
Other inputs	w_7^1	$/kg	4.1	2.8	4.0	4.1	2.8	2.8	8.1	0.0	3.9	4.1	4.1
Machinery	w_8^1	$/hour	17.4	19.7	19.7	19.7	19.7	19.7	19.7	18.6	18.6	19.7	19.7
Labor	w_9^1	$/hour	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Other expenses	w_{10}^1	$/unit	51.8	51.0	50.7	49.8	49.5	50.9	50.2	36.3	53.5	53.0	52.6
Capital Fixed costs	w_{11}^1	$/unit	17.0	17.6	17.6	18.2	15.2	17.6	17.1	23.5	20.3	19.5	19.5
Diesel (transport)	w_{12}^1	$/kg	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Stage 2													
Hexane, electricity	w_1^2	$/unit	59.2	59.2	59.2	59.2	59.2	59.2	59.2	59.2	59.2	59.2	59.2
Stage 3													
Diesel (transport)	w_1^3	$/kg	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Stage 4													
Bunker fuel	w_1^4	$/kg	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Quantification of externalities

Global Warming Potential (GWP)

As proposed by IPCC (2006) GWP at each life cycle stage ($b_1^1, b_1^2, b_1^3, b_1^4,$) was calculated as:

$$GWP = b_1^z = \sum_{i=1}^{I} GHG_i^z \times GWP_i \ ,$$

Where the GWP at each stage z = 1, 2, 3, 4 is the sum of the emission of greenhouse gas i (kg CO_2, CH_4 and N_2O) times its global warming potential over a time frame of 100 years (Table 3A.4).

Table 3A.4 Global Warming Potential of different green-house gases over a time frame of 100 years (IPCC 2006).

Global Warming Potential of green-house gases (GWP_i)		
Carbon Dioxide (CO_2)	CO_2-eq/kg CO_2	1.0
Methane (CH_4)	CO_2-eq/kg CH_4	25.0
Nitrous Oxide (N_20)	CO_2-eq/kg N_2O	298.0

Emission of greenhouse gas i on each stage z (GHG_i^z) is quantified as:

$$GHG_i^z = \sum_{n=1}^{N} x_n^z \times EF_{ni},$$

where x_n^z is the mass (kg) of the input n multiplied by its corresponding emission factor EF_{ni} (Table 3A.5). Inputs n on each stage z included: z = 1: seeds, lime, fertilizer, pesticides (herbicides, insecticides, fungicides) and diesel; z = 2: electricity; z = 3: diesel; z = 4: bunker fuel.

Table 3A.5 CO_2 emission factor for the different inputs (ECOINVENT 2007).

Input	Unit	Emission factors (EF_{ni})
Lime	kg CO_2/kg	0.1
Pesticides	kg CO_2/kg	10.2
Fertilizer (P_2O_5)	kg CO_2/kg	2.3
Potassium chloride	kg CO_2/kg	0.5
Electricity	Kg CO_2/kw hour	0.5
Diesel	kg CO_2/TJ	74,100.0
Diesel	kg CH_4/TJ	4.2
Diesel	kg N_2O/TJ	28.6
Bunker fuel	kg CO_2/kg	0.1

To apply the emission factors to the fuel inputs, i.e. diesel and bunker fuel, we used the conversion factors described in Table 3A.6.

Table 3A.6 Conversion factors for fuel (diesel and bunker fuel) (IPCC 2006).

Conversion factors for fuel		
Density diesel	kg /liter	0.8
Net Calorific Value (NCV)	TJ/kg diesel	4.22867E-05
Density bunker fuel	kg/liter	0.95

Relationship between eutrophication and fertilizer application

The Eutrophication Potential (b_2^1) was calculated in kg of elemental phosphorous (P) per ton of soybean meal as:

$$EP = [(x_3^1 \times P_2O_5\% \times CF) - u \times CF],$$

Where x_3^1 is the fertilizer usage rate per ton of soybean meal on each municipality and farming system; $p\%$ is the percentage of P_2O_5 in the formulation of the fertilizer; u refers to the phosphorous (P) uptake by the soy plants; and CF is the factor that converts P_2O_5 into P.

To estimate the EP the following assumptions were made:

- A NPK 0-20-20 fertilizer mix was assumed (Embrapa Soja 2014). Thus, the amount of P_2O_5 applied to non-GM and GM soybean production on each municipality was calculated as 20% of total fertilizer usage rate.
- It was used an average uptake of 25 kg P per ha in soybean cultivation, either for the non-GM and GM system (Smit et al. 2009).
- Conversion factor: 1 kg P_2O_5 = 0.4 kg P (IFIA 2013).

Soybean production and deforestation of natural areas in Brazil

Deforestation of natural areas (b_3^1) was expressed in m^2 per soybean meal ton and was estimated as:

$$DEF = b_3^1 = \frac{\left([(\sum(Def1) + \sum(Def2) + \sum(Def3))/years] \times soyshare(\%)\right)}{yield},$$

Where Def1, Def2 and Def3 represent the deforestation of natural areas per municipality (m$_2$ per soybean hectare) in three different periods: 2002-2008, 2008-2009 and 2009-2010; $years$ is the total of years in the three periods; soyshare (%) is the soybean planted area in relation to the total municipality area; and $yield$ is the average production of soybeans in the given municipality expressed in soybean ton per hectare. The outcome of the indicator was afterwards allocated to soybean meal production.

The main assumptions to estimate the indicator "Deforestation":

- The impact of soybean production on natural areas is proportional to the soybean surface in relation to the total municipal area ($soyshare$). Thus, if 60% of the municipality area is covered by soybean crops, 60% of the deforestation was allocated to soybean production.

- Given that both soybean farming systems, non-GM and GM, have a share of about 50% in the total soybean production of Brazil (IBGE 2013), the annual deforestation rate allocated to soybean production was divided in equal proportions in case both farming systems are found in a given municipality.

Environmental toxicity, farmworker toxicity and consumer toxicity

The Environmental Impact Quotient developed by Kovack et al. (1992) is divided in three components: The environmental component which is the effect of the pesticide on fish, birds, bees and beneficial arthropods; the farmworker component defined as the sum of applicator exposure plus picker exposure to the pesticide times the long-term health effect or chronic toxicity; and the consumer component defined as the sum of consumer exposure potential plus the potential groundwater effects (For an overview of the method see Kovack et al. 1992).

Table 3A.7 The Environmental Impact Quotient (EIQ) scores for the pesticides used in non-GM and GM farming systems in Brazil (EIQ scores were obtained from the New York State Integrated Pest Management Program, Cornell University 2013).

EIQ per kg of active ingredient	non GM	GM	EIQe	EIQf	EIQc
Azoxistrobine	X	X	66.6	8.1	6.1
Beta-ciflutrina	X	X	85.4	6.9	2.5
Carbaryl	X	X	47.7	15.0	5.5
Carbendazim	X	X	86.0	25.0	40.5
Chlorimuron-ethyl	X	X	42.6	8.0	7.0
Ciproconazole	X	X	68.0	20.3	25.9
Clethodim	X		31.0	12.0	8.0
Fipronil	X	X	193.8	60.0	11.0
Fludioxonil	X	X	60.5	8.1	3.1
Fomezafen	X		32.6	32.0	8.8
Glyphosate		X	35.0	8.0	3.0
Imidacloprid	X	X	92.9	6.9	10.4
Lambda-cihalotrine	X	X	96.7	39.3	5.7
Metalaxyl- M	X	X	37.0	8.1	12.2
Paraquat	X	X	35.9	32.0	6.3
Pyraclostrobine	X	X	68.9	8.1	4.1
Tepraloxidim	X		44.2	12.0	9.5
Thiamethoxam	X	X	77.5	10.4	12.0
Thiophanate-methyl	X	X	40.0	16.2	15.3
Tiodicarbe	X	X	46.0	18.0	6.0

The EIQ scores for each component and each specific active pesticide ingredient (Table 3A.7) were multiplied by the usage rate on each municipality and farming system and by the percentage of active pesticide ingredient in the commercial product. Doing so, the EIQ field use for each component and active pesticide ingredient was obtained. The EIQ field use scores for the different active pesticide ingredients were then summed to determine the total EIQe, EIQf and EIQc.

Loss of employability

The indicator "Loss of employability" was estimated as:

$$LE = b_{k7}^{1} = \text{wolu} - \text{wsp},$$

Where LE is the difference between the average workload of different the land uses on each municipality (wolu) minus the amount of labor required in soybean production (Table 3A.8).

Table 3A.8 Average workload of land uses in the selected municipalities of Brazil.

non-GM systems	wolu	GM systems	wolu
Andirá	6.0	Cafelândia	6.8
Cafelândia	6.4	Marialva	5.9
Marialva	5.5	Anahy	4.8
Arapoti	4.2	Campo Mourão	6.8
Anahy	4.5	Guarapuava	4.5
Campo Mourão	6.4	Londrina	5.4
Guarapuava	4.2	Campos Novos	3.6
Londrina	5.1	Araguari	2.4
Campos Novos	3.4	Palmeira das Missões	8.2
Pedro Afonso	0.7	Passo Fundo	8.0
Sorriso	1.0	Cruz Alta	2.9

a. The "wolu" was computed using data from the IBGE (2013) –Agricultural Censous 2006: Brasil, Grandes Regiões e Unidades da Federação. Brazil.

Estimation of (shadow) price information associated to externalities

Shadow price of CO_2 emissions

CO_2 estimates found in literature sources (Table 3A9):

Table 3A.9 Estimates used for the calculation of the shadow price for CO_2-eq.

Source	US $ per t CO_2[a]	Description
Titus (1992)	25-62	Estimation of the marginal cost of climate change from burning one gallon of gasoline
Tol (2005)	6.5-20	Compilation of 103 estimates of the marginal damage costs of carbon emissions. From the estimates a probability density function was derived to calculate the best estimate. Excluding studies in the grey literature and using a discount rate of 3%, the mean estimate was of about US $16 per tC. Costs of carbon are unlikely to exceed US $50 per tC (1995 US $)
Tol (2008)	9.3-31	Update of the meta-analysis done by Tol (2005). It included over 200 estimates gathered from 47 studies. The mean estimate was US $23 per tC and there is 1% probability that the social cost of carbon is greater than US $78 per tC. (1995 US $)
Nordhaus (2007)	8.5	Study using the Dynamic Integrated model of Climate and the Economy (DICE) to analyze different approaches to cope with global warming. Includes the estimation of the social price of carbon which measures the present value of additional economic damages now and in the future caused by the release of an additional metric ton.
European Commission (2005)	7.3-29	External costs based on two methods: 1) estimation of the damage costs occurring due to impacts from climate change and 2), avoidance costs estimated as an equivalent for the preferences followed when focusing on a target.

Source	US $ per t CO_2[a]	Description
Emission Allowance Price (EEX 2013)	9-15	Prices of buying an allowance if emission exceeds what is permitted (carbon dioxide price). The CO_2 price is what companies are willing to pay for emission reductions and does not necessarily reflect effects on the environment and human health
a. If necessary original estimates were inflated to 2011 US $ using the Consumer Price Index.		

Shadow price for the environmental, farmworker and consumer toxicity of pesticide use

First step: Base values for external costs reported by Pretty et al. (2000) and (2001) were redistributed over the three EIQ model components (derived from Leach and Mumford (2008) and adapted to the Brazilian context). Based values were adjusted to the Brazilian context (Table 3A.10).

Table 3A.10 Redistributed base values for an average active pesticide ingredient (derived from Leach and Mumford, 2008).

US $ per kg pesticide active ingredient	Pretty et al. (2001) categories						
	Sour. water	Poll. incidents	Biod.	CLT	Bee losses	Hum.	Total
EIQ categories							
Applicator effects	0.64	-	-	-	-	0.34	3.90
Picker effects	0.64	-	-	-	-	0.06	2.79
Subtotal Farmworker component							**6.69**
Consumer effects	3.87	-	-	0.80	-	0.02	1.59
Ground water	0.64	0.44	-	-	-	-	0.37
Subtotal consumer component							**1.96**

US $ per kg pesticide active ingredient	Sour. water	Poll. incidents	Biod.	CLT	Bee losses	Hum	Total
Aquatic effects	0.64	0.44	0.20	0.32	-	-	0.54
Bird effects	-	-	0.20	0.16	-	-	0.12
Bee effects	-	-	0.07	0.32	0.17	-	0.19
Beneficial insect effects	-	-	0.20	-	-	-	0.07
Subtotal Environmental component							**0.92**
Total	**6.45**	**0.87**	**0.65**	**1.59**	**0.17**	**0.43**	**9.57**

External costs estimated by Pretty et al. (2001) and redistributed to the EIQ categories and converted to 2011 US $.

GDP per capita PPP (current Int. US $): Brazil 14,034; average UK, the USA, and Germany 44,228. Source: The World Bank (2014b). Adjustment factor for Brazil external costs: 0.34.

Share of agricultural labor Brazil = 17; average % agricultural labor UK, the USA and Germany = 1.47. Source: The World Bank (2014b). Farm worker adjustment factor= 17/1.47= 11.59
Sources (Sourc.) Water; Pollution (Poll.) incidents; Biodiversity (Biod.); Cultural, landscape and tourism (CLT); Humans (Hum.)

Second step: The adjusted external costs of the application of one kg of an average active pesticide ingredient (US $9.57 per kg of active ingredient) were multiplied by the total quantity of active pesticide ingredients used in the USA in the year 2001 (425 million of active ingredient). Afterwards the product was divided into the three EIQ components according to the external cost share of the average active pesticide ingredient (Table 3A.11).

Table 3A.11 External cost share of the average active pesticide ingredient.

	Environment	Farmworker	Consumer
Share of external costs (%/US $.)	10	70	20
Share of total US $ (millions)	389.6	2,841	830.0

Total US $ = 425 million kg of pesticide active ingredients by the average external cost per kg (US $ per kg of active ingredient) (derived from Pretty et al. (2000)
Share of the redistributed external costs of an average pesticide active ingredient = Farmer 70%, Consumer 20%, and Environmental 10% respectively

Third step: The quantity of the most commonly used active pesticide ingredients in the USA for the year 2001 and their associated EIQ scores were collected (Table 3A.12).

Table 3A.12 Most commonly used pesticide active ingredients in USA for the year 2001.

	a.i. (million kg)[a]	EIQ farmer[b]	EIQ consumer[b]	EIQ environment[b]
Glyphosate	51.0	410.9	154.1	1797.7
Atrazine	36.0	290.9	254.6	1947.3
Metam sodium	28.0	680.6	227.7	1340.1
2,4-D	28.0	225.5	140.9	930.0
Acetochor	16.0	169.4	84.8	693.5
Malathion	15.0	130.9	65.5	843.6
Methyl Bromide	11.0	840.9	118.2	867.1
Dichloropropene	11.0	470.5	89.8	385.8
Metolachlor-s	11.0	130.9	98.2	490.9
Metolachlor	10.0	120.0	90.0	450.0
Pendimethalin	14.0	163.6	75.0	995.5
Trifluralin	7.0	65.5	40.0	305.5
Chlorothalonil	5.0	100.0	55.0	406.3
Copper Hydroxide	5.0	110.4	41.1	301.1
Cholorpyrifos	5.00	27.27	9.1	329.8
Alachlor	4.00	43.57	21.8	153.8
Propanil	4.00	43.57	21.8	153.8
Chloropicrin	4.00	141.1	30.5	349.2
Dimethenamid	4.00	32.73	16.4	82.0
Mancozeb	4.00	73.64	29.6	177.4
Ethephon	4.00	77.45	20.55	172.6
EPTC	4.00	21.82	14.55	66.6
Simazine	3.00	33.89	46.07	125.4
Dicamba	5.00	60.00	40.00	295.0
Sulfosate	3.0	25.5	19.1	210.0
Diazinon	3.0	18.8	6.7	334.8
MCPP	3.0	21.8	19.1	84.6

	a.i. (million kg)[a]	EIQ farmer[b]	EIQ consumer[b]	EIQ environment[b]
Carbaryl	2.0	27.3	10.0	86.7
Copper sulfate	3.0	66.3	35.9	404.3
Chlorothalanil	2.0	36.4	20.0	147.7
Chlorpyrifos	2.0	10.9	3.6	131.9
Diuron	2.0	36.4	15.5	92.6
MSMA	2.0	14.6	9.1	74.6
DCPA	1.0	12.3	5.5	45.4
Benefin	1.0	12.3	5.5	53.2
Subtotal	311.0	4,747.5	1,934.9	15,325.4
Remaining	114.0	1,732.7	706.2	5,593.2
TOTAL	**425.0**	**6,480.1**	**2,641.2**	**20,918.5**

a. Derived from: Kiely et al. (2004).

b. EIQ scores were obtained from the New York State Integrated Pest Management Program, Cornell University 2013).

Fourth step: Adding the EIQ scores for the environmental, farmworker and consumer component of the most commonly used active pesticide ingredients and, dividing the corresponding total external costs by these amounts, the shadow price of one EIQ for each component was estimated (Table 3A.13).

Table 3A.13 Shadow price for the environmental, farmworker and consumer toxicity associated to pesticide use.

Shadow prices associated to pesticide use (ET, FT AND CT)			
	Environment	Farmworker	Consumer
Share of total US $ (millions)	389.6	2,841.0	830.0
Total EIQs of most commonly used pesticide active ingredients [a]	20,918.5	6,480.1	2,641.0
US $/EIQ	0.44	0.32	0.02

a. EIQs scores derived from the most commonly used pesticide active ingredients in the USA, 2001 (Kiely et al. 2004)

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CHAPTER 4

Integrated indicators for benchmarking agricultural production systems: the case of specialized potato farms in North-Western Europe

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Abstract

Discriminating trade flows of agricultural commodities in terms of their sustainability requires an internationally accepted performance measure. This paper proposes two indicators, *Social Profit* and *Technical Inefficiency*, for benchmarking farm systems in terms of their economic and environmental performance. The *Social Profit* indicator uses prices and shadow prices to integrate the different economic and environmental criteria into a single metric, whereas *Technical Inefficiency* uses a directional distance function and Data Envelopment Analysis (DEA). The empirical illustration applies the two indicators to specialized potato farms in Germany and the Netherlands. Results of both indicators show that Dutch farms overall perform slightly better than German farms. The Dutch farms generate higher social profit and are technically and environmentally more efficient. Higher *Social Profit* of Dutch farms relative to German farms are mainly the result of higher aggregated productivity. Nevertheless, German farms overall have higher partial productivities for inputs such as capital and variable inputs. On the other hand, Dutch farms are slightly less technically and environmentally inefficient than German farms due to lower pure technical inefficiency and technology gap inefficiency. Nevertheless, the main source of *Technical Inefficiency* in both countries is the pure technical inefficiency. This suggests that in both countries there is a poor or inadequate use of the existing production potential. Both countries could improve their performance substantially following recommendations on optimal output combinations and technical advice on the use of inputs. Also, German farms can reduce the greenhouse gas emissions. Such recommendations, however, should be specific for each group of performers in each country and should be subject to the available technology and to the environmental conditions.

Key words: Farm system, performance, Social Profit, Technical Inefficiency

Abbreviations: Data Envelopment Analysis (DEA); Total Factor Productivity (TFP); Total Price Recovery (TPR); non-radial directional distance function (NDDF); social profit (SP); technical inefficiency with respect to the meta-frontier (TIM); pure technical inefficiency (PTI); scale inefficiency (SI); technology gap (TG).

Introduction

Potato is the fourth most important crop in terms of global production after rice, wheat, and maize (Jones 2014). The crop has great potential to improve food and income security, mitigate poverty, and reduce farmers' risk in vulnerable agricultural environments (Birch et al. 2012). Approximately half of the world's potato production is supplied as fresh (table) potatoes and the remainder is processed into food products, such as french-fries, potato flours, and snacks, or used as animal feed or seed potatoes (Birch et al. 2012; Rudelsheim and Smets 2012). Europe plays a leading role in potato production, accounting for more than 40% of world production (seven European countries are among the top 10 global producers) (FAOSTAT 2015). North-western European countries, in particular, devote a significant proportion of their utilizable agricultural area to potatoes (Smit et al. 2008). Among them, Germany and the Netherlands are the most prominent producers[1]. Despite the importance of potato production for Germany and the Netherlands, there is growing concern about the impact of this activity on the environment. The intensive mode of production needed to maintain high yields involves the extensive use of chemical crop protection products, fertilizers, energy, and water, which can potentially pollute water bodies, soil, and air (Haase and Haverkort 2006; Smit et al. 2008; Vos 1992). Potato production suffers from a large number of diseases, especially from potato late blight *Phytophthora infestans* (Suffert and Ward 2015). Consequently, farmers apply a large amount of pesticides with inevitable impacts on the environment and human health (Haase and Haverkort 2006; Spiertz et al. 1996). Potato crops also require large amounts of nitrogen, phosphorous, and potassium (Haase and Haverkort 2006), leading to soil and water pollution (Spiertz et al. 1996; Vos 1992). Finally, potato production is energy intensive, in terms of the use fossil fuels for operations such as tillage, planting, spraying, spreading, and harvesting, and in terms of the energy embedded in chemical fertilizers and pesticides. All these factors involve the release of greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide, which contribute to climate change (Haverkort and Hillier 2011).

[1] Germany is the seventh largest potato producer in the world, and the biggest in Western Europe. In 2007, Germany produced 11.6 million tons of potatoes. The Netherlands is the ninth largest potato producer in the world, and produced approximately 7.2 million tons in 2007 (FAOSTAT 2015).

Approximately 70% of the potato crop produced in Germany and the Netherlands is exported, either as fresh potatoes or processed products (Rudelsheim and Smets 2012). Buyers increasingly prefer potatoes produced using sustainable practices. Such differentiation is currently based on sustainability schemes that use single-item indicators to measure the environmental performance of farm systems, such as CO_2 emissions and energy intensity (Gerbens-Leenes et al. 2003). However, single-item indicators do not provide the necessary information for the multidimensional decision making needed in sustainability assessment (Yu and Choi 2014). This limitation coupled with the proliferation of sustainability schemes (different schemes ranging from voluntary to private and using different sustainability criteria) may lead to mistrust and protectionism in world trade and may hamper the production of sustainable products (Haase and Haverkort 2006; Lines 2005). A widely accepted integrated approach to measure the economic and environmental performance of farm systems would therefore be a key step towards improving the market access of sustainable products, which in turn may trigger the adoption of best economic and environmental management practices (Lines 2005).

Following Gaitán-Cremaschi et al. (2015), this paper proposes two integrated indicators that are based on the micro-economic theory of production. The two indicators take into account the multiple input-output nature of agricultural production systems, account for the negative externalities of agricultural production, and provide a single integrated measure of economic and environmental performance. In the first integrated indicator, *Social Profit*, multiple outputs, inputs, and externalities are converted into a common metric, i.e. money. Performance in this case is expressed as social profit, which is defined as the profitability of a farm system adjusted for the external costs of production. To identify specific areas of performance improvement, *Social Profit* is decomposed into a Total Factor Productivity (TFP) component and a Total Price Recovery (TPR) component (Fox 2006).

The second integrated indicator, *Technical Inefficiency*, uses Data Envelopment Analysis (DEA) to reflect the best practice frontier. In this approach, a farm system is benchmarked in terms of its capacity to increase outputs, reduce inputs and reduce negative externalities exerted on the environment. *Technical Inefficiency* is computed using the non-radial directional distance function (NDDF). *Technical Inefficiency* is measured relative to the best-practice frontier and can be used to identify potential areas for the improvement of performance. Although many studies have employed

DEA and directional distance functions to measure technical inefficiency and eco-efficiency (see for example Ball et al. (2001); Ball et al. (2005); Beltrán-Esteve et al. 2014; Färe et al. (2007); Färe et al. (2010) Färe et al. (2012), Hoang and Coelli (2011); Kumar (2006); Kuosmanen and Kortelainen (2004), Pérez Urdiales et al. (2015); Picazo-Tadeo and Prior (2009); Yu and Choi (2014); Zhang et al. (2013), to our knowledge none of these studies have applied the NDDF to assess the performance of farm systems and to identify potential areas for the improvement of technical and environmental performance.

The primary objective of this study was to assess the integrated performance of specialized potato farms in the Netherlands and Germany using *Social Profit* and *Technical Inefficiency*. The secondary objective was to compare the outcomes of the two indicators and to identify potential areas for improvement of the technical and environmental performance in each country.

Methodological approach

Consider two countries (Germany and the Netherlands) indicated by *c= (1, 2)*, each with *k = 1,...K* specialized potato farms (referred to as decision-making units (DMU) in the remainder of the paper). Throughout the paper the terms DMU, farm, and farm system are used interchangeably. Each DMU k uses N inputs to produce M outputs and produces J negative externalities, such as waste and pollution. Let vector $y_k^c = (y_{k1}^c, y_{k2}^c, \dots y_{kM}^c) \in \Re_+^M$ represent the outputs, vector $x_k^c = (x_{k1}^c, x_{k2}^c, \dots x_{kN}^c) \in \Re_+^N$ represent the inputs, and vector $b_k^c = \left(b_{k1}^c, b_{k2}^c, \dots b_{kJ}^c\right) \in \Re_+^J$ represent the externalities of DMU k in country c, $\mathrm{DMU}_\mathrm{k}^\mathrm{c}$.

Social profit as a relative measure of economic and environmental performance

The *Social Profit* (*SP*) indicator of $\mathrm{DMU}_\mathrm{k}^\mathrm{c}$ is defined as the difference between the values of the outputs and the values of the inputs and negative externalities:

$$SP_k^c = p'^c_k y_k^c - w'^c_k x_k^c - r'^c_k b_k^c, \tag{4.1}$$

where p'^{c}_{k} is a vector of prices of outputs, w'^{c}_{k} a vector of prices of inputs, and r'^{c}_{k} a vector of prices or shadow prices of externalities for DMU k of country c (where prime indicates the transpose of the vector). The *SP* for DMU k is computed on a per-hectare basis. This approach implicitly assumes that DMUs operate under a production technology that is characterized by constant returns to scale (CRS). A $\mathrm{DMU}_{\mathrm{k}}^{\mathrm{c}}$ is considered to perform better than any other DMU if its *SP* per hectare is higher.

To obtain insight in the variation of the *SP* score of DMUs between the two countries, the Bennet Total Factor Productivity (TFP) indicator and the Bennet Total Price Recovery (TPR) indicator are computed. The Bennet TFP and TPR indicators reflect the difference in *SP* between two countries, as shown in the following equation:

$$\begin{aligned} B^{1,2} = &\left[\frac{1}{2}\left(p'^{2}_{\tilde{k}} + p'^{1}_{\tilde{k}}\right)\left(y^{2}_{\tilde{k}} - y^{1}_{\tilde{k}}\right)\right] - \left[\frac{1}{2}\left(w'^{2}_{\tilde{k}} + w'^{1}_{\tilde{k}}\right)\left(x^{2}_{\tilde{k}} - x^{1}_{\tilde{k}}\right)\right] - \left[\frac{1}{2}\left(r'^{2}_{\tilde{k}} + r'^{1}_{\tilde{k}}\right)\left(b^{2}_{\tilde{k}} - b^{1}_{\tilde{k}}\right)\right] \\ + &\left[\frac{1}{2}\left(y^{2}_{\tilde{k}} + y^{1}_{\tilde{k}}\right)\left(p'^{2}_{\tilde{k}} - p'^{1}_{\tilde{k}}\right)\right] - \left[\frac{1}{2}\left(x^{2}_{\tilde{k}} + x^{1}_{\tilde{k}}\right)\left(w'^{2}_{\tilde{k}} - w'^{1}_{\tilde{k}}\right)\right] - \left[\frac{1}{2}\left(b^{2}_{\tilde{k}} + b^{1}_{\tilde{k}}\right)\left(r'^{2}_{\tilde{k}} - r'^{1}_{\tilde{k}}\right)\right], \end{aligned} \tag{4.2}$$

where the superscript denotes the country (1 for the Netherlands and 2 for Germany) and the subscript $\tilde{k}$ denotes a farm that is on the median value of *SP* for a country. The Bennet TFP indicator (first line of Eq. 4.2) captures differences in the quantities of outputs, inputs, and externalities between the two countries. The Bennet TPR indicator (the second line in Eq. 4.2) captures differences in the prices of outputs, inputs, and externalities between country 1 and 2 (Fox 2006). The sum of the Bennet TFP and TPR indicators reveals in monetary terms the difference in *SP* of the Dutch farm relative to the German farm (benchmark). A positive value indicates better performance of the Dutch farm. The decomposition of the *SP* differences into TPR and TFP indicates the potential areas for improving the production of each output, and for reducing the use of each input, and the production of each externality in the two countries.

Technical Inefficiency

The second indicator, *Technical Inefficiency*, aggregates multiple outputs, inputs, and externalities using a NRDDF. In this approach, a DMU k is said to be technically efficient if it produces at the frontier. DMUs from different countries, however, operate under country-specific production technologies. Therefore, the performance of DMUs cannot be compared directly across countries (Battese et al. 2004). To obtain a consistent cross-country comparison, this paper follows Rao et al. (2003) and constructs a meta-technology defined as the totality of the two country-specific technologies. Thus, if a particular output vector y^c and externality vector b^ccan be produced using a given input vector x^c in any of the two countries, then (y^c, x^c, b^c) belongs to the meta-technology, Ψ^o, which is defined as (Rao et al. 2003):

$$\Psi^o = \{(y, x, b): y \geq 0, x \geq 0, b \geq 0,\ \ x \text{ can produce } y \text{ and } b \text{ in at least one country} \\ -specific\ technology\ \Psi^1, \dots, \Psi^C\}, \tag{4.3}$$

From this definition, it follows that $\Psi^o \supseteq \{\Psi^1 \cup \dots \cup \Psi^C\}$ (Rao et al. 2003).

The DMUs lying on the meta-frontier are the best cross-country performers. Both the country-specific production technology, Ψ^c, and the meta-technology, Ψ^o are not directly observed (Zhou et al. 2012). Hence, this paper uses Data Envelopment Analysis (DEA) for the approximation of the meta-frontier and the country-specific production frontier.

A NRDDF is used to measure the performance of DMUs relative to the meta-frontier and the country-specific frontier. This function provides a measure of the *Technical Inefficiency* indicator relative to the meta-frontier (*TIM*) and technical inefficiency relative to the country-specific frontier.

Formally, the NRDDF for DMU k relative to the meta-frontier is defined assuming constant returns to scale (CRS) as:

$$\vec{D}^o(y_k^c, x_k^c, b_k^c; g|CRS) = sup\left[\frac{1}{3}\left(w_1\sum_{m=1}^{M}\beta_m^o + w_2\sum_{n=1}^{N}\delta_n^o + w_3\sum_{j=1}^{J}\mu_j^o\right):\left((y_{k1}^c + \beta_1^o g_{y1}, x_{k1}^c - \delta_i^o g_{x1}, b_{k1}^c - \mu_1^o g_{b1}), \dots, (y_{kM}^c + \beta_M^o g_{yM}, x_{kN}^c - \delta_N^o g_{xN}, b_{kJ}^c - \mu_J^o g_{bJ})\right) \in \Psi^o(y, b, x);\ \beta_m^o \geq 0(\forall m), \delta_n^o \geq 0(\forall n), \mu_j^o \geq 0(\forall j)\right], \qquad (4.4)$$

Where g is a vector of directions in which the DMU k is assessed relative to the meta-frontier. In our case, the objective function in Eq. 4.4 seeks to jointly optimize the outputs, inputs, and externalities, by increasing the outputs and, reducing the inputs and the externalities, $g = (g_{y1}, \dots g_{yM}, -g_{x1}, \dots -g_{xN}, -g_{b1}, \dots - g_{bJ})$. Each computed value of β^o, δ^o, and μ^o, provides the mth output-specific, nth input-specific, and jth externality-specific technical inefficiency scores if a DMU k has to operate technically efficient given the directional vector[2]. Given that in this study the directional vectors are required to be equal to the observed data, the specific technical inefficiencies are interpreted as a percentage by which each output can be increased and each input and negative externality reduced (Färe and Grosskopf 2010). The computed mth output-specific, nth input-specific, and jth externality-specific measures of technical inefficiency are weighted respectively by the total number of outputs, inputs, and externalities, i.e. w_1, w_2, and w_3. The objective function in Eq. 4.4, *Technical Inefficiency* relative to the meta-frontier (*TIM*), represents the average of the weighted technical inefficiencies of the outputs, inputs, and externalities. In this case, the outputs, inputs, and externalities each contribute one third of the *TIM* score. The choice of weights for each specific output, input, and externality as well as for the objective function can vary; this choice is subject to political debate and may depend on the purpose of the application. For any *Technically Inefficient* DMU_k^c with respect to the meta-frontier, $\vec{\mathrm{D}}^o(\mathrm{y}_k^c, \mathrm{x}_k^c, \mathrm{b}_k^c; \mathrm{g}|\mathrm{CRS}) > 0$. In contrast, for a *Technically Efficient* DMU_k^c ,

[2] This is in contrast with the generalized directional distance function introduced by Chung et al. (1997), in which outputs, inputs, and bad outputs are scaled at the same rate.

$\vec{D}^{o}(y_k^c, x_k^c, b_k^c; g|CRS) = 0$. The linear programming model to compute the NRDDF defined on the meta-technology is presented in Annex 4A.

To obtain insight in the sources of technical inefficiency with respect to the meta-frontier, the *TIM* score for each DMU was decomposed into three additive components: 1) pure technical inefficiency (*PTI*), 2) scale inefficiency (*SI*); and 3) Technology Gap (*TG*). *PTI* measures the degree of technical inefficiency under variable returns to scale (VRS) of DMU_k^c relative to the country-specific frontier. The measure of *PTI* for DMU *k*, PTI_k, was obtained by estimating the NRDDF relative to the country-specific production frontier, Ψ^c, under the assumption of variable returns to scale (VRS). The NRDDF for DMU *k* relative to the country-specific frontier is defined assuming VRS as:

$$\begin{aligned}
&\vec{D}^{c}(y_k^c, x_k^c, b_k^c; g|VRS) \\
&\quad = sup\left[\frac{1}{3}\left(w_1\sum_{m=1}^{M}\beta_m^c + w_2\sum_{n=1}^{N}\delta_n^c \right.\right. \\
&\quad \left. + w_3\sum_{j=1}^{J}\mu_j^c\right): \left(\left(y_{k1}^c + \beta_1^c g_{y1}, x_{k1}^c - \delta_i^c g_{x1}, b_{k1}^c - \mu_1^c g_{b1}\right), \dots, \left(y_{kM}^c\right.\right. \\
&\quad \left.\left. + \beta_M^c g_{yM}, x_{kN}^c - \delta_N^c g_{xN}, b_{kJ}^c - \mu_J^c g_{bJ}\right)\right) \in \Psi^c(y, x, b);\ \beta_m^c \geq 0(\forall m), \delta_n^c \\
&\quad \left. \geq 0(\forall n), \mu_j^c \geq 0(\forall j)\right], \qquad (4.5)
\end{aligned}$$

The objective function in Eq. 4.5, *PTI*, represents the average of the weighted pure technical inefficiencies, of the outputs, inputs, and externalities. For any purely technically inefficient DMU_k^c, $\vec{D}^{c}(y_k^c, x_k^c, b_k^c; g|VRS) > 0$ and for any pure technically efficient DMU_k^c, $\vec{D}^{c}(y_k^c, x_k^c, b_k^c; g|VRS) = 0$.

The second component, *SI*, reflects the ability of DMU_k^c to choose the optimal size of its operations. It is computed for DMU *k* as the difference between the value of the country-specific NRDDF under CRS and VRS.

$$SI_k = \vec{D}^{c}(y_k^c, x_k^c, b_k^c; g|CRS) - \vec{D}^{c}(y_k^c, x_k^c, b_k^c; g|VRS), \qquad (4.6)$$

Finally, TG provides a measure of the distance between the production frontier of an individual country and the meta-frontier. TG reflects the role of country-specific environmental conditions, such as soil and climate, on the production technology. For each DMU k , TG is computed as:

$$TG_k = \vec{D}^o(y_k^c, x_k^c, b_k^c; g|CRS) - \vec{D}^c(y_k^c, x_k^c, b_k^c; g|CRS), \tag{4.7}$$

The linear programming models used to compute the country-specific NRDDF under both scale assumptions, CRS and VRS, are presented in Annex 4A.

The mth output-specific, nth input-specific, and jth externality-specific technical inefficiency scores computed in Eq. 4.4 for each DMU can be decomposed into output-specific, input-specific, and externality-specific PTI, SI, and TG scores. This decomposition provides deeper insight in the sources of TIM of specialized potato farms.

Cross-country performance comparison

Social Profit (SP) and *Technical Inefficiency* relative to the meta-frontier (TIM) were computed for each DMU in each country. Next, for each of the two indicators, the DMUs of each country were divided into four quartiles, i.e. four groups denoted by Q1-Q4. The Q4 group represents the DMUs with the best performance and the Q1 group represents the DMUs with the worst performance. The farms were grouped into quartiles to provide information on the distribution of performance scores and to enable the comparison of farm performance between the Netherlands and Germany.

To determine whether the two indicators produce the same performance ranking of farms, a Spearman Rank Correlation test was conducted (null hypothesis is that the Spearman correlation coefficient, ρ (rho), is 0). A ρ value of 0 indicates that the rank of one indicator is not correlated with the rank of the other indicator. A ρ value closer to 1 indicates that the ranks of the two indicators are strongly correlated.

Performance improvement

Cross-country differences were examined to identify potential areas for improving performance. The two indicators were calculated for the median farms of each quartile, and then compared between countries. The cross-country differences in *SP* were assessed by computing the Bennet TFP indicator and the Bennet TPR indicator (Eq. 4.2); the DMU on the median *SP* value of each quartile in the Netherlands was compared to the DMU on the median *SP* value in Germany (benchmark). Cross-country differences in *TIM* were assessed by comparing the *TIM* values and *PTI*, *SI*, and *TG* components for the median farms of each quartile between the two countries. By comparing the median farms of each quartile between countries, we ensured that the differences in *SP* and *TIM* between countries are assessed taking into account existing farms in the dataset. Additionally, these median farms better reflect the central tendency in the *SP* and *TIM* scores. The mean *SP* and *TIM* scores of each quartile were not used for the comparison because these values may be affected by outliers, which represent the best and worst performing farms in each of the two countries.

Data and selection of outputs, inputs, and externalities

Data for this study were obtained from the Farm Accountancy Data Network (FADN). The dataset contained the costs and revenues of 205 specialist potato farms in the Netherlands (112 farms) and Germany (93 farms), for the year 2008. Specialist potato farms were defined in this study as those farms that derived at least 40% of total revenue from potato sales. We selected two outputs (potatoes as the main output and 'other outputs' representing all other farm products), five inputs (variable inputs, land, capital, natural-resource-based inputs, and labor), and one negative externality associated with potato production (greenhouse gas emissions). Data for the outputs and inputs were obtained from the FADN, and data for the externality was estimated from FADN data and using the Cool Farm Tool software (Haverkort and Hillier 2011).

The implicit quantity of *potatoes* is expressed as annual revenue from potato sales in Euros (EUR); the implicit quantity of *other outputs* consists of the sum of annual revenues (in EUR) from all other outputs produced at the farm, e.g. cereals, oilseeds, forage products, vegetables, mushrooms and flowers, crop products, and other field cash crops. The implicit quantity of *variable inputs* is expressed as annual aggregated expenditures (in EUR) on seeds, fertilizers, pesticides, and other variable inputs, such as packing, soil analysis, plastic coverings, storage, and market preparation. *Land* is measured as the total utilized agricultural area (UAA) measured in hectares, including owned land, land in sharecropping, and rented land. *Capital* represents the average replacement value (in EUR) of the opening and closing values for machinery, equipment, and buildings. *Labor* is measured as the total annual number of hours worked at the farm, including both family and hired labor. *Natural-resource-based inputs* (termed *natural-based inputs* in this paper) consist of annual expenditures (in EUR) on water, electricity, motor fuels, and heating fuels used in the farm.

Finally, the negative externality *green-house gas emissions* is measured as the annual amount of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emitted to the atmosphere as a result of the use of direct energy during agricultural production and fertilizer use. This variable is not available in the FADN database and was estimated as follows. (i) Proxy quantities of energy (kWh) and diesel (liters) were estimated by dividing total expenditures on these inputs by the country-specific annual price of energy and diesel respectively. Quantities of nitrogen (N), phosphorous (P), and potassium (K) were estimated for each farm by dividing the total fertilizer use by an average price per kg of commercial N, P, and K respectively (all calculations and data sources are fully detailed in Annex 4B). (ii) Once the quantities of energy, electricity, and the three main nutrients were estimated, the Cool Farm Tool software was used (Haverkort and Hillier 2011) to calculate the amount of greenhouse gas emissions expressed in kg CO_2-equivalents. The amount of greenhouse gas emissions is calculated by the Cool Farm Tool software using country-specific grid electricity, fuel, and fertilizer emission factors (Haverkort and Hillier 2011). Table 4.1 shows the descriptive statistics of the quantity data for each specific output, input, and externality.

Our study uses implicit quantities of most inputs and outputs, which were obtained by expressing them as the monetary value in a base year. By using implicit quantities of inputs and outputs, we capture the sources of variation in prices between farms. Farm-specific prices reflect differences between farms in the quality of inputs and outputs, differences in marketing strategies, distances of farms to markets, and differences in the size of the farm. In our approach these factors are reflected in differences in the implicit quantities of inputs and outputs. Farms that produce higher quality products, are closer to the market, have better marketing strategies, or benefit from discounts related to size, produce higher implicit quantities of outputs and use lower implicit quantities of inputs. Therefore, the efficiency estimates reflect both the physical quantities and the input and output prices.

Table 4.1 Descriptive statistics of the quantity data for outputs, inputs, and the externality.

Symbol	Variable	Unit	Mean	Std. dev.	Min.	Max.
Germany						
Outputs						
y1	Potatoes[a]	Thousand EUR	125.5	116.4	10.9	702.3
y2	Other outputs[b]	Thousand EUR	99.6	102.1	2.2	841.2
Inputs						
x1	Natural-based[c]	Thousand EUR	22.5	18.4	2.1	142.7
x2	Variable inputs[d]	Thousand EUR	110.3	105.7	14.1	817.2
x3	Capital[e]	Thousand EUR	213.4	192.4	5.1	1054.3
x4	Land	Hectares	59.1	47.4	7.2	217.7
x5	Labor	Hours	3,713.8	2,829.7	270.0	2,3760.0
Externality						
b1	CO_2 emissions	Tons	92.4	73.3	8.6	514.0
Netherlands						
Outputs						
y1	Potatoes[a]	Thousand EUR	208.1	208.1	208.1	208.1
y2	Other outputs[b]	Thousand EUR	107.2	95.1	4.9	800.9
Inputs						
x1	Natural-based[c]	Thousand EUR	27.3	21.1	1.9	151.1
x2	Variable inputs[d]	Thousand EUR	141.9	97.6	13.1	705.6
x3	Capital[e]	Thousand EUR	399.5	311.3	26.0	2,496.1
x4	Land	Hectares	74.1	51.8	12.0	275.1
x5	Labor	Hours	3,760.9	2,025.7	630.0	12,199.8
Externality						
b1	CO_2 emissions	Tons	94.4	67.0	8.8	473.6

a. Output of potatoes consists of potatoes for starch and other potatoes, and is measured as total revenue (EUR) converted to PPS.
b. Revenues (EUR) converted to PPS of cereals, oilseeds, proteins, forage, vegetables, and cash crops.
c. Includes total farm expenditures (EUR) on energy and water, converted to PPS.
d. Includes total farm expenditures (EUR) converted to PPS on fertilizers, pesticides, seeds, and other farm costs.
e. Replacement value (EUR) converted to PPS of farm machinery, buildings, and permanent crops.
GDP Purchasing Power Parities (PPP) Germany = 116, GDP (PPP) the Netherlands 134. Index (EU28 countries is the baseline = 100).

The computation of the *SP* indicator requires prices or shadow prices for all outputs, inputs, and the externality. Per unit prices (EUR) were used for land, labor, and CO_2-equivalents. The quantities of the composite outputs and inputs (*potatoes*, *other outputs, natural-based inputs*, and *variable inputs*) were measured as revenues and expenditures, which were made comparable across countries by using the purchasing power parity (PPP) of the given country relative to the average European purchasing power parity. This conversion correct for the effect of the difference in the price levels between both countries.

A description of the prices for each specific output, input, and externality and the sources of the price data are shown in Table 4.2.

Table 4.2 Description of price data.

Symbol	Variable	Unit	Unit price		Source
			Germany	Netherlands	
Outputs					
p1	Potatoes	PPP	0.86	0.74	Eurostat(2015)[a]
p2	Other outputs	PPP	0.86	0.74	Eurostat (2015) [a]
Inputs					
w1	Natural-based	PPP	0.86	0.74	Eurostat (2015)[a]
w2	Variable	PPP	0.86	0.74	Eurostat (2015)[a]
w31	Capital (machinery)	Depreciation[b] + interest	25%	18%	FADN
w32	Capital (buildings)	Depreciation[b] + interest	7%	7%	FADN
w4	Land	EUR/hectare[c]	259	469	Eurostat (2015); Breustedt and Habermann (2011)
w5	Labor	EUR/hour[d]	9.9	11.5	Agri-info Europe (2015)
Externality					
r1	CO_2 emissions	EUR/ton CO_2-eq.	20	20	Gaitán-Cremaschi et al. (2015)

a. GDP Purchasing Power Parities (PPP) Germany = 116, GDP (PPP) Netherlands = 134. Index (EU28 countries is the baseline = 100).
b. Mean value across farms (average depreciation / average replacement value).
c. Rental price of farmland.
d. Agricultural wage.

Results and discussion

The results in section 'Social Profit and relative economic and environmental performance of specialized potato farms', provide the distribution of the computed *SP*, consistent with Eq. 4.1, for the four quartiles in Germany and the Netherlands. Next, the difference in *SP* between farms on the median value of each quartile in Germany and the Netherlands was decomposed, according to Eq. 4.2, into TFP contributions and TPR contributions for each specific output, input, and externality. Section 'Technical Inefficiency with respect to the meta-frontier (TIM), Pure Technical Inefficiencies (PTI), Scale Inefficiencies (SI) and Technology Gaps (TG)', provides the distribution of the *TIM* scores, computed based on Eq. 4.4, for each of the four quartiles in each country. To identify areas of low performance, the *TIM* scores for the farms on the median *TIM* value of each quartile in Germany and the Netherlands were decomposed into output-specific, input-specific, and externality-specific *PTI (*Eq. 4.5), *SI* (Eq. 4.6), and *TG* (Eq. 4.7) inefficiencies. Section 'Comparison of indicators', compares the ranking of the relative performance of farms between Germany and the Netherlands for both indicators and highlights potential areas to improve the performance of specialized potato farms in each country.

Social Profit and relative economic and environmental performance of specialized potato farms

Figure 4.1 shows the distribution of the computed *SP* for the four quartiles of farms in Germany and the Netherlands. In spite of the higher costs for inputs for most of the quartiles in the Netherlands, farmers in this country obtained higher *SP* per hectare of land than farmers in Germany. The overall performance of farms in the Netherlands can be considered as slightly better, mainly because of the higher revenues (except for Q1) obtained from the sale of potatoes and other outputs. Higher revenues may either be due to a higher yield per hectare of land or a higher price paid per ton of product produced at the farm. Nevertheless, it should be noted that the median value of *SP* computed for Q1 and Q2 yielded a negative result for both countries.

The external costs associated with the greenhouse gas emissions are small relative to the conventional costs and do not significantly vary between the two countries, for all the quartiles. As *SP* decreases, external costs also decrease, which might be related to the fact that lower production is related to lower use of fertilizers, energy, and fuel.

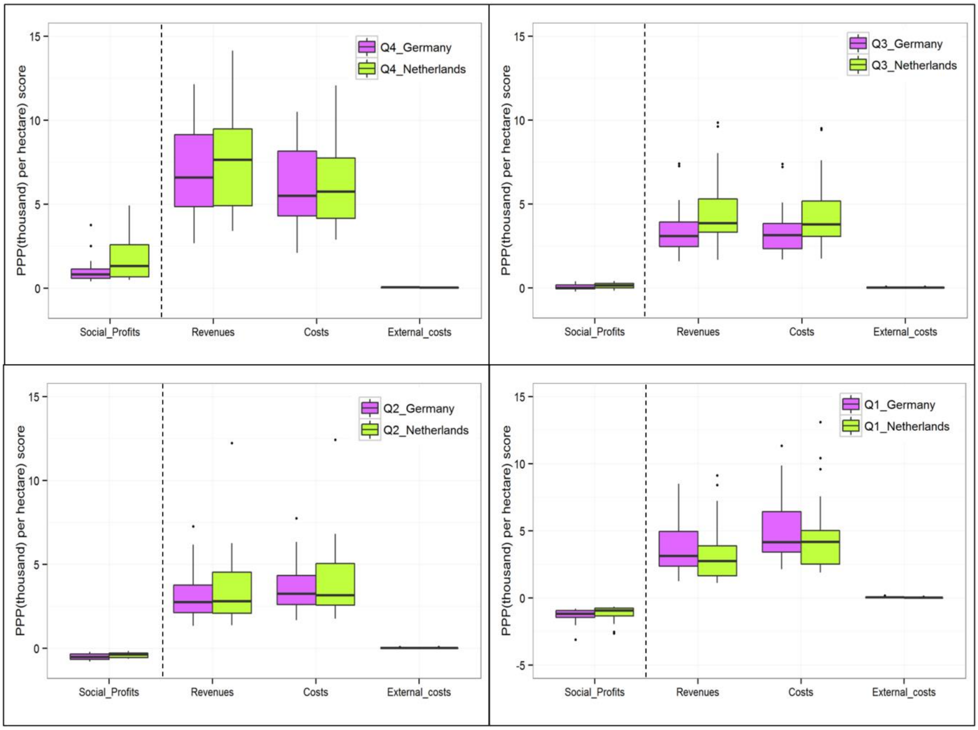

Figure 4.1 Distribution of computed *Social Profit* (*SP*) and its components for Germany and the Netherlands for the four groups (Q1-Q4). The Q4 group represents the farms with the highest *SP* and the Q1 group represents the farms with the lowest *SP*. *SP* is the difference between the Revenues = $p'y$ (second column) and the Costs = $w'x$ (third column) and External costs = $r'b$ (fourth column). The black line on the interior of each box plot indicates the median value. Maximum and minimum values are represented by the end of the vertical lines. Black dots represent outliers (values greater than 1.5 times the upper quartile or less than 1.5 times the lower quartile).

To explore the differences in the performance of the groups of farms between Germany and the Netherlands, the computed *SP* for the farms on the median value of each quartile were compared and decomposed into the TFP and TPR components (Figure 4.2).

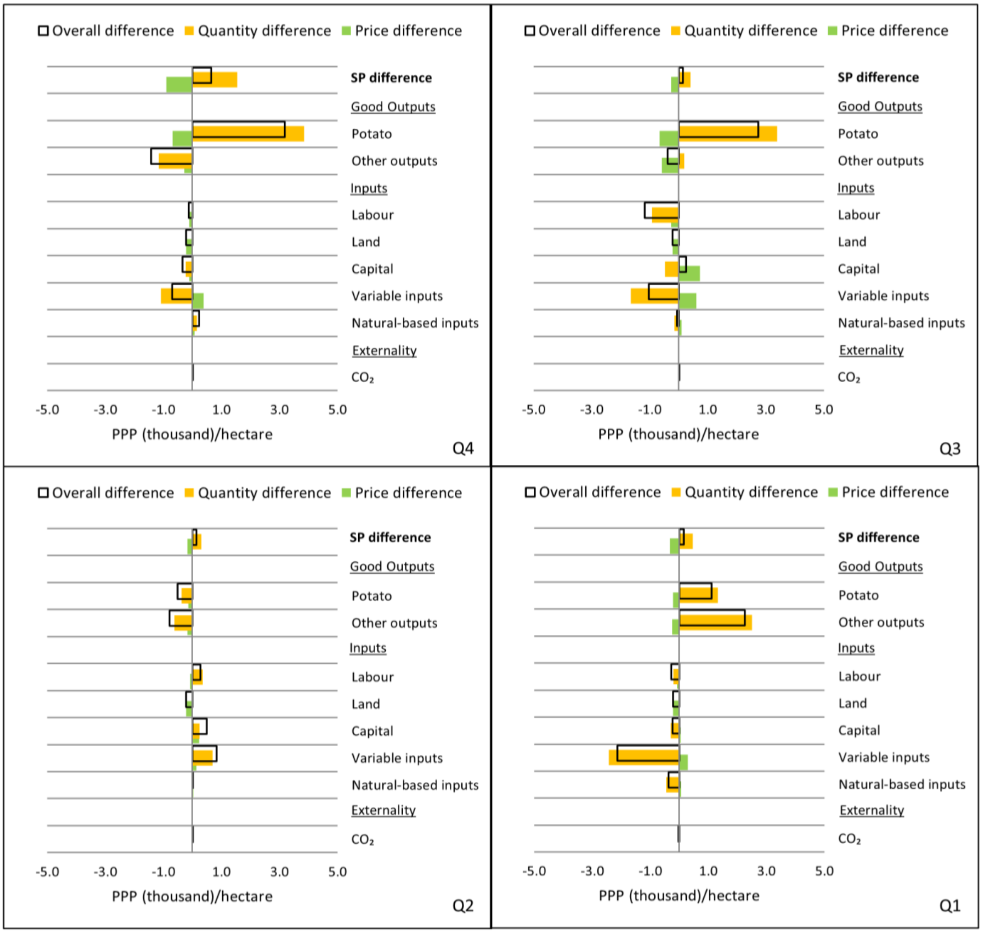

Figure 4.2 Decomposed *Social Profit* differences between the farms on the median values of each group (Q4-Q1) into TFP and TPR contributions. The Q4 group represents the farms with the highest *SP* and the Q1 group represents the farms with the lowest *SP*. The bars represent the deviations of each Dutch farm relative to its analogous German farm (benchmark) in terms of TFP (quantity difference) and TPR (price difference) for each output, input, and externality (consistent with Eq. 4.2). The higher the deviation, the better the performance of the Dutch farm.

The decomposition of the differences in *SP* between the farms of Q4 and the farms of Q3 in the two countries (left and right upper part of Figure 4.2) identifies several main differences. The Dutch farms are less productive using labor, capital, and variable inputs. Equally, the Dutch farm in Q4 produces a lower amount of other outputs. This lack of productivity coupled with a higher cost of labor and land, and a lower price for potatoes and other outputs, reduced the *SP* by 3,732 PPP (Q4) and 4,741 PPP (Q3) in comparison to the German farms. Nevertheless, this lower performance is more than compensated by a higher production per hectare of potatoes and other outputs in the case of the Dutch farm in Q3 and, by a lower cost of capital and variable inputs. This increased the *SP* of the Dutch farms by 4,249 PPP (Q4) and 4,937 PPP (Q3) per hectare compared to the German farms. Hence, overall the farms of Q4 and Q3 in the Netherlands are performing better than the German farms, and this is reflected in higher SP, namely 649 PPP (Q4) and 149 PPP (Q3) per hectare.

Differences in *SP* between the farms of Q2 and Q1 are not large (left and right bottom part of Figure 4.2). For the farms of Q2, the SP difference is 148 PPP per hectare, implying that the Dutch farm performs better than its analogous German farm. The Dutch farm has lower productivity for both potato and other output. However, this farm has higher performance in terms of its better use of labor, variable inputs, and capital. In the case of the farms in Q1, the Dutch farm has higher *SP* per hectare, i.e. 155 PPP per hectare. Higher performance of this farm is mainly due to higher production of potatoes and other outputs. Nevertheless, this farm has a much lower productivity in the use of variable inputs if compared with its analogous German farm. Although the difference in *SP* is similar for Q2 and Q1, its decomposition shows that the underlying causes of the difference in *SP* are different for the farms in Q2 and Q1.

Technical Inefficiency with respect to the meta-frontier (TIM), Pure Technical Inefficiencies (PTI), Scale Inefficiencies (SI) and Technology Gaps (TG)

Figure 4.3 shows the comparative assessment of the distribution of *TIM* scores for Germany and the Netherlands for each of the four quartiles, and the decomposition into the *PTI*, *SI*, and *TG* components. The distribution of farms in Q4 shows that farms are almost fully technical efficient in both countries with respect to the meta-frontier (the median value of *TIM* is zero). The German farms and most of the Dutch farms are located on the frontier of the meta-technology. Although the median *TIM* score for the Dutch farms in this quartile indicates full technical efficiency, some of the Dutch farms have *TIM* scores between 0 and 10%, which are mainly related to *TG* inefficiencies. For the other quartiles, German farms are slightly more technically inefficient than Dutch farms (higher *TIM* scores) i.e. 1% in Q3, 2% in Q2, and 4% in Q1.

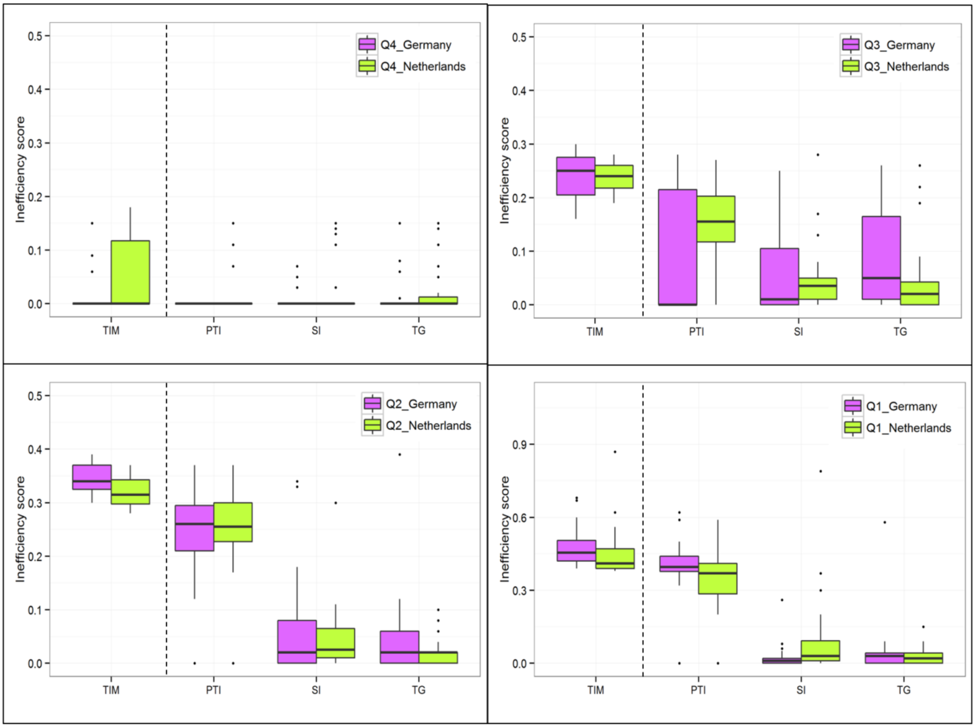

Figure 4.3 Distribution of the computed *Technical Inefficiency* (*TIM*) score computed relative to the meta-frontier (*TIM*) (first column) and its three additive components in each country, for the four groups (Q4-Q1). The Q4 group represents the farms with the lowest *TIM* score and the Q1 group represents the farms with the highest *TIM* score. *PTI* = Pure Technical Inefficiency (second column), *SI* = Scale Inefficiency (third column), and *TG* = Technology Gap (fourth column). Zero values indicate full technical efficiency with respect to the meta-frontier. The interior black line of each box plot indicates the median value. The upper quartile and lower quartile are represented by the top and bottom of each box plot. Maximum and minimum values are represented by the end of the vertical lines. Black dots represent outliers (values greater than 1.5 times the upper quartile or less than 1.5 times the lower quartile).

The main sources of *TIM* for these three quartiles in both countries are pure operational inefficiencies (*PTI* scores), with the caveat that the median of this value in Q3 for Germany indicates full operational efficiency. In these three quartiles, pure operational inefficiencies account for 75% to 87% of the *TIM* scores in Germany and for 65% to 90% of the *TIM* scores in the Netherlands. With regard to sources of technical inefficiency related to the scale of the operations (*SI* scores), scale inefficiencies account for around 7% to 14% of the *TIM* scores in the Netherlands and for around 4% to 5% for farms in Germany, suggesting that the size of some farms in both countries is not optimal. The contribution of *TG* inefficiencies to the *TIM* scores is higher for German farms in the three quartiles. The *TG* inefficiencies account for 7% to 14% of the *TIM* scores for German farms, but only 1% to 5% for Dutch farms. This indicates that the specialized potato farms in Germany operate in a less favorable production environment (poorer environmental conditions or technological limitations) than the Dutch farms, and that this leads to losses in technical efficiency for German farms compared to Dutch farms.

To explore the sources of differences in the *TIM* scores of Germany and the Netherlands for the different quartiles, the computed *TIM* scores for the farms on the median values for Q3, Q2, and Q1 in each country were compared and decomposed into the output-specific, input-specific, and externality-specific sources of technical inefficiency (Figure 4.4) [3]. The comparison of farms on the median value of Q3 in each country shows that higher input-output specific technical inefficiencies for the Dutch farm are due to pure technical inefficiencies (*PTI*) and scale inefficiencies (*SI*) for potato production and the use of labor and land, and to technological limitations (*TG*) in the use of capital in comparison to the German farm. In contrast, lower input-output specific technical inefficiencies are associated with the better scale in the use of variable and natural-based inputs and with a better environmental performance. The comparison of farms for Q2 shows that higher input-output specific technical inefficiencies for the Dutch farm are caused by gap differences in technology (*TG*) for natural-based inputs, poorer potato production (*PTI*) and inefficiencies in the use of land (*SI*) and variable inputs in comparison to the German farm. Lower input-output specific technical inefficiencies for this farm are mainly related to better production of the other output (*PTI*), lower overall inefficiency in the use of labor and lower amounts of greenhouse gas emissions per unit of outputs (*PTI*).

[3] Farms in the fourth quartile, Q4, where not compared because their median *TIM* values and the output-specific, input-specific, and externality-specific technical inefficiency scores were all zero.

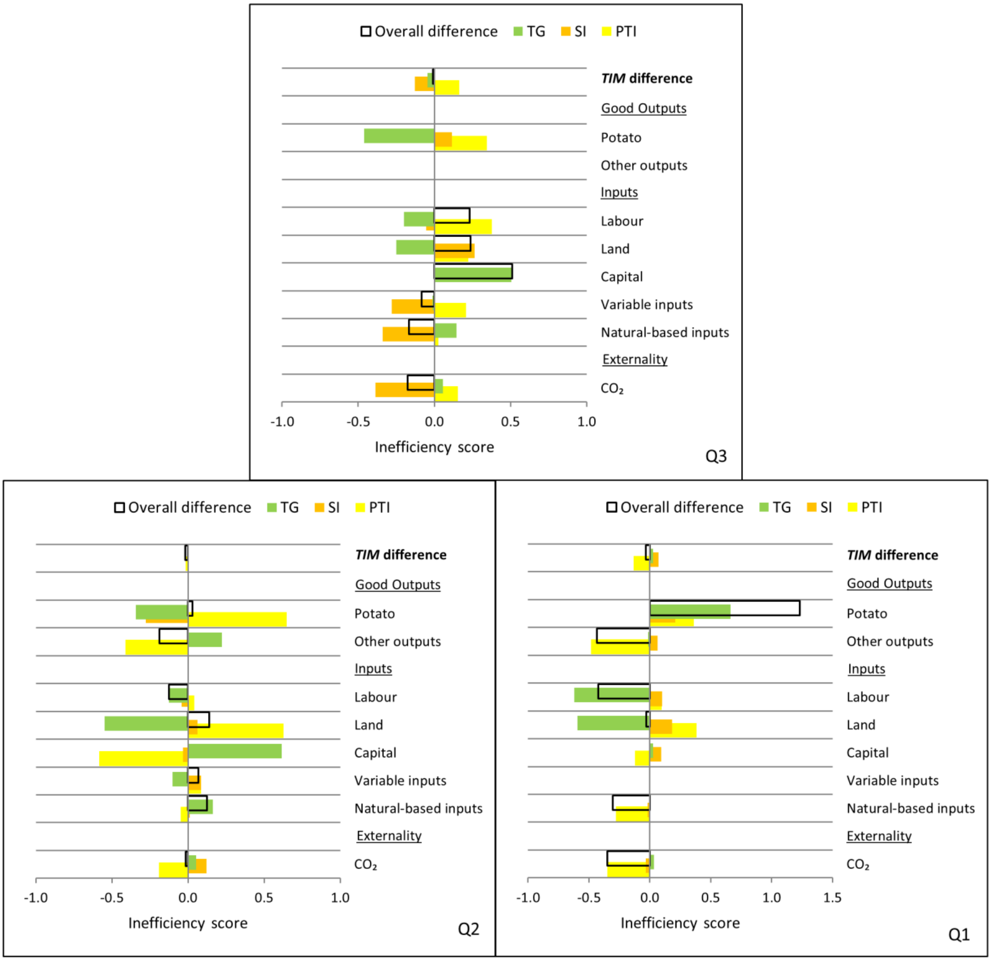

Figure 4.4 Differences in *Technical Inefficiency* with respect to the meta-frontier (*TIM*) and in output-specific, input-specific, and externality-specific technical inefficiencies between the farms on the median value for three groups in Germany and the Netherlands (Q3-Q1). In addition, output-specific, input-specific, and externality-specific technical inefficiencies are decomposed into inefficiencies related to the operation of the farm (*PTI*), size of operations (*SI*), and environmental and technological conditions (*TG*). The bars represent the deviations of each Dutch farm relative to its analogous German farm (benchmark). The higher the deviation, the more technically inefficient the Dutch farm.

Lastly, differences in the *TIM* score between the farms of Q1 show that the Dutch farm is highly technically inefficient in the production of potatoes, mainly caused by technological limitations (*TG*). In spite of these limitations, the Dutch farm is overall more technically efficient than the German farm (lower *TIM* score). This farm has better use of labor (*TG*), lower inefficiency in the use of land and natural-based inputs (*PTI*), a higher technical efficiency in the production of other outputs (*PTI*) and a lower production of greenhouse gases per unit of outputs.

Comparison of indicators

To determine whether the two indicators yielded the same performance outcomes, we conducted the Spearman Rank Correlation test (Table 4.3). Based on the results of the test we concluded that the null hypothesis (the two rankings show significant differences) is rejected at the 0.1% level. This implies that the rankings do not differ, thus providing support that both indicators provide similar results.

Table 4.3 Correlation between the ranking obtained from the *SP* indicator (Rank 1) and the ranking obtained from the *TIM* indicator (Rank 2)

			Rank *SP*	Rank *TIM*
Spearman's rho		Correlation Coefficient	1.000	**,702****
	Rank *SP*	Sig. (2-tailed)		.000
		N	205	205
		Correlation Coefficient	**,702****	1.000
	Rank *TIM*	Sig. (2-tailed)	.000	
		N	205	205

**. Correlation is significant at the 0.01 level (2-tailed).

Moreira and Bravo-Ureta (2010) suggest that the high correlation between the two indicators can be explained by the fact that farmers benefit directly from gains in output and input efficiency. Such gains are transformed into higher yields produced at a lower cost, which in turn translates into improvements in profit. Therefore, it is expected that farms with lower *TIM* scores obtain higher *SP* per unit of land.

Although both indicators yield the same ranking of performance, Figure 4.2 and Figure 4.4 show that the decomposition of the two indicators produces some inconsistencies in the gains and losses of the median Dutch farms relative to the median German farms. The *SP* indicator shows that most of the four farms representing the Dutch quartiles produce higher quantities of potatoes than German farms, but have lower production of other outputs. In contrast, the decomposition of the *TIM* indicator shows that these Dutch farms have the same technical efficiency or are technically more inefficient in the production of potatoes but these farms are technically less inefficient producing other outputs. Such specific differences in the decomposition of the two indicators may be caused by an overestimation of the TFP component of outputs and variable inputs. A proportion of the difference in *SP* between Dutch and German farms should be regarded as a TPR component (price difference) rather than a TFP difference (quantity difference), given that direct information on prices for the outputs and the variable inputs was not used in the estimation. Price differences for the aggregate outputs and aggregate inputs only reflect differences in the aggregate price level of revenues and expenditures between the two countries.

Potential areas of performance improvement

Although the overall result for the two indicators indicates that specialized potato farms in the Netherlands perform slightly better than German farms, the decomposition of the two indicators provides insights in areas where the performance in both countries can be improved. Considering that the main cause of *TIM* in both countries is related to inadequate technical operations, farmers could improve their managerial performance by following technical recommendations. These recommendations should focus on two main aspects: 1) recommendations on appropriate output combinations (potatoes and other crop combinations and rotations) to improve output technical efficiency and maximize land use; and 2) recommendations to increase the productivity and reduce the technical inefficiency of inputs, especially natural-based inputs for German farms and, land and capital for the Dutch farms. For the German farms the strategies should also be focused on reducing the amount of greenhouse gas emissions per unit of output. It can be achieved by reducing the consumption of natural-based inputs such as motor and heating fuels, and especially by reducing the amount of nutrients such as phosphates and potassium. The use of these two nutrients in potato production in Germany is much higher than their use in the Dutch farms. The reduction in the consumption of nutrients would in turn help reduce potential pollution of soils and water. Equally important, a lower use of natural-based inputs and nutrients would decrease the operational costs of the farms. For example, reducing the quantity of labor, fuels, and electricity has been found to have a significant relation to cost savings in potato production (Rudelsheim and Smets 2012). Such recommendations, however, should be specific for each group of performers in each country and should be subject to the available technology and environmental conditions.

In addition to policies and strategies focused on improving the managerial performance of farms, the following efforts could also be undertaken in each of the two countries. Part of the *TIM* scores for German and Dutch farms for Q3, Q2, and Q1 is related to technology gap inefficiencies. These inefficiencies can be assumed to be explained, at least in part, by differences in the production environment, i.e. environmental conditions, weather effects, soil quality and labor quality. However, these inefficiencies also suggest that farms in these groups could pursue different types of micro and macro strategies to overcome the technological limitations. At the macro level, efforts could focus on adaptive research and personal training, and on transferring technology and innovations from the best performing German and Dutch farms to local conditions (Beltrán-Esteve et al. 2014; Moreira and Bravo-Ureta 2010). Our results suggest that for German farms, technological improvements should focus on the quality of labor and land. The quality of labor can be increased by training farmers in good practices when performing activities such as fertilizing and harvesting whereas improvements in land can be achieved by improving soils and reducing tillage practices. On the other hand, technological improvements in the Netherlands should focus on capital and natural-based inputs. This range of policies and strategies may facilitate farms to achieve production on the meta-frontier.

For Dutch farms that are not on the boundary of the meta-frontier, managers could also adopt strategies to change the management and structure of the farm to improve their scale efficiency, for example improving the ability of the farm to procure new resources and expand or reduce its size. These actions could reduce inefficiencies by 7% to 14%. Finally, although the best performing farms in Germany and the Netherlands are operating technically fully efficient with respect to the meta-frontier, technological differences with other potato producing regions around the world could be evaluated. This could be achieved by performing a similar analysis for other potato production technologies. Such an analysis could highlight potential additional investments in research or technologies that can be adapted from other regions to potato production in these two countries.

Methodological implications of the Social Profit indicator and the Technical Inefficiency indicator for stakeholders

The two proposed integrated indicators are expected to be useful for differentiating trade flows of commodities in terms of how sustainably they are produced. A diverse set of negative externalities such as soil, water and air pollution, biodiversity loss and erosion, can be brought into the two indicators to provide a single measure of sustainability performance that takes into account the multiple input-output-externality nature of agricultural production. Equally important, the aggregation of outputs, inputs and externalities using either prices or distance functions, partially overcome the incommensurability and subjectivity problem that decision makers face when deciding about sustainability based on single-item indicators. Hence, it is expected that the implementation of the integrated indicators can guide decision making by politicians, managers, and consumers by presenting a systematic and consistent approach to compare products, which accounts for a variety of economic and environmental criteria and their tradeoffs (Kuosmanen 2005).

Although the application of the two indicators yielded similar results, each indicator has advantages and disadvantages that make them suitable for different situations, and we believe that these differences merit special attention. Measuring integrally the performance of a farm system requires that the complex set of interactions between physical, natural, and economic aspects are known (Moldan et al. 2012). Although a comprehensive understanding of the relationship between these aspects cannot be adequately modelled with a single approach, our two integrated indicators provide us with information about the relative level of performance of different farm systems.
The *Social Profit* indicator integrates economic and environmental criteria (in terms of negative externalities) and their trade-offs by attaching monetary values to outputs, inputs, and negative externalities. Therefore prices and shadow prices function as a representation of social preferences and reflect the tradeoffs between economic and environmental criteria (Farber et al. 2002). Taking into account that prices reflect information (current and past information) regarding diminishing natural assets and

the cost of accumulated environmental liabilities, such criteria would therefore imply maximizing social welfare (Atkinson et al. 2007). The 'true' shadow price, which reflects changes in natural assets and degradation of the environment, is thus a crucial element to take decisions based on of this approach (Atkinson et al. 2007). A good estimation of shadow prices requires understanding of natural thresholds, knowledge about the irreversibility of some components of natural capital, information on an ecosystem's resilience, and quantitative information on the temporal and spatial distribution of external effects (Kuosmanen 2005; Moldan et al. 2012). Although the estimation of shadow prices and prices as the weights to aggregate outputs, inputs, and externalities is a value judgment, this estimation is explicit and transparent along the decision-making process and can be subject to social and political debate. If sufficient scientific and economic information on the natural system is periodically obtained and updated, the *SP* estimation could therefore approach the absolute value of sustainability performance of farm systems. The use of the *Social Profit* indicator also has some disadvantages. It can be costly to apply (time and monetary resources needed to estimate the shadow prices of the main negative externalities of commodity production), and even though accurate shadow prices can be estimated, these can be ethically contested, e.g. commodification of nature, selection of discounting rates, and power asymmetries between those that produce the negative externality and those that bear its effects (Arrow et al. 1996; Atkinson and Mourato 2008; Farber et al. 2002, van den Bergh 2010).

Our second integrated indicator, *Technical Inefficiency*, overcomes these limitations. It does not require prices to aggregate the multiple variables, which is especially advantageous for externalities for which there is a high uncertainty or disagreement about their value. Therefore, decision makers do not need to choose pre-defined weights. This flexibility is also one of the weaknesses of this approach. Weights are data driven (the DEA model derives weights for the outputs, inputs, and externalities of each DMU in such a way that each DMU achieves the maximum feasible technical efficiency) and decision makers have no input in deciding the importance of the economic and environmental criteria. Hence, the approach works as a black-box for decision makers in real situations (Allen et al. 1997; Ng 2008).

A second limitation of this approach is that a large number of output-input variables and externalities will affect the results by increasing the probability that the DMUs are technically fully efficient (Dyson et al. 2001). Many economic and environmental indicators could be included in performance assessments, and condensing these indicators into a few variables could be problematic. This would require aggregation of different sub-variables into one common variable, which implicitly requires incorporating subjectivity in the assessment (Van der Kerk and Manuel 2008). In spite of these two limitations, the *Technically Inefficiency* indicator provides an outcome that might be easier to communicate to policy makers, managers, and consumers. It provides useful information to make short-term improvements in performance, taking into account the technical operations and the technological limitations of a production system in comparison to production systems in other areas and at different scales. Additionally, this approach accounts for the impact of the scale of the operations in the technical efficiency, which is not considered in the *Social Profit* indicator. Finally, this approach is less costly to implement.

Conclusions

The computation of the *Social Profit* and *Technical Inefficiency* indicators showed that specialized potato farms in the Netherlands performed slightly better than German farms. Dutch farms had higher *SP* per hectare and were technically more efficient in economic and environmental terms. Our study identified areas, where the performance of specialized potato farms in Germany and the Netherlands could be improved. Both countries could improve their performance by improving the pure managerial operations of the farms, such as following technical recommendations on appropriate output combinations and technical advice on the use of inputs, especially natural-based inputs for German farms and, land and capital for the Dutch farms. Equally, German farms can reduce substantially their emissions of greenhouse gases by reducing consumption of motor and heating fuels, and especially by reducing the amount of nutrients used in potato production. Additionally, for those German and Dutch farms that were not ranked as best performers (do not belong to the Q4 group), performance could be improved by adopting production practices from the best performing German and Dutch farms.

The two indicators produced a similar ranking of farms in terms of their performance. Thus, both provided useful information to assist decision making in trade negotiations, while providing managers with sound information to improve their farm systems.

Annex 4A.

Linear programming model to compute the NRDDF involved in the Technical Inefficiency estimation.

The NRDDF defined on the country-specific technology and computed using linear programming techniques

$$\vec{D}^c(y^c, x^c, b^c; g|\text{CRS}) = \max_{\beta,\delta,\mu}\left[\frac{1}{3}\left(\frac{1}{M}\sum_{m=1}^{M}\beta_m^c + \frac{1}{N}\sum_{n=1}^{N}\delta_n^c + \frac{1}{J}\sum_{j=1}^{J}\mu_j^c\right)\right]$$

s.t.

$$\sum_{k=1}^{K^c}\alpha_k^c y_{km}^c \geq y_m^c + \beta_m^c g_{ym}, \qquad m = 1, \dots, M,$$

$$\sum_{k=1}^{K^c}\alpha_k^c x_{kn}^c \leq x_n^c - \delta_n^c g_{xn}, \qquad n = 1, \dots, N,$$

$$\sum_{k=1}^{K^c}\alpha_k^c b_{kj}^c \leq b_j^c - \mu_j^c g_{bj}, \qquad j = 1,2, \dots, J,$$

$$\alpha_k^c \geq 0, \;\; k^c = 1,2, \dots, K^c, c = 1, \dots, C$$

$$\beta_m^c \geq 0(\forall m), \delta_n^c \geq 0(\forall n), \mu_j^c \geq 0(\forall j)$$

The model has a set α_k^c of non-negative intensity variables that is restricted to be greater or equal to zero, implying a production technology that exhibits constant returns to scale (CRS). To relax the CRS assumption to assess the DMUs under a country-specific technology that exhibits variable returns to scale (VRS), the sum of the intensity variables is constrained to be equal to one, $\sum_{k=1}^{K^c}\alpha_k^c = 1$.

The NRDDF defined on the meta-technology and computed using linear programming techniques

$$\vec{D}^o(y^c, x^c, b^c; g|\text{CRS}) = \max_{\beta,\delta,\mu}\left[\frac{1}{3}\left(\frac{1}{M}\sum_{m=1}^{M}\beta_m^o + \frac{1}{N}\sum_{n=1}^{N}\delta_n^o + \frac{1}{J}\sum_{j=1}^{J}\mu_j^o\right)\right]$$

s.t.

$$\sum_{c=1}^{C}\sum_{k=1}^{K^c}\alpha_k^o y_{km}^c \geq y_m^c + \beta_m^o g_{ym}, \qquad m = 1, \dots, M,$$

$$\sum_{c=1}^{C}\sum_{k=1}^{K^c}\alpha_k^o x_{kn}^c \leq x_n^c - \delta_n^o g_{xn}, \qquad n = 1, \dots, N,$$

$$\sum_{c=1}^{C}\sum_{k=1}^{K^c}\alpha_k^o b_{kj}^c \leq b_j^c - \mu_j^o g_{bj}, \qquad j = 1,2, \dots, J$$

$$\alpha_k^o \geq 0, \qquad k^c = 1,2, \dots, K^c, \qquad c = 1, \dots, C$$

$$\beta_m^o \geq 0(\forall m), \delta_n^o \geq 0(\forall n), \mu_j^o \geq 0(\forall j)$$

The DEA model of the NRDDF defined on the meta-technology has a set of non-negative intensity variables that is restricted to be greater or equal to zero, implying that DMUs are assessed based on a meta-production technology that exhibits CRS.

Annex 4B.

Underlying assumptions, data and the related sources used to impute the non-observed farm-specific quantity of the bad output, i.e. greenhouse-gas emissions (GHGs).

Estimation of the bad output, GHGs

Quantification of inputs with potential to emit GHGs

The inputs considered as having the potential to emit GHGs were energy, fuel and fertilizer (nitrogen, phosphate and potassium oxide). Given that observed quantities for these inputs are not available in the FADN database[4] those were estimated by:

Energy: The quantity of energy was measured in kilowatts and was estimated by dividing the farm-specific expenditures in energy that is found in the FADN database by the country-specific average price per kilowatt (the country-specific price per kWh is found in Table 4B.1).

Fuel: The quantity of fuel, either motor fuel and heating fuel was measured in liters and was estimated by dividing farm-specific expenditures in these two inputs by a country-specific average price per liter (the country-specific price per liter of fuel is found in Table 4B.1).

Table 4B.1 Country-specific prices for energy and fuel (Prices are expressed in 2008 Euros).

Input	Unit	Price	
		Germany	Netherlands
Energy	EUR/kWh	0.2	0.2
Fuel	EUR/liter	1.1	1.1
Source: (Eurostat 2015)			

[4] A variable for energy, fuel and fertilizers (total of Nitrogen, Phosphorous and Potassium), is found in the FADN database in terms of farm-specific expenditures (Euros).

Fertilizer (N, P_2O_5 and K_2O): To estimate farm-specific amounts of Nitrogen, Phosphate (P_2O_5) and Potassium oxide (P_2O5) the following steps were undertaken:

a. The average use (kilograms) of each type of nutrient in each country in a per-hectare basis was taken from the Forecast of Food, Farming and Fertilizer Use in the European Union 2012-2022 published by Fertilizer Europe (Fertilizer Europe, 2012) (Table 4B.2)

b. A country-specific average price per kg of each nutrient was estimated by multiplying the price of the commercial product by the concentration of the nutrient (Table 4B.2).

c. To estimate the average country-specific expenditures on each nutrient in a per-hectare basis, we multiplied the average use of each nutrient by its price per kg. Given that we assumed that 40% of total Nitrogen consumption in potato production comes from the slurry, which is not purchased by the farmer, we subtracted this amount from the total expenditures in Nitrogen (Table 4B.2).

Table 4B.2 Step a, b and c of the estimation of farm-specific amounts of Nitrogen (N), Phosphate (P_2O_5) and Potassium oxide (K_2O).

	Germany			Netherlands		
	kg/ha	Price/kg	Total EUR/ha	kg	Price/kg	Total EUR/ha
Nitrogen (N)	76.2	2.9	224.0	87.0	2.7	230.6
Phosphate (P_2O_5)	54.2	4.9	262.8	44.5	4.9	215.9
Potassium oxide (K_2O)	152.2	0.7	100.4	57.6	0.7	38.0
			587.3			**484.5**

This amount corresponds to 60% of total Nitrogen consumption as given in Fertilizer Europe (2012). The remaining 40% was subtracted as it is assumed it comes from the application of slurry which is not purchased by the farmer
Price of N based on the commercial price of Ammonium nitrate (N concentration 34%)
Price of P_2O_5 based on the average commercial price of single and triple superphosphate (P_2O_5 average concentration 33%)
Price of K_2O based on the commercial price of Muriate of potash (K_2O concentration of 60% (Index Mundi 2015)

d. Based on the average country-specific expenditures per hectare, the country-specific share of expenditures for each type of nutrient was calculated.

e. To calculate the amounts of each of the three nutrients in each farm, the farm-specific expenditures in fertilizer (variable that is available in the FADN database) was allocated to each of the nutrients based on the share of each type of nutrient that was estimated in step d.

f. The farm-specific quantities of each input were imputed by dividing the farm-specific expenditures in each nutrient by the price per kg of each nutrient.

Quantification of the farm-specific bad output, i.e. greenhouse gas emissions

The bad output, GHGs expressed in kg of CO_2-equivalents, in each farm was quantified as:

$$GHG_k^c = b_{kj}^c = \sum_{n=1}^{N} x_{kn}^c \times EF_n,$$

where x_{kn}^c is the quantity of input n (energy, fuel, N, P_2O_5 and K_2O) for DMU k of country c multiplied by its corresponding emission factor EF_n. The calculation of greenhouse gas emissions was done using the Cool Farm Tool – Potato (CFT-Potato), which is a spreadsheet program that allows the calculation of the amount of GHG emissions that resulted from the use of fertilizers, chemicals, energy, fuel, among others, and during the potato production process, e.g. from the soil after nitrogen fertilization. A detailed explanation of the tool and the used emission factors can be found in Haverkort and Hillier (2011).

(Shadow) price for the bad output greenhouse-gas emissions

To select an appropriate shadow price for CO_2-equivalents, the mean value of the estimates found in some existing literature sources was computed. As a result, we used a shadow price of EUR 0.02 per kg CO_2-eq (Table 4B.3).

Table 4B.3 Estimates from the existing literature sources used for the calculation of the shadow price for the bad output CO_2-eq.

Source	EUR per kg CO_2-eq. [a]
Titus (1992)	18-44
Tol (2008)	7-22
Nordhaus (2007)	6
European Commission (2005)	5-20
Emission Allowance Price (EEX, 2013)	6-11

a. Original estimates were converted to 2008 EUR.

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CHAPTER 5

Assessing the sustainability performance of coffee farms in Vietnam: a social profit inefficiency approach

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Abstract

A first step towards achieving sustainable agricultural production is an integrated assessment of the current relative sustainability levels of farms and increased knowledge on the factors affecting the sustainability level. We propose to use the social profit, that is, the profit of the farm adjusted for the external costs of production, as a the basis for a relative sustainability assessment. Under this approach farms that achieve the maximum attainable social profit are considered as zero social profit inefficient and thus, performing sustainable. To illustrate the usefulness of this approach, we assessed both the relative sustainability of coffee farms in Vietnam to determine the sources of inefficiency in social profit, and the impact of a set of socio-economic characteristics and management practices on the relative sustainability level. Sustainability issues included in the assessment were profitability, greenhouse gas emissions, nitrate pollution, and pesticide toxicity. The results show that coffee farms, on average, could increase their social profits threefold at given prices and given the current production technology. The main source of social profit inefficiency for coffee farms in Vietnam is associated with sub-optimal allocation of resources and levels of production, which are mainly the result of the under-utilization of labor and variable inputs, and the under-production of coffee. The assessment of the external determinants of social profit inefficiency shows that increasing values for socio-economic characteristics such as the distances from the coffee farm to the closest town/city center and to the closest coffee factory/traders, and, increasing frequency of spraying increases social profit inefficiency. On the contrary, coffee producers belonging to the ethnic group JoRai and increasing values for hired labor and frequency of fertilizing and pruning activities reduces social profit inefficiency. Improving the sustainability performance of coffee farms in Vietnam would require corrective actions to ensure the efficient use of inputs and the correct frequency of management activities that were found to affect negatively the level of social profit inefficiency. At the regional level policies should focus on providing technical assistance by extension services. It is also recommended to perform an in-depth study on the management of coffee farms by the JoRai ethnic group to disseminate their good management practices to other ethnic groups in Vietnam.

Keywords: Social profit inefficiency, relative sustainability performance; externalities

Introduction

Coffee is one of the most widely traded agricultural commodities in the world, produced by 20 million to 25 million producers in more than 14 countries (Giovannucci et al. 2008; Reinecke et al. 2012). Vietnam is the second largest exporter of coffee after Brazil, with a 12% to 15% share in the world market (Giovannucci et al. 2008; Nguyen et al. 2015). In 2013, coffee exports accounted for approximately 2% of Vietnam's gross domestic product (GDP) (OEC 2016) and 17% of all commodity exports (Nguyen et al. 2015). Currently, an area of 500,000 hectares is planted in coffee, with a production of approximately one million tons (Nguyen et al. 2015). Vietnam produces two coffee varieties, Robusta and Arabica, with 90% of the planted area under Robusta (D'haeze et al. 2005). Approximately 80% of coffee production is cultivated in four provinces located in the Central Highlands, i.e. Kon Tum, Dak Lak, Gia Lai, and Lam Dong, typically by smallholder farmers (Amarasinghe et al. 2015; Luong and Tauer 2006). The majority of farmers obtain the largest part of their income from coffee production (Kuit et al. 2004).

Coffee production is important for the Vietnamese economy and crucial for the Central Highlands. However, the unshaded monoculture farming system used by most producers generates harmful environmental impacts that may degrade ecosystems. The coffee farming system in Vietnam requires high application of fertilizers to provide the necessary nutrients for coffee plants (Ho and Huynh 2007). High fertilization rates cause emissions of greenhouse gases and emissions of nutrients to water bodies. Emission of greenhouse gases contributes to climate change, whereas emission of nutrients to water bodies has adverse effects on biodiversity and water quality (Tilman et al. 2002). Chemical biocides are used to control fungal and pest diseases, and to remove a variety of weeds. Fungal diseases affecting coffee production include antracnosis (by *Collelotrichum* spp.) and brown eye disease (*Cercospora coffeicola*); pest diseases include brown scale (*Sassetia coffea*), green scale (*Coccus viridis*), the coffee berry borer (*Hypothenemus hampei*), and the mealy bug (*Planococcus lilacinus*) (Kuit et al. 2004; Lan and Wintgens 2008). Improper application of chemical pesticides in coffee production has adverse effects on the environment, biodiversity, and human health, especially farm workers (Garcia and Shively 2011; Lan and Wintgens 2008). Ensuring adequate production levels requires irrigation of coffee plantations (Carr 2001). Experience in Vietnam shows that farmers often use more water than needed during dry periods and over-irrigate coffee plantations (Ho and Huynh 2007). Over-irrigation is especially harmful during drought years, when water resources (from groundwater and basins) deplete (Luong and Tauer 2006). Scarcity of water may drive additional investments for construction of deeper wells and also negatively affect ecosystems.

Profitability of the coffee farming system is continuously under pressure, due to increasing production costs for fertilizers and labor (Kuit et al. 2004), and the volatility of coffee prices in the world market (Nguyen et al. 2015; Tran 2007). At low coffee price levels, the revenues of coffee production may not cover production costs, while other crops, such as pepper, may become more profitable. This situation leads to (partial) replacement of coffee plantations by other crops or to the abandonment of coffee farms (Nguyen et al. 2015), impacting in turn on the livelihood of rural communities, especially the relatively poor.

The challenges facing coffee production center around the three pillars of sustainability, i.e. environmental, economic, and social. A first step towards achieving sustainable coffee production in Vietnam is an integrated assessment of the current relative sustainability level of coffee farms. A following step is to explore how the socio-economic characteristics and management practices of farmers affect the sustainability level. The most common approach for sustainability assessment is the use of a diverse set of performance indicators, which measure the extent to which sustainability goals are achieved (Smith and McDonald 1997). Quantification of a set of performance indicators is feasible in many cases. However, it is difficult to combine indicators reflecting different aspects of sustainability into an overall measure e.g. to combine profitability and greenhouse gas emissions (Gerbens-Leenes et al. 2003; Kusiima and Powers 2010). To overcome these difficulties, several authors propose using a single metric, namely money, to express the performance on the different aspects of sustainability (Atkinson 2000; Ehui and Spencer 1992; Figge and Hahn 2004; Gaitán-Cremaschi et al. 2015; 2016b). Our approach for an integrated sustainability performance measure is the use of social profit, i.e. profit of the system (revenues minus production costs) adjusted for the external costs of production (environmental and social dimensions of sustainability) (Gaitán-Cremaschi et al. 2015; 2016b; Kusiima and Powers 2010; Van Passel et al. 2007). In this approach, farms that achieve the largest attainable (positive) social profit are considered to perform sustainably, that is, are classified as zero social profit inefficient.

Some studies have assessed the benefits and the private and social costs of agricultural production (see for example Gaitán-Cremaschi et al. (2015); Hartridge and Pearce (2001); Pimentel et al. (2009); Pretty et al. (2000) and (2005); Tegtmeier and Duffy (2004). Several studies have also employed Data Envelopment Analysis (DEA) and directional distance functions (DDF) to measure the environmental and economic inefficiency of farm systems (see for example, Ball et al. (2004); Beltrán-Esteve et al. (2014); Hoang and Coelli (2011); Gaitán-Cremaschi et al. 2016b; Pérez Urdiales et al. (2015); Picazo-Tadeo et al. (2011) and (2012). However, the literature lacks an assessment of the extent to which farms achieve the maximum attainable social profit. Such an assessment enables the identification of sources of inefficiency: the extent to which the current production potential is used, the sub-optimal choice of the scale of operation, and the sub-optimal allocation of resources at given prices.

In the light of the foregoing, the objectives of this study are: (1) assess the sustainability performance of a sample of coffee farms in Vietnam in terms of their social profit inefficiency and sources of inefficiency, and (2) determine the socio-economic characteristics and management practices that influence the relative sustainability performance. This assessment will identify opportunities to improve the relative sustainability performance of coffee production in Vietnam.

Measuring relative farm sustainability using the Nerlovian social profit inefficiency (*NI*) indicator

Nerlovian social profit inefficiency (NI) indicator

Suppose there are $k = 1,...K$ coffee farms (termed decision making units – DMUs) using N inputs and D fixed inputs to produce M outputs. In the production process, J negative externalities are produced, such as waste and pollution. Let vectors $y = (y_1, y_2, \dots y_M) \in \Re_+^M$, $x = (x_1, x_2, \dots x_N) \in \Re_+^N$, $(f_1, f_2, \dots f_D) \in \Re_+^D$, and $b = \left(b_1, b_2, \dots b_J\right) \in \Re_+^J$ represent the outputs, inputs, fixed inputs, and negative externalities, respectively. The production possibility set is defined as the set of all feasible input–output-externality vectors and is represented as:

$$T = \{(y, x, f, b) \colon x, f \ can\ produce\ y, b\}, \tag{5.1}$$

If the k-th DMU faces output prices represented by the vector $p = (p_1, p_2, \dots p_M) \in \Re_+^M$, input prices by the vector $w = (w_1, w_2, \dots w_N) \in \Re_+^N$, fixed input prices by vector $v = (v_1, v_2, \dots v_D) \in \Re_+^D$, and external unit cost estimates for the externalities represented by the vector $r = (r_1, r_2, \dots r_J) \in \Re_+^J$, then the observed social profit is defined as:

$$SP = p'y - w'x - f'v - r'b, \tag{5.2}$$

Hence, social profit is defined as revenues (*p'y)* minus conventional costs (*w'x)*, fixed costs (*f'v),* and the external costs of production (*r'b*).

To evaluate the efficiency with which the k-th DMU operates in terms of social profit, the observed social profit in (Eq. 5.2) is compared to the maximum social profit the DMU could attain given the current technology used by the sample of DMUs, the available levels of the fixed inputs *f*, and the (shadow) prices. The difference between the maximum attainable social profit and the observed social profit provides a measure of social profit inefficiency. The maximum social profit for the k-th DMU is defined as:

$$\Pi(p, w, r, f) = \max_{y,x,\mathrm{b}}\{p'y - w'x - r'b \mid (y, x, f, b) \in T\} = p'y^* - w'x^* - r'b^*, \tag{5.3}$$

where y^*, x^*, and b^* are the optimal output, input, and externality combinations that provide the maximum attainable social profit, given the production technology, prices (shadow), and the available levels of the fixed inputs. To provide a unit-free measure of social profit inefficiency (Färe and Grosskopf 2005; Fried et al. 2007), the Nerlovian social profit inefficiency (*NI*) is used. The *NI* is defined as the difference between the maximum social profit defined in (Eq. 5.3) and the observed social profit defined in (Eq. 5.2), normalized by the value of the directional vectors $g_y \in \Re_+^M$, $g_x \in \Re_+^N$, and $g_b \in \Re_+^J$ (Chambers et al. 1998). This normalization arises from the duality between the profit function and the DDF, providing the basis for its decomposition (Chambers et al. 1998)[1]. The DDF and the directional vector are discussed in more detail in subsection 'Decomposition of the *NI* indicator'.

Accordingly, the *NI* indicator for the k-th DMU is defined as:

$$NI\left(p, w, r, y, x, f, b; g_y, g_x, g_b\right) = \frac{\Pi(p, w, r, f) - (p'y - w'x - r'b)}{p'g_y + w'g_x + r'g_b}, \tag{5.4}$$

In this approach, the k-th DMU is performing sustainably, i.e. has zero Nerlovian social profit inefficiency, if the observed social profit is equal to the maximum highest attainable social profit. In other words, when $NI\,(.) = 0$. If the DMU is Nerlovian social profit inefficient, $NI\,(.) > 0$, then the DMU has scope to improve its sustainability performance.

The *NI* score can be decomposed to identify the contributions of output-specific, input-specific, and externality-specific inefficiencies:

$$\begin{aligned} &NI\left(p, w, r, y, x, f, b; g_y, g_x, g_b\right) \\ &\quad = \frac{p'(y^* - y)}{p'g_y + w'g_x + r'g_b} + \frac{w'(x - x^*)}{p'g_y + w'g_x + r'g_b} + \frac{r'(b - b^*)}{p'g_y + w'g_x + r'g_b}, \end{aligned} \tag{5.5}$$

Decomposition shows whether outputs are under- or over-produced, inputs are under- or over-used, and whether externalities are below or above optimum levels. Hence, decomposition can help identify opportunities to improve the relative sustainability performance of coffee farms. The inefficiency in social profit and the variable-specific contributions are illustrated in Figure 5.1, using a simple example with one input, one output, and one externality.

[1] For a detailed explanation of this dual relation see Chambers et al. (1998).

Sources of farm sustainability

Decomposition of the NI indicator: pure technical inefficiency (PTI), scale inefficiency (SI), and allocative inefficiency (AI)

Exploiting the dual relation between the profit function and the DDF, the *NI* indicator for the k-th DMU is decomposed into overall technical inefficiency *(OTI)* and allocative inefficiency *(AI)* (Chambers et al. 1998). The *OTI*, in turn, is decomposed into pure technical inefficiency *(PTI)* and scale inefficiency *(SI)*:

$$NI = OTI + AI = PTI + SI + AI, \tag{5.6}$$

The *OTI* component reflects the technical inefficiency relative to the best practice frontier, assuming a production technology that exhibits constant returns to scale (CRS). It reflects the percentage by which a DMU could jointly increase the outputs and reduce the inputs and externalities, given the production technology T (Chung et al. 1997). If the DMU cannot make further improvements, it is zero technical inefficient and therefore operating at the best practice frontier (Chung et al. 1997). Estimation of the O*TI* component requires the use of the DDF associated with an explicit direction in which inefficiency is measured. Choosing the directional vector enables the projection of the input, output, and externality vectors onto the production frontier as defined by the directional vector $g = \left(g_y, -g_x, -g_b\right)$. Formally, the DDF measuring technical inefficiency under CRS is defined as (Chung et al. 1997):

$$OTI = \vec{D}_T\left(y, x, f, b; g_y, g_x, g_b | CRS\right) = max\left\{\beta : \left(y + \beta g_y, x - \beta g_x, b - \beta g_b\right) \in T_{CRS}\right\}, \tag{5.7}$$

The k-th DMU is overall zero technically inefficient if $\vec{D}_T(y, x, f, b; g|CRS) = 0$ and overall technically inefficient if $\vec{D}_T(y, x, f, b; g|CRS) > 0$.

The *OTI* measure can be further examined by decomposition into *PTI* and *SI*. *PTI* is obtained by estimating (Eq. 5.7), assuming a production technology that exhibits variable returns to scale (VRS), as follows:

$$PTI = \vec{D}_T\left(y, x, f, b; g_y, g_x, g_b | VRS\right) = max\left\{\beta : \left(y + \beta g_y, x - \beta g_x, b - \beta g_b\right) \in T_{VRS}\right\}, \tag{5.8}$$

The second component, SI, is computed as the difference between the values obtained from (Eq. 5.7) and (Eq. 5.8). This measure reflects the extent to which the k-th DMU succeeds in choosing the optimal size of its operations, as follows:

$$SI = \vec{D}_T(y, x, f, b; g_y, g_x, g_b|CRS) - \vec{D}_T(y, x, b; g_y, g_x, g_b|VRS), \tag{5.9}$$

The AI component refers to the loss of potentially attainable social profit as a result of a sub-optimal choice on the mix of inputs, outputs, and externalities, given their corresponding (shadow) prices (Jayaraman and Srinivasan 2014). The AI component is derived as the residual of the difference between (Eq. 5.4), (Eq. 5.8), and (Eq. 5.9):

$$AI = NI - PTI - SI, \tag{5.10}$$

The PTI, SI, and AI components are necessarily non-negative, which implies that if the k-th DMU has zero Nerlovian social profit inefficiency, then it must be pure technical efficient, scale efficient and allocative efficient (Jayaraman and Srinivasan 2014).

The concept of social profit inefficiency and its decomposition into the PTI and AI components is illustrated in Figure 5.1, using a simple example with two DMUs (A and B), one input (x), one output (y), one externality (b), and with prices (w, p and r). The social profit function $\pi=py-wx-rb$ is rewritten in the form $y=(\pi+rb/p)+(w/p)x$, i.e. the equation of the isoprofit line with intercept $\pi+rb/p$ and slope w/p that gives all input-output-externality combinations capable of producing social profit level π. The isoprofit line is tangent to the production technology T at point R, where an optimal input-output combination (y^*, x^*) maximizes social profit given their prices.

In the first case, DMU^A is social profit inefficient, as observed input-output combination (y^A, x^A) generates a lower social profit than it could attain at point Q, given prices and the production technology. The inefficiency in social profit for this DMU is attributable to pure technical inefficiency (DMU^A could increase the output and decrease the input in the direction defined by g = $(g_y, -g_x)$ to reach the production frontier at point P), and allocative inefficiency (given the prices, DMU^A is under-using the input and under-producing the output). An optimum combination would allow the DMU^A to increase social profit, i.e. shift from point P to point Q on the isoprofit line.

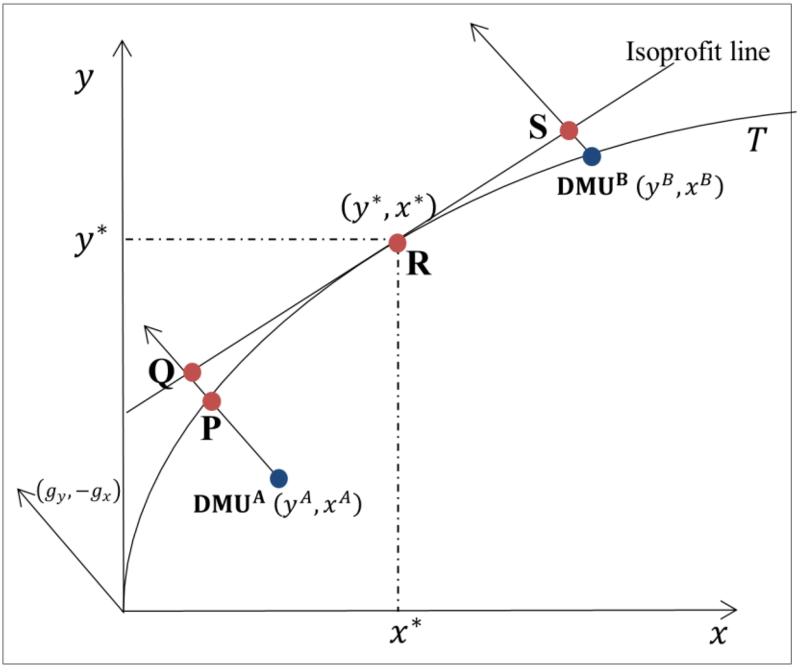

Figure 5.1 Inefficiency in social profit and the decomposition into pure technical inefficiency and allocative inefficiency (see text for explanation).

In the second case, DMU^B is also social profit inefficient. The observed input-output combination (y^B, x^B) does not yield the maximum attainable social profit. This DMU is pure technical efficient as it lies on the boundary of the production frontier. The inefficiency in social profit is only attributable to allocative inefficiency mainly caused by over-use of the input and over-production of the output. In this case, an optimum combination would allow the DMU^B to increase social profit, i.e. shift from the boundary of the production frontier to point S on the isoprofit line.

This paper uses DEA to estimate social profit inefficiency and its components *(PTI, SI*, and *AI)*. The linear programming models used in the computations are presented in Annex 5A.

Socio-economic characteristics, management practices and social profit inefficiency

We hypothesize that a set of farm-specific variables (socio-economic characteristics and management practices) affects social profit inefficiency and its components. To investigate this, we used a bootstrap truncated regression model (Algorithm number 1) as proposed by Simar and Wilson (2007). For details of the algorithm we refer the reader to Simar and Wilson (2007). Following Simar and Wilson (2007), the bootstrap truncated regression model is defined as:

$$I \quad = a + z_k\beta + \varepsilon_k, \tag{5.11}$$

where the inefficiency scores I (*NI, PTI, SI and AI*) obtained in (Eq. 5.4), (5.8), (5.9), and (5.10) are regressed on the vector $z = 1, \dots V$ of farm-specific socio-economic characteristics and management practices that may affect the sustainability performance of coffee farms in Vietnam. The variables in this vector are different from the outputs, inputs, and externalities used to calculate the *NI* indicator. β denotes the regression coefficients and ε_k represents the error term with a normal distribution $N(0, \sigma_\varepsilon^2)$. Inefficiency scores are truncated between 0 and infinity, where 0 relates to the most efficient farms. The dependent variables (*NI, PTI, SI* and *AI*) reflect the level of inefficiency of coffee farms. A positive coefficient indicates that the variable is positively associated with inefficiency, hence this variable increases the inefficiency of coffee farms.

Data

Data used to estimate the *NI* indicator and the bootstrap truncated regression were collected between 2007 and 2009 in Chu Se District, Gia Lai Province. Data was collected by the project 'Quality and Sustainability Improvement of Robusta

Production and Trade in Gia Lai, Vietnam', funded by the Douwe Egberts Foundation and conducted by EDE Consulting. Gia Lia province is one of the main coffee-producing regions. It has 80,000 hectares planted in coffee (Quan & Ward 2015) and accounts for 13.5% of total Robusta coffee production in Vietnam. Farm-level data were recorded in farmer field books by 361 farmers and then digitalized by project staff. The data consist of socio-economic characteristics (e.g. field size and education level) and information on daily crop management, such as the type, quantity, and price of inputs used and coffee output produced. Farmers who participated in the survey voluntarily participated in training on data recording. Furthermore, 'key farmers' gathered and reviewed the data to check for potential errors. Participating farmers received feedback through annual individual reports, containing detailed analysis of the financial and physical performance of their farm, and 'group reports' that enabled farmers to compare themselves with their peers (EDE 2009). Coffee farms in this sample are similar in terms of the coffee variety produced, tree age, and soils conditions, but vary in farm size and intensity of input use.

For the estimation of the *NI* indicator, data were selected for the year 2009 and cover one production cycle. One output (*coffee beans)* and four inputs (*variable inputs, labor, land,* and *water)* were distinguished. Land was assumed to be a fixed input in coffee production. The environmental impacts of coffee production in Vietnam are mainly caused by high fertilization, inadequate use of pesticides, deforestation, and depletion of groundwater (Ahmad 2000; D'haeze et al. 2005; Lindskog et al. 2005, Wintgens 2009). Therefore, the following negative environmental externalities were selected: *greenhouse gas emissions, nitrate pollution,* and *pesticide toxicity*. Due to data limitations, externalities related to deforestation and groundwater reduction were not included in this assessment.

Quantity of outputs, inputs, and externalities

The quantity of *coffee beans* is expressed in tons of green bean equivalents (GBE) produced in a production cycle (one year in Vietnam). The implicit quantity of *variable inputs* is expressed as annual aggregated expenditures on fertilizers and biocides (herbicides, insecticides, and fungicides) in 2009 US dollars ($). *Labor* is measured as the total number of working days used at the farm, including both family and hired labor (a working day equals eight hours of work). *Land* is defined as the area utilized for coffee production, measured in hectares (ha). The quantity of *water* used for irrigation is expressed in cubic meters (m^3).

The negative externality *greenhouse gas emissions* is expressed in CO_2 equivalents (CO_2-eq.). Three greenhouse gasses were considered: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). For each greenhouse gas, the annual amount of gas emitted to the atmosphere was multiplied by its global warming potential over a time frame of 100 years, relative to that of CO_2 (IPCC 2006). These amounts were then summed to obtain the total annual amount of greenhouse gas emissions emitted to the atmosphere. We estimated the annual emission of greenhouse gases for two sources associated with coffee production: (1) emissions that are intrinsically associated with the production of fertilizers and pesticides (embedded emissions); and (2) N_2O emissions due to direct and indirect Nitrogen (N) emissions (see below).

The externality *nitrate pollution* captures the amount of N that is released to the environment in the form of nitrates (NO_3-N) and is expressed in kilograms of nitrates as N (kg NO_3-N). This externality was calculated for each coffee farm as the difference between the amount of N that enters the system and the amount of N that leaves the system, as we assumed that coffee farm systems are in equilibrium with respect to N in the system. N enters the system through the application of fertilizers and pruning residues. The amount of N that leaves the system includes the amount of N that is lost via background emissions (N_2O-N), fertilizer-induced and crop residue emissions (N_2O-N and NO-N), N lost via volatilization (NH_3-N and NO-N), and N that is exported in the harvest material.

N inputs from fertilizers were estimated as the quantity of each type of fertilizer (kg of synthetic and organic fertilizer) multiplied by the known (or estimated[2]) N concentration per kilogram of fertilizer. Nitrogen inputs from crop residues were estimated as the annual amount of crop residues (kg of dry matter per year), multiplied by the average estimated N concentration per kilogram of dry matter (% N per kg dry matter). N_2O-N background emissions were calculated based on the emission factor proposed by the IPCC (2006) for tropical climates on a per-hectare basis. Fertilizer-induced and crop-residue N emissions were estimated using the generic emission factors of Bouwman et al. (2002), which reflect the percentage of the

[2] N contents of organic material used as fertilizer are generally not measured and estimates are based on existing literature.

applied N that is lost via N_2O-N and NO-N emissions. The generic emission factors differ per type of fertilizer; the average emission factor of Bouwman et al. (2002) is approximately 1% of total N fertilizer. This value is similar to the default value published by the IPCC (2006) and to the results of N_2O-N emissions found in the field by Harmand et al. (2007) and Hergoualc'h et al. (2008) in coffee plantations in Costa Rica. N loss via volatilization was estimated using Tier II IPCC (2006). N export through the coffee harvest was estimated using yield data and data on nutrient removal from harvesting coffee beans (Wintgens 2009).

The externality *pesticide toxicity* is expressed using the environmental impact quotient (EIQ) score and was estimated using the EIQ model developed by Kovach et al. (1992) to provide an assessment of the risks involved with biocide use. The EIQ model does not provide exact measurements of the impact of biocide application, but allows the comparison of potential impacts from different farm management practices regarding the use of biocides. The model gives an EIQ score to each active ingredient for three components: environment, farm worker and consumer. The EIQ score for the environmental component reflects the impact of the active ingredient on aquatic life, bees, birds, and beneficial insects. The EIQ score for the farm worker component reflects the impact on applicators and pickers, and the EIQ score for the consumer component reflects the impact of the pesticide active ingredient on the consumer, caused by residues in groundwater and food (Praneetvatakul et al. 2013). The total EIQ score is calculated as the average of the three components and reflects the overall toxicity of each pesticide active ingredient. To estimate the toxicity of the weed, pest, and disease control strategy of each coffee farm, the total EIQ score for each active ingredient used at each farm was multiplied by its application rate (kg of active ingredient). The EIQ scores were summed over all the active ingredients used at the farm, yielding the externality *pesticide toxicity*. Higher scores represent a higher potential impact of the weed, pest, and disease control strategy of a given coffee farm.

Table 5.1 shows the descriptive statistics for the quantities of output, inputs, and externalities. The equations, emission and conversion factors, assumptions, and calculations of the three externalities are fully detailed in the supplementary material (Annex 5B).

Table 5.1 Descriptive statistics for the quantities of outputs, inputs, and externalities for the year 2009.

Symbol	Variable	Unit	Mean	Std. dev.	Min.	Max.
Output						
y1	Coffee	tons GBE	2.9	1.5	0.4	9.0
Inputs						
x1	Labor	working days	239.9	109.0	36.10	638.5
x2	Water	m^3	1,463.0	836.9	240.0	5,900.0
x3	Variable inputs	US $	947.2	563.3	44.1	4,558.8
x4	Land	hectares	1.1	0.6	0.1	6.0
Externalities						
b1	Pesticide toxicity	EIQ	20.8	51.6	0.0	457.1
b2	N pollution	kg NO_3-N	143.8	85.4	0.0	842.6
b3	Greenhouse gas emissions	tons CO_2-eq.	4.3	2.4	0.2	22.0

GBE = green bean equivalents; *EIQ* = environmental impact quotient score; *NO_3-N* = nitrates as Nitrogen; *CO_2-eq.* = CO_2 equivalents

Prices for outputs, inputs and externalities

Prices for outputs and inputs and the shadow prices for externalities are all expressed in 2009 US dollars ($).

Prices for outputs and conventional inputs

Observed market prices for the output and the conventional inputs were obtained from field book data. The price used for the output *coffee beans* is the average annual price per ton of Robusta coffee received by coffee farmers in 2009 ($ per ton). The quantities of pesticides and fertilizers are expressed in total expenditures. As these quantities implicitly incorporate farm-specific prices, the price of the *variable input* was set to one. The price of labor is the daily minimum wage in Vietnam ($ per working day); this implicitly assumes that the shadow price of family labor is equal to the market wage[3]. The annual rental value of agricultural land is used as the proxy price of *land* ($ per ha of agricultural land per year). The price of irrigation water in

[3] The social profit indicator is a measure of social welfare and measures the net benefits of the farm system for society. Hence, family labor is taken as a cost in coffee production.

Vietnam is computed as the cost of the fuel, electricity, and labor needed to irrigate one cubic meter of water ($ per m^3).

Shadow prices for externalities

The externalities of coffee production are not traded in well-defined markets and therefore market price information does not exist. Shadow prices for the three externalities were transferred from empirical studies in published literature. Shadow prices were adjusted to the Vietnamese context using the ratio of GDP per capita of Vietnam to the average GDP per capita of the country, where the estimation was made, expressed in purchasing power parities (PPP). This assumes that the willingness to pay (WTP) to avoid or to mitigate the damages is proportional to the per capita income of each country (Silalertruksa et al. 2012) and is locally determined.

<u>Shadow price of greenhouse gas emissions</u>

We used the value estimate reported by Gaitán-Cremaschi et al. (2015) as an appropriate shadow price for *greenhouse gas emissions* that reflects the associated impacts of climate change. In this study, an average shadow price of $19 per ton of CO_2-eq. was calculated based on external costs that were reported in peer-reviewed journals.

<u>Shadow price of nitrate pollution</u>

Nitrate pollution associated with the over-fertilization of agricultural fields affects streams, rivers, and lakes. Nitrate pollution can cause serious environmental problems, such as eutrophication, and human health problems related to water quality impairments (Addiscott et al. 1991; Wick et al. 2012). A comprehensive overview and estimation of the context-specific external costs of nitrate pollution is a difficult task (Van Grinsven et al. 2013). The external cost of a unit of nitrate from agricultural areas can depend on the weather conditions that influence its transport and on the exposure of humans and ecosystems to the pollutant (Van Grinsven et al. 2013; Wick et al. 2012). Attempts have been made to quantify the external costs of nitrate pollution by assessing the expenditures on drinking water treatment (Pretty et al. 2000, 2001; Tegtmeier and Duffy 2004), and by estimating the economic damage associated with health impacts and ecosystem degradation (Van Grinsven et al. 2013). As an appropriate shadow price for *nitrate pollution*, we used the results of the study of Van Grinsven_et al. (2013). This study provides a comprehensive assessment of the external costs of different N flows for the EU27 in the year 2008, including the unit costs for health damage and eutrophication damage associated with nitrate leaching. As external cost estimates from WTP studies are closely linked to income levels, we used the lower bound of the external costs for the EU27: \$0.1 per kg of N for health-related damages and \$2.0 per kg of nitrate for eutrophication-related damages. The per capita income in Vietnam is substantially lower than in the EU (World Bank, 2015). We therefore assumed that the awareness of environmental and health problems derived from nitrate pollution is lower in Vietnam than in most European countries, and that Vietnam's WTP for treating polluted water and eutrophication may be lower than in the EU. Adding together the unit damage costs, and adjusting them to the Vietnamese context (using the ratio of GDP per capita), we obtained a shadow price for *nitrate pollution* of \$2.0 per kg of nitrate.

<u>Shadow price of pesticide toxicity</u>

A proxy shadow price for *pesticide toxicity* was estimated using the pesticide environmental accounting (PEA) tool developed by Leach and Mumford (2008), combined with the approach of Gaitán-Cremaschi et al. (2015). We used base values reported by Pretty et al. (2001) for the external costs associated with the application of one kg of pesticide active ingredient. These base values are based on studies in the USA, Germany, and the UK, and include expenditures on pesticide monitoring, poisonings, water treatment costs, and biodiversity loss.

Using the PEA tool, the set of base values were redistributed over the three components of the EIQ model, i.e. environmental, farmworker, and consumer components. This provided an external cost for each component associated with the application of one kg of an average pesticide active ingredient. The average EIQ score of an average pesticide active ingredient for each of the three components was then estimated, by identifying the pesticide active ingredients that were used in the USA in 2001 and collecting their respective EIQ scores for each component. The redistributed base values for external costs for each component were then divided by their respective EIQ scores to obtain an external cost per unit of EIQ. We adjusted the estimated external costs per unit of EIQ for each component to reflect the difference in socio-economic conditions in Vietnam compared to the countries for which the base values were estimated. To adjust the costs, we used the ratio of the GDP per capita of Vietnam to the average GDP per capita of the USA, Germany and the UK.

The base values associated with the farmworker EIQ component depend on the number of people that potentially come into direct contact with pesticides. Therefore, the farmworker external costs were adjusted by a factor that represents the difference between the share of agricultural employment in Vietnam and the average share of agricultural employment in the USA, Germany, and the UK (Praneetvatakul et al. 2013). This procedure resulted in a shadow price for *pesticide toxicity* of $0.15 per EIQ. The detailed calculation of the shadow price for pesticide toxicity, including the assumptions, is provided in the supplementary material (Annex 5B).

Table 5.2 provides the descriptive statistics for the farm-specific (shadow) prices of outputs, inputs, and externalities.

Table 5.2 Descriptive statistics for prices of outputs, inputs, and externalities in 2009 US dollars ($).

Symbol	Variable	Unit	Unit price
Outputs			
p1	Coffee	$/ton GBE	1764.7
Inputs			
w1	Labor	$/working day	4.1
w2	Water	$/m^3	0.1
w3	Variable inputs		1.0[4]
w4	Land	$/hectare per year	352.9
Externalities			
r1	Pesticide toxicity	$/EIQ	0.15
r2	N pollution	$/kg NO_3-N	2.00
r3	Greenhouse gas emissions	$/ton CO_2-eq.	19.00

Determinants of Nerlovian social profit inefficiency

We selected twelve socio-economic and management variables (Table 5.3) as potential determinants of *NI* and its components. The socio-economic variables were: (i) distance of the farm to the fertilizer shop (measured in kilometers); (ii) distance of the farm to the closest city/town center (measured in kilometers); (iii) distance to the closest coffee trader/factory (measured in kilometers); (iv) family members

[4] No additional price estimates were needed for 'variable inputs' because these inputs were already defined in monetary terms (Table 5.1).

(measured as the number of family members); (v) two variables representing the education of the husband and the education of the wife (each measured as a categorical variable, where 0 reflects five years of primary education, 1 reflects an additional 4 years of intermediate education, and 2 reflects an additional 3 years of secondary education); and (vi) ethnic group (binary variable, where 0 refers to the ethnic group Kinh, which is the major group in Vietnam, and 1 to the ethnic group JoRai). Five explanatory variables reflecting management practices in coffee production were included: the frequency of (i) pruning, (ii) fertilization, (iii) weeding, and (iv) pest and disease control (each measured as the number of times that the activity is performed in one production cycle), and (v) the share of hired labor in total labor (measured as the percentage of total labor). Only coffee farms with complete information for the selected variables were used in the bootstrap truncated regression: 302 of the 361 coffee farms in the sample were used.

Table 5.3 Descriptive statistics for socio-economic characteristics and management practices (302 DMUs).

Variable	Unit	Mean	Std. dev.	Min.	Max.
Continuous variables					
Distance to fertilizer shop	kilometers	2.3	2.2	0.1	12.0
Distance to city/town center	kilometers	36.4	6.8	2.0	53.0
Distance to coffee factory/trader	kilometers	3.3	3.0	0.0	15.0
Family members	number	4.0	2.0	1.0	9.0
Hired labor	% of total labor	39.3	23.8	0.0	94.6
Pruning	frequency	6.4	2.6	0.0	11.0
Spraying	frequency	0.4	0.6	0.0	2.0
Fertilizing	frequency	3.9	1.2	1.0	7.0
Weeding	frequency	4.8	1.6	0.0	9.0
Categorical variables					
Education husband		1.1	0.6	0.0	2.0
Education woman		1.0	0.6	0.0	2.0
Ethnic group		0.1	0.3	0.0	1.0

Education = 0 reflects primary education, 1 reflects intermediate education, and 2 reflects secondary education); *Ethnic group* = 0 refers to the ethnic group Kinh and 1 to the ethnic group JoRai

We hypothesized that the inefficiency scores (*NI*, *PTI*, *SI*, and *AI*) are positively associated with the variables related to distance, spraying, and ethnic group, and that the inefficiency scores are negatively associated with family members, hired labor, pruning, fertilizing, weeding, and education. Our hypotheses are based on the following assumptions:

- The greater the distance to the fertilizer shop, town/city center, and coffee factory/trader, the more difficult or costly it is for farmers to commercialize products and to have access to credit and extension services;
- A large number of spraying events indicates overuse of biocides;
- The JoRai ethnic group has lower profit maximization behavior in comparison to the Kinh group (Tran 2007);
- Families with more members have more potential labor (time) to allocate to coffee production;
- Higher education levels of adults indicate higher managerial skills and specific professional training (Picazo-Tadeo et al. 2011);
- Hired labor is better qualified to perform (particular) field activities (Latruffe et al. 2004), hence a more efficient use of labor is achieved with hired labor; and
- More frequent pruning, fertilizing, and weeding leads to better crop productivity, because the availability and uptake of nutrients is higher, which in turn leads to more efficient use of inputs.

Results

Composition of the Nerlovian social profit inefficiency

Table 5.4 presents summary statistics for the observed social profits, the computed *NI* scores, and the decomposition into *PTI*, *SI*, and *AI*.

The average observed social profit for our sample of coffee farms in Vietnam is approximately $2,300. The distribution of the observed social profits shows that 95% of the sampled coffee farms obtained a positive social profit. This indicates that, on average, the revenues of coffee sales cover the costs of inputs used in coffee production as well as the social costs associated with the environmental externalities.

However, our results show a large potential for improvement in social profit. *NI* scores for our sample range between 0.00 and 4.76, with mean values per quartile[5] varying between 0.36 and 1.47 (Table 5.4).

Table 5.4 Mean values for the total sample and mean values for each quartile (Q1 – Q4) for the observed social profit and *NI*, *PTI, SI*, and *AI* scores. The Q1 group represents the farms with the lowest inefficiency scores and the Q4 represents the farms with the highest inefficiency scores.

Variable	Mean	Std. dev.	Q1	Q2	Q3	Q4
Observed social profit	2,279.3	1,829.7	3,949.6	2,334.4	1,877.8	959.7
NI	0.84	0.48	0.36	0.62	0.89	1.47
PTI	0.26	0.15	0.14	0.22	0.31	0.38
SI	0.02	0.05	0.01	0.02	0.03	0.03
AI	0.56	0.40	0.21	0.38	0.55	1.06

PTI = pure technical inefficiency; *SI* = Scale inefficiency; *AI* = Allocative inefficiency. *NI* = Nerlovian social profit inefficiency = *PTI* + *TI* + *AI*

The *NI* indicator equals zero when the observed farm is located on the production frontier. This means that, on average, the farms in our sample could increase their social profit by at least 290%, that is, 84% or more of the value of the *NI* denominator (normalization of the *NI* indicator). This can be achieved by choosing an optimal mix of inputs, outputs, and externalities at given prices and, if the production potential is fully used.

The decomposition of the *NI* scores into the three components highlights the following findings. (1) Up to 67% of the social profit inefficiency (allocative inefficiency accounts for 0.56 of the value of the *NI* denominator, which is 0.84) can be attributed to allocative inefficiency. This component is the main source of social profit inefficiency. Hence, a significant improvement in sustainability performance could be achieved by choosing a better combination of inputs and pollution levels in coffee production. (2) Pure technical inefficiency, with 26% of the value of the *NI* denominator, is the second source of social profit inefficiency. Although we did not find any study that used a DDF

[5] Each quartile consists of 25% of farms. The first quartile (Q1) represents the farms with the lowest *NI* scores and Q4 represents the farms with the highest *NI* scores.

to measure the pure technical inefficiency of coffee farms in Vietnam, our results are similar to those found by Rios and Shively (2005), who estimated a technical inefficiency of about 18% for Robusta coffee farms in Dak Lak province. (3) The loss of social profit due to scale inefficiency is small in our sample, suggesting that farmers generally operate close to the optimal size and therefore there is little potential to improve the efficiency of production by adjusting the scale at which they operate.

Table 5.5 presents the results of the decomposition of *NI* scores to identify the output-specific, input-specific, and externality-specific contributions. The results of this decomposition highlight the following findings. (1) The main source of *NI* is under-production of the output; the production of most coffee farms is low, compared to the maximum possible production level. (2) Inputs in coffee production are, on average, under-used in our sample. The use of variable inputs can be increased to reach optimum coffee production levels. However, we cannot indicate which variable input (fertilizers or biocides) contributes the most to the increase. (3) The quantities of externalities produced are generally close to the optimum levels.

Table 5.5 Mean values for the total sample and each quartile (Q1 – Q4) for the decomposition of *NI* scores into output-specific, input-specific, and externality-specific inefficiencies. The Q1 group represents the farms with the lowest *NI* scores and the Q4 represents the farms with the highest *NI* scores.

	Mean	Q1	Q2	Q3	Q4
Coffee	1.13	0.54	0.86	1.17	1.97
Labor	-0.16	-0.09	-0.13	-0.16	-0.27
Water	-0.01	-0.01	-0.01	-0.01	-0.02
Variable inputs	-0.10	-0.06	-0.07	-0.09	-0.17
Pesticide toxicity	0.00	0.00	0.00	0.00	0.00
N pollution	-0.02	-0.01	-0.01	-0.01	-0.03
Greenhouse gas emissions	-0.01	0.00	0.00	-0.01	-0.01
NI	0.84	0.36	0.62	0.89	1.47

A positive (negative) sign for the output indicates that it is under-produced (over-produced).
A positive (negative) sign for the inputs indicate that they are over-used (under-used).
A positive (negative) sign for the externalities indicates that these are produced above (below) the optimum pollution level.
The land input is not included as it is taken as fixed factor of production.

The sustainability of coffee production in Vietnam depends on the world market price of coffee and on the local prices of labor, variable inputs, and water. We conducted a sensitivity analysis to explore the effect of changes in these prices on the sustainability of coffee production in Vietnam. A further reason for the sensitivity analysis is the likelihood that we underestimated the price of water.

Table 5.6 Maximum attainable and observed values for social profits and quantities of outputs, inputs, and externalities for the three price changes. Change 1: reduction of coffee price by 15%; Change 2: increase in the unit price of labor by 40%; Change 3: a one dollar increase in the unit price of water.

Variable	Unit		Current	Change 1	Change 2	Change 3
Social Profit	$	Max.	7475.3	5500.0	6711.4	5368.7
		Obs.[a]	2128.9	1332.5	1761.0	732.6
Outputs						
Coffee	tons GBE	Max.	6.8	6.3	6.5	5.5
		Obs.	2.6	2.6	2.6	2.6
Inputs						
Labor	working days	Max.	482.0	410.4	433.6	282.0
		Obs.	226.6	226.6	226.6	226.6
Water	m^3	Max.	2200.0	2030.5	2085.3	1723.0
		Obs.	1396.4	1396.4	1396.4	1396.4
Variable inputs	$	Max.	1465.8	1227.5	1304.6	799.9
		Obs.	877.2	877.2	877.2	877.2
Externalities						
Pesticide toxicity	EIQ	Max.	52.2	37.5	42.2	11.4
		Obs.	17.6	17.6	17.6	17.6
N pollution	kg NO_3-N	Max.	192.0	151.0	164.3	77.3
		Obs.	142.2	142.2	142.2	142.2
Greenhouse gas emissions	tons CO_2-eq.	Max.	6.0	5.0	5.3	3.3
		Obs.	4.0	4.0	4.0	4.0

a. Under the three price changes, the revenues and expenditures change. Therefore, the term "observed social profit", in this case, refers to the social profit that would be obtained under each price change. The term “observed” for the output, inputs and externalities refers to the actual quantities.

In the sensitivity analysis, we analyzed the sensitivity of the results for three price changes: (1) a reduction in the unit price of coffee of 15%, (2) an increase in the unit price of labor of 40%, and (3) a one dollar increase in the unit price of water. The latter price change reflects the internalization of external costs that might result from reduced groundwater availability, changes in recharge and discharge patterns, waterlogging, salinity, and loss of biodiversity.

The results of the sensitivity analysis in Table 5.6 show that the maximum attainable social profits decreased by 26%, 10%, and 28%, and the observed social profits by 37%, 17%, and 66% for the price change 1, 2, and 3, respectively. Equally important, the distribution of the observed social profits shows that the percentage of farms in the sample that obtained a positive social profit declined from 95% to 88% under price change 1, 92% under price change 2, and 69% under price change 3. Maximum attainable social profit and observed social profit are both lower in the three price changes because fewer economic resources are available for production. To maximize social profits, farmers have to reduce their expenditures by allocating fewer economic resources, especially for those inputs for which the price has increased, which in turn would imply a lower production of coffee beans and a lower gross income.

Determinants of Nerlovain social profit inefficiency

After the calculation of *NI* and its components *PTI*, *SI*, and *AI*, the next step was to explore the effect of socio-economic characteristics and management practices on the sustainability performance of the farms. Table 5.7 presents the coefficient estimates and confidence intervals for the bootstrap truncated regression of the *NI* scores and the *PTI*, *SI*, and *AI* components. The dependent variables are framed in terms of inefficiency, so a positive (negative) coefficient indicates greater (lower) inefficiency. Most of the explanatory variables were found to be highly statistically significant in explaining farm-specific *NI* scores (Table 5.7), and are mainly associated with allocative inefficiencies. Exceptions are the variables *distance to the fertilizer shop, family members and weeding* and the categorical variables for *education*. None of these variables have a statistically significant effect on social profit inefficiency or its components.

Distance to city/town center: The positive effect on farm-specific *NI* scores and the *AI* component shows that distance is associated with a higher inefficiency in social profit; this effect is attributable to allocative inefficiency. This result suggests that farmers farther away from city or town centers may have less access to credit, which may hamper an efficient allocation of inputs (The World Bank 2004). Distance of the farm could also increase the costs of bringing inputs to the farm and hiring labor. Furthermore, extension services may have more difficulty to reach remote areas of Vietnam. A study by the World Bank (2004) stated that, although the Vietnamese government has attempted to improve the access of farmers to extension services, poor infrastructure still reduces access for those farmers located further from centers.

Distance to coffee factory/traders: The positive values for *NI* and *AI* indicate that greater distance to regional traders leads to higher social profit inefficiency; this effect is mainly due to an inefficient allocation of resources (*AI*). Most farmers in Vietnam sell their coffee production to regional traders or deliver it themselves to coffee processing factories (The World Bank 2004). Farmers located farther away from traders need to allocate more economic resources, i.e. labor and time, to the transportation of coffee. Hence, a larger distance could lead to sub-optimal allocation of inputs and outputs.

Hired labor: NI, *PTI,* and *AI* all have negative coefficients associated with the share of hired labor. This shows that greater use of hired labor decreases pure technical inefficiency and allocative inefficiency, thereby leading to lower social profit inefficiency. Hired labor is generally more qualified to perform specialized tasks, compared with family labor (Latruffe et al. 2004, 2008). Coffee plantations with higher productivity levels tend to use labor more efficiently, as more time is spent on picking from heavily loaded trees and relatively less time is needed to find the cherries and to walk from tree to tree. Therefore, a higher use of specialized hired labor may be associated with more productive farms. More efficient use of labor reduces labor costs and increases the profitability of the coffee farm.

Ethnic group: The variable *ethnic group* has a negative effect on the *NI*, *PTI*, and *AI* scores. This indicates that the minority group JoRai has a lower pure technical inefficiency and a better allocation of resources than the other ethnic group.

Table 5.7 Effect of socio-economic characteristics and management practices on the *NI* scores and the *PTI* and *AI* components. Effects on farm-specific *SI* scores were excluded, as differences between farms were negligible.

	Nerlovian social profit inefficiency (NI)			***Pure technical inefficiency (PTI)***			***Allocative inefficiency (AI)***		
Variable	Estimated parameter	Upper bound	Lower bound	Estimated parameter	Upper bound	Lower bound	Estimated parameter	Upper bound	Lower bound
Distance fertilizer shop	0.000	0.034	-0.034	-0.005	0.004	-0.014	0.000	0.036	-0.037
Distance to city/town center	0.016	**0.031**	**0.003**	0.003	0.007	0.000	0.018	**0.036**	**0.004**
Distance to factory/traders	0.023	**0.044**	**0.002**	-0.001	0.005	-0.007	0.032	**0.055**	**0.010**
Family members	-0.027	0.018	-0.069	-0.006	0.006	-0.017	-0.034	0.012	-0.080
Education man	-0.024	0.105	-0.153	-0.023	0.011	-0.058	-0.005	0.133	-0.145
Education woman	0.030	0.151	-0.095	0.008	0.040	-0.024	0.032	0.170	-0.103
Hired labour	-0.006	**-0.003**	**-0.010**	-0.001	**-0.001**	**-0.002**	-0.007	**-0.004**	**-0.011**
Ethnic group	-0.341	**-0.039**	**-0.675**	-0.109	**-0.029**	**-0.199**	-0.337	**-0.015**	**-0.691**
Pruning	-0.035	**-0.002**	**-0.068**	0.005	0.013	-0.004	-0.059	**-0.023**	**-0.098**
Spraying	0.124	**0.230**	**0.015**	0.042	**0.069**	**0.013**	0.129	**0.251**	**0.012**
Fertilizing	-0.019	0.036	-0.081	0.022	**0.036**	**0.005**	-0.081	**-0.024**	**-0.150**
Weeding	0.018	0.063	-0.029	0.011	0.022	-0.002	-0.004	0.042	-0.055
Constant	0.614	1.211	-0.053	0.081	0.235	-0.088	0.516	1.154	-0.210
Sigma	0.463	**0.516**	**0.410**	0.129	**0.142**	**0.116**	0.404	**0.469**	**0.343**

Confidence intervals for significant variables are marked in bold type. A positive estimate parameter indicates greater inefficiency

This finding is contrary to our expectations, as minority groups, such as the JoRai, often farm areas that are less favorable for coffee production and sometimes cannot afford to purchase inputs, such as fertilizers and water (Thang 2011; The World Bank 2004).

One reason for the lower social profit inefficiency could be the higher dependency of the JoRai on coffee production for their livelihood. Consequently, the members of this group may undertake key farm activities, such as pruning and fertilizing, with more care. In contrast, the Kinh people tend to have relatively more diversified sources of income (The World Bank 2004; Tran 2007). Thus, less effort and family labor may be allocated to coffee production

Pruning: The negative coefficient for *NI* shows that the frequency of pruning activities is negatively associated with social profit inefficiency, consistent with our expectations. More frequent pruning improves ventilation and increases reception of sunlight, avoids excessive competition for nutrients and water between the cherries, and reduces non-productive structures of trees (Kuit et al. 2004; Wintgens 2009). Additionally, a part of the nutrients taken up by coffee trees is available to coffee plants in following years, by placing the pruning residues into soils (van der Vossen 2005). Coffee trees with better structural and physiological characteristics have higher yields and therefore reduce the social profit inefficiency of coffee farms.

Spraying: NI, PTI, and *AI* are all positively associated with spraying, meaning that more applications of biocides increase the social profit inefficiency, and the technical and allocative inefficiencies. The most likely reason is that the application of biocides is not effective, especially for control of fungal diseases and insect pests, possibly due to improper use of biocides and incorrect timing of spraying. Coffee plantations with higher incidences of diseases and pests may also require more frequent use of pesticides to maintain productivity. However, as most farms in the sample are operating under similar agro-ecological conditions, there is little difference in the intensity of diseases and pests (observation by Don M. Jansen).

Fertilizing: The coefficient for the effect of *fertilizing* on farm-specific *NI* scores is statistically not significant. However, coefficients for the effect of *fertilizing* on *AI and PTI* scores indicate that these are statistically significant. This effect is complex however, as increasing the frequency of fertilizer application increases the *PTI* component, but reduces the *AI* component. An explanation for the positive effect on *PTI* is that more frequent application of fertilizers implies higher input use per unit of output, and therefore increased pure technical inefficiency. An explanation for the negative effect on *AI* is suggested by the results of a previous study on fertilizer application (Kuit et al. 2004; Tillman 2002). These studies showed that an adequate application of fertilizers during periods of greatest crop demand, in smaller and more frequent applications, was positively related to reduced nutrient losses and improvements in yields. Hence, a higher allocation of labor for this activity is expected to decrease the allocative inefficiency, and thereby the social profit inefficiency.

Policy implications

The net benefits to society of coffee production can be maximized by minimizing the conventional and external costs of coffee production and maximizing the revenues. The results of this study can help farmers, researchers, and policy makers identify opportunities to improve the sustainability performance of coffee farms in Vietnam.

At the farm level, the inefficiency in social profit may be greatly reduced by decreasing the inefficient use of nutrients. An optimal use of nutrients not only positively affects coffee yields, but also reduces greenhouse gas emissions, reduces the emission of nitrates into soils and water bodies, and leads to a lower need for the application of pesticides. Greater use of pesticide inputs is caused, in some cases, by nutrient deficiencies or over-fertilization of coffee plantations (Kuit et al. 2004). Corrective actions to reach an optimal use of fertilizer inputs would reduce expenditures and the amount of labor required to perform activities, such as weeding and spraying. Some of the labor used to perform these activities could then be allocated to other activities, such as pruning, which are negatively associated with social profit inefficiency.

At the regional level, we recommend that policies stimulate the adoption of optimal management practices on farms (proper timing and frequency). An appropriate policy tool is the provision of technical assistance by extension services. In remote areas, where access to extension services is limited, the focus should be on first improving access. This is expected to provide additional benefits: (1) help integrate the coffee chain (producers, traders, and processing companies), (2) increase the bargaining power of farmers (access to information on coffee prices, traders, and new products and technologies) and, (3) increase the access of farmers to credit.

Finally, we recommend performing an in-depth study on the management of coffee farms by the JoRai ethnic group. These farmers were found to be less inefficient in terms of social profit. The results of the study can be used to identify best management practices; extension services can then disseminate this information and stimulate the adoption of best management practices on more inefficient farms.

Conclusions

This paper compared the sustainability performance of a sample of coffee farms in Vietnam using the Nerlovian social profit inefficiency (*NI*) indicator. Furthermore, this study identified the socio-economic characteristics and management practices that affect social profit inefficiency. The results show that farms, on average, could improve their social profits by almost three times the current social profit levels (84% of the value of the *NI* denominator). This suggests a large potential for performance improvements. The main source of *NI* is allocative inefficiency (58% of the value of the *NI* denominator), rather than pure technical inefficiency or scale inefficiency. The determination of variable-specific contributions to *NI* provides evidence of the sources of inefficiency. The comparison between the actual and optimal quantities of each specific output, input, and externality reveals that inefficiencies are mainly driven by the low level of coffee production and the under-utilization of inputs, particularly labor and variable inputs. Most coffee farms have optimum pollution levels, given the shadow prices of externalities and the prices of inputs and outputs.

The assessment of the external determinants of *NI* shows that most of the selected variables (socio-economic characteristics and management practices) have statistically significantly effects on inefficiency. Farm-specific *NI* scores are positively associated with the variables distance to city/town center, distance to traders and spraying. Farm-specific *NI* scores are negatively associated with the following variables: hired labor, ethnic group, pruning, and fertilizing. Corrective actions to ensure the efficient use of inputs and the correct timing and frequency of farm management activities would reduce social profit inefficiency for most coffee farms.

Although our study focused on assessing the relative sustainability performance of coffee production at the farm level, this can be extended to include other stages throughout the coffee chain. Future development of this sustainability assessment approach could provide a decision support tool that can be used to translate the concept of sustainability into concrete management actions, thereby helping to maximize the total net benefits to society of food production.

Annex 5A.

The maximum social profit is obtained by solving the following linear programming model:

$$\Pi(p, w, r, f) = \max_{y,x,b}\left(\sum_{m=1}^{M} p_m y_m - \sum_{n=1}^{N} w_n x_n - \sum_{j=1}^{J} r_j b_j\right)$$

$s.t.$

$$\sum_{k=1}^{K} \alpha^k y_m^k \geq y_m, \quad m = 1,2,\dots,M$$

$$\sum_{k=1}^{K} \alpha^k x_n^k \leq x_n, \quad n = 1,2,\dots,N$$

$$\sum_{k=1}^{K} \alpha^k f_d^k \leq f_d\,, \quad d = 1,2,\dots,D$$

$$\sum_{k=1}^{K} \alpha^k b_j^k \leq b_j, \quad j = 1,2,\dots,J$$

$$\alpha \geq 0; \quad k = 1,2 \dots, K$$

The model yields the optimum output, input and externality combinations that provide the maximum attainable social profit given the production technology, prices (shadow), and the available level of the fixed inputs.

In the model, the set α of intensity variables is restricted to be greater or equal to zero, implying a production technology that exhibits constant returns to scale (CRS).

The Overall Technical Inefficiency (OTI) and Pure Technical Inefficiency (PTI) component for DMU k' is obtained by solving the following linear programming model:

$$\overrightarrow{D_T^{k'}}\left(y^k, x^k, f^k, b^k; g_y, g_x, g_b | CRS\right) = max\beta$$

$s.t.$

$$\sum_{k=1}^{K} \alpha^k y_m^k \geq y_m^{k'} + \beta g_y, \quad m = 1,2, \dots, M$$

$$\sum_{k=1}^{K} \alpha^k x_n^k \leq x_n^{k'} - \beta g_x, \quad n = 1,2, \dots, N$$

$$\sum_{k=1}^{K} \alpha^k f_d^k \leq f_d^{k'}, \quad d = 1,2, \dots, D$$

$$\sum_{k=1}^{K} \alpha^k b_j^k \leq b_j^{k'} - \beta g_b, \quad j = 1,2, \dots, J$$

$$\alpha^k \geq 0; \quad k = 1,2 \dots, K$$

The Overall Technical Inefficiency (OTI) is computed with this model that has a set α^k of intensity variables that is restricted to be greater or equal to zero, implying a production technology that exhibits constant returns to scale (CRS). To compute the Pure Technical Inefficiency (PTI) the CRS assumption is relaxed to assess the DMUs under a production technology that exhibits variable returns to scale. In this case the sum of intensity variables is constrained to be equal to one $\sum_{k=1}^{K} \alpha^k = 1$.

Annex 5B.

Underlying assumptions, data and the related sources used for the calculation of the externalities and their respective shadow prices.

Nitrate pollution

A tentative Nitrogen (N) balance was calculated to estimate the nitrate pollution externality. As it is assumed that coffee farm systems are in equilibrium with respect to N in the system, the nitrate pollution (leaching) externality was calculated for each coffee farm as the difference between the N that enter the system (N inputs) and the N that leaves the system (N outputs and N loss):

$$NO_3^- - N = N\ inputs - (N\ outputs + N\ loss) * Fpol,$$

Where: N inputs = amount of N in fertilizers (synthetic and organic) + N amount in residues; N outputs = amount of N in harvest material; N loss = N loss via background N_2O-N emissions (N_2O-N+NO-N) + fertilizer induced and crop residue N_2O-N emissions (N_2O-N+NO-N) + volatilization (NH_3-N and NO-N). Fpol = given that about 50% of the difference between the N that enters and leaves the system remains stored in soils and plants for several years in the permanent framework of roots, stems and branches (Van der Vossen 2005), it is assumed that only the remaining 50% causes nitrate pollution problems.

N inputs:

<u>N amount in fertilizers (NI)</u>

Nitrogen inputs via fertilizer were estimated by multiplying the quantity of fertilizer (synthetic and organic) in kilograms by the known (or estimated) N concentration.

$$NI_i = F_i * CN_i,$$

Where: F_i = amount of fertilizer type *i* (kg product year^{-1}); CN_i: N concentration in fertilizer *i* (kg N per kg product).

N content in residues (*NR*)

Nitrogen inputs via crop residues were estimated by calculating the annual amount of pruning residues (kg of dry matter per year), times the average estimated N concentration per kg of dry matter (% N per kg dry matter). As it is assumed that the amount of pruning residues proportionally increases with the number of coffee trees our estimate was corrected for each farm according to number of trees per hectare.

$$NR = R * CN_R,$$

Where: R = amount of residues (kg dry matter year^{-1}); CN_R = N concentration in residues (kg N per kg dry matter).

N harvest material (NH)

Nutrient export through the coffee harvest was estimated using yield data and published values of nutrient removal in coffee beans.

$$NH = Y * CN_H,$$

Where: Y = yield (kg year^{-1}); CN_H = N concentration in harvest (kg N per kg of coffee cherries).

N loss:

N loss via N_2O and NO background emissions

Based on IPCC (2006) N loss as N_2O-N+NO-N in background emissions is of about 16 kg N_2O–N ha^{-1} yr^{-1}, which refers to the mineralization rates in tropical climates.

$$N_2O_{(bkg)} - N = EF_{bkg} * area,$$

Where: $N_2O_{(NIR)}$–N= annual background N_2O–N emissions from tropical areas (kg N_2O–N yr^{-1}); EF_{bkg} = emission factor annual direct N_2O–N emissions from tropical areas (kg N_2O–N yr^{-1}). The default value f is 16 kg N_2O–N ha year as it is assumed to be twice the N_2O emission for temperate climates (mineralization rates are assumed to be about 2 times greater in tropical climates) (IPCC 2006).

Nitrogen loss via fertilizer and crop residues – N_2O emissions

N_2O-N (N_2O-N+NO-N) emissions were estimated based on the generic emission factors of Bouwman et al. (2002) which reflect the percentage of applied N for different fertilizer types that is lost via N_2O-N and NO-N emissions. N loss via N_2O fertilizer induced and crop residue emissions is estimated as:

$$N_2O_{(NIR)} - N = \sum_i NI_i * EF_{(NI_i)} + NR * EF_{(R)},$$

Where: $N_2O_{(NIR)}$–N = annual amount of N_2O–N produced from fertilizer use and crop residues (kg N_2O–N yr^{-1}); NI_i = N amount via fertilizer *i* (kg N yr^{-1}); NR = applied N via crop residues (kg N yr^{-1}); $EF_{(NIi)}$ = Bouwman N_2O-N (N_2O-N+NO-N) emission factor for fertilizer *i* (kg N_2O–N per kg N^{-1}) (Table 5B.1); $EF_{(R)}$ = N_2O-N emission factor for crop residues (kg N_2O–N per kg N^{-1}). Based on the IPCC (2006) the emission factor for crop residues is 1%.

N loss via NH_3 volatilization

Nitrogen loss via NH_3 volatilization is estimated using Tier II IPCC (2006) as:

$$N_2O_{(V)} - N = \left[\sum_i NI_i * Frac_{V_i} + \left(NR * Frac_{(R)}\right)\right] * EF_{(V)},$$

Table 5B.1 Generic emission factors ($EF_{(NIi)}$) as percentage of applied N for different fertilizer types (Bouwman et al. 2002).

Fertilizer type	Bouwman N_2O-N (N_2O-N+NO-N)-$EF_{(NIi)}$	Volatilization (NH_3) - $Frac_{Vi}$
Ammonium Bicarbonate	0.0107	
Ammonium nitrate	0.0101	0.037
Ammonium sulphate	0.0107	0.013
Ammonium sulphate nitrate	0.0105	
Anhydrous ammonia	0.0107	0.011
Calcium ammonium nitrate	0.0099	0.022
Calcium nitrate	0.0088	0.009
Compound NK	0.0088	0.037
Compound NPK	0.0094	0.037
Diammonium phosphate	0.0094	0.113
Kainit / Magnesium Sulphate	0.0000	
Lime - 52% CaO	0.0000	
Limestone - 55% $CaCO_3$ / 29%CaO	0.0000	
Lime, algal - 30% CaO	0.0000	
Monoammonium phosphate	0.0094	0.113
Muriate of potash / Potassium Chloride	0.0000	
Phosphate/Rock Phosphate	0.0000	
Potassium sulphate	0.0000	
Super phosphate	0.0000	
Triple super phosphate	0.0000	
Urea	0.0112	0.243
Urea ammonium nitrate solution	0.0057	0.125
Compost (zero emissions)	0.0037	
Manure	0.0037	

Emission factors for N_2O-N fertilizer induced emissions from soils (kg N_2O-N kg N year^{-1}) (Bouwman et al. 2002); Emission factors for total NH_3 emissions from soils due to N fertilizer volatilization and foliar emissions (kg NH_3 kg N year^{-1}) EMEP and EEA (2013)

Where: $N_2O_{(V)}$–N = annual amount of N_2O–N produced from atmospheric deposition of N volatilized (kg N_2O–N yr^{-1}); NI_i = amount of N applied via fertilizer *i* (kg N year^{-1}); NR = applied N via crop residues (kg N yr^{-1}); $Frac_{Vi}$ = fraction of fertilizer *i* that volatilizes as NH_3 (kg N applied year^{-1}) (Table 5B.1); $Frac_{(R)}$ = fraction of N in crop residues that volatilizes as NH_3 (kg N year^{-1}); $EF_{(V)}$ = emission factor for N_2O emissions from atmospheric deposition of N on soils and water surfaces (kg N-N_2O per kg NH_3–N volatilized year^{-1}).

Global Warming Potential

The Global Warming Potential (GWP) of the greenhouse gases (GHGs) emitted in a coffee farm is the result of the sum of the emission of GHG *i* (kg CO_2, CH_4 and N_2O) times its global warming potential over a time frame of 100 years (Table 5B.2).

Table 5B.2 Global Warming Potential of greenhouse gases (*GWPs*)

Carbon dioxide	CO_2-eq./kg CO_2	1.00
Methane	CO_2-eq./kg CO_2	25.00
Nitrous Oxide	CO_2-eq./kg CO_2	298.00
Source: IPCC (2006)		

We estimated the emission of GHGs in coffee production as:

$$Total\ GWP = GHG(embodied) + GWP(N_2O),$$

Where: GWP come from the emission of GHGs from two different sources: 1) emission of GHGs embodied in fertilizers and pesticides, GHG(embodied) and 2) N_2O emissions from managed soils, GWP(N_2O).

Greenhouse Gas Emissions embodied in fertilizer and pesticide production:

GHGs emitted in the production of the fertilizers and inputs that are used in coffee production. The GHGs embodied in inputs (CO_2-eq. year^{-1}) are estimated as:

$$GHG(embodied) = \sum_i F_i * EF_{F_i} + \sum_j P_j * EF_{P_j},$$

Table 5B.3 Emission Factors of production of fertilizers (CO_2-eq. per kg N; kg P_2O_5 , kg K_2O or product).

Fertilizers	Emission Factor per kg	Unit
Ammonium nitrate - 35% N	11.80 (10.18-16.71)	per kg N
Ammonium sulphate - 21% N	5.20 (1.69-8.17)	per kg N
Ammonium sulphate nitrate - 26%N [a]	1.14	per kg product
Anhydrous ammonia - 82% N	6.36 (5.16-7.98)	per kg N
Calcium ammonium nitrate -27% N	11.86 (10.24-16.77)	per kg N
Calcium nitrate - 15% N [a]	1.49	per kg product
Compound NK - 14% N; 44% K_2O [a]	2.67	per kg product
Compound NPK 15%N 15% K_2O 15% P_2O_5	8.98 (8.11-9.67)	per kg N
Diammonium phosphate - 18% N; 46% P_2O_5	6.76 (3.97-8.38)	per kg N
Kainit / Magnesium Sulphate - 11% K_2O; 5% MgO [a]	0.00	per kg product
Lime - 52% CaO	0.074 (0.054-0.089)	per kg lime
Monoammonium phosphate - 11% N; 52% P_2O_5	7.06 (2.42-9.37)	per kg N
Muriate of potash / Potassium Chloride - 60% K_2O	0.91 (0.62-1.12)	per kg K_2O
Phosphate/Rock Phosphate - 25% P_2O_5	0.31 (0.03-0.34)	per kg P_2O_5
Potassium sulphate - 50% K_2O; 45% SO_3	0.31 (0.08-0.37)	per kg K_2O
Single Super phosphate - 21% P_2O_5	0.21 (-1.10-0.74)	per kg P_2O_5
Triple super phosphate - 48% P_2O_5	0.59 (-0.07-0.83)	per kg P_2O_5
Urea - 46.4% N	7.41 (6.64-8.34)	per kg N
Urea ammonium nitrate solution - 32% N (UAN)	9.65 (5.23-17.12)	per kg N
Compost (zero emissions) - 1% N [a]	0.00	per kg product
Compost (fully aerated production) - 1% N [a]	0.24	per kg product
Compost (non-fully aerated production) - 1% N [a]	0.36	per kg product

Source: Values for China and India in Kool et al. (2012). [a.] Not available values for China-India were taken from The European Fertilizer Manufacturers Association (EFMA, 2002) in Cool Farm Tool.

Where: F_i = amount of fertilizer type *i* (kg product year^{-1}); P_j = amount of active pesticide ingredient j (kg active pesticide ingredient year^{-1}); EF_{Fi} = CO_2-eq. emission factor for fertilizer type *i* (kg CO_2-eq. per kg of product year^{-1}) (Table 5B.3); EF_{Pj} = CO_2-

eq. emission factor for pesticide type *j* (kg of CO_2-eq. per kg of active pesticide ingredient year^{-1}) (Table 5B.4).

Table 5B.4 Emission Factors of production of pesticides (CO_2-eq. per kg a.i.).

Herbicides	**CO_2-eq. per kg a.i.**	**Fungicides**	**CO_2-eq. per kg a.i.**
2, 4-D	6.23	Ferbam	4.40
Alachlor	20.53	Maneb	7.33
Atrazine	13.93	Captam	8.43
Diquat	29.33	Benomyl	29.33
Glyphosate	33.37	**Insecticides**	
Metolachlor	20.17	Methyl Parathion	11.73
Paraquat	33.73	Phorate	15.40
Propachlor	21.27	Carbofuran	33.37
Diuron	19.80	Carbaryl	11.37
Dicamba	21.63	Cypermethrin	42.90
Linuron	21.27	Chlorodimeform	18.33
		Methoxychlor	5.13
		Malathion	16.87

Source: Values according to Lal (2004). Values were converted from C to CO_2-eq using the factor 44/12.

GHG emission resulting from direct and indirect N_2O-N emissions:

$$Total\ N_2O\ = \left(N_2O_{(bkg)} - N + N_2O_{(NIR)} - N + N_2O_{(V)}\right) * \frac{44}{28},$$

Where N_2O-N emissions estimated in the subsection 'Nitrate pollution', are converted to N_2O emissions using the factor 44/28.

$$GWP(N_2O) =\ Total\ N_2O * GWP_{N_2O},$$

N_2O emissions are afterwards converted to CO_2-eq. by using the Nitrous Oxide Global Warming Potential (GWP_{N2O}) (Table 5B.2).

Table 5B.5 Description of variables, emission factors and sources.

Variable name	Variable	Unit	Value	Source	Description
N outputs					
N concentration in harvest	CN_H	kg N per 100 kg of coffee cherries	0.55	Vietnam data	
N inputs					
Crop residues	*R*	kg dry matter ha^{-1} $year^{-1}$	5,764	Glover and Beer (1986) Hergoualc'h et al. (2008)	
N concentration crop residues	CN_R	kg N per kg dry matter	0.02	Glover and Beer (1986) Hergoualc'h et al. (2008) Cannavo et al. (2013)	Average concentration of N in litterfall and pruning (leaves and branches).
N loss					
Emission Factor background	EF_{bkg}	kg N_2O–N ha^{-1} yr^{-1}	16	IPCC (2006)	Mineralization rates are assumed to be about 2 times greater in tropical climates than in temperate climates.
Emission Factor crop residues	$EF_{(R)}$	kg N_2O–N per kg N $year^{-1}$	0.01	IPCC (2006)	N losses from crop residues are comparable with application of N in fertilizers and manure.
N_2O emission factor from N volatilized	$EF_{(V)}$	kg N_2O-N per kg NH_3–N volatilized $year^{-1}$	0.01	IPCC (2006)	
Fraction of N in fertilizers and crop residues that volatilizes	$Frac_{(R)}$	kg NH_3-N per kg of N additions $year^{-1}$	0.10	IPCC (2006)	

Shadow price Pesticide toxicity

Shadow price for the environmental, farmworker and consumer toxicity of pesticide use:

First step: External costs associated with the application of one kg of pesticide active ingredient reported by Pretty et al. (2001), were redistributed over the three components of the EIQ model, i.e. environmental, farmworker, and consumer components (derived from Leach and Mumford (2008) (Table 5B.6).

Table 5B.6 Redistributed base values for an average active pesticide ingredient (derived from Leach and Mumford, 2008).

US $ per kg pesticide active ingredient	Pretty et al. (2001) categories						
	Sour. water	Poll. incidents	Biod.	CLT	Bee losses	Hum.	Total
EIQ categories							
Applicator effects	0.64	-	-	-	-	0.34	0.98
Picker effects	0.64	-	-	-	-	0.06	0.70
Subtotal Farmworker component							**1.68**
Consumer effects	3.87	-	-	0.80	-	0.02	4.69
Ground water	0.64	0.44	-	-	-	-	1.08
Subtotal consumer component							**5.77**
Aquatic effects	0.64	0.44	0.20	0.32	-	-	1.60
Bird effects	-	-	0.20	0.16	-	-	0.36
Bee effects	-	-	0.07	0.32	0.17	-	0.56
Beneficial insect effects	-	-	0.20	-	-	-	0.20
Subtotal Environmental component							**2.72**
Total	**6.45**	**0.87**	**0.65**	**1.59**	**0.17**	**0.43**	**10.17**

External costs estimated by Pretty et al. (2001) and redistributed to the EIQ categories and converted to 2011 US $.

Sourc. Water = Sources of water; Poll. incidents = Pollutions incidents; Biod. = Biodiversity; CLT = Cultural, landscape and tourism; Hum. = Humans

Second step: The average EIQ score of an average pesticide active ingredient on each of the three components was estimated. It was done by listing the pesticide active ingredients that were used in the USA in 2001 and collecting their respective EIQ scores for each component (Table 5B.7).

Table 5B.7 Average EIQ score for the three components for an average pesticide active ingredient.

Product [a]	EIQ farmer per kg a.i. [b]	EIQ farmer per kg a.i. [b]	EIQ environment per kg a.i. [b]
Glyphosate	8	3	35
Atrazine	8	7	53.55
Metam sodium	24.15	8.08	47.55
2,4-D	8	5	33
Acetochor	10.65	5.33	43.59
Malathion	9	4.5	58
Methyl Bromide	74	10.4	76.3
Dichloropropene	41.4	7.9	33.95
Metolachlor-s	12	9	45
Metolachlor	12	9	45
Pendimethalin	12	5.5	73
Trifluralin	9	5.5	42
Chlorothalonil	20	11	81.25
Copper Hydroxide	24.3	9.05	66.25
Cholorpyrifos	6	2	72.55
Alachlor	10.65	5.33	37.59
Propanil	10.65	5.33	37.59
Chloropicrin	34.5	7.45	85.36
Dimethenamid	9	4.5	22.55
Mancozeb	20.25	8.13	48.79
Ethephon	21.3	5.65	47.45
EPTC	6	4	18.3
Simazine	10.65	14.48	39.42
Dicamba	12	8	59
Sulfosate	8	6	66
Diazinon	6.9	2.45	122.75
MCPP	8	7	31
Carbaryl	15	5.5	47.7
Copper sulfate	24.3	13.15	148.25
Chlorothalanil	20	11	81.25
Chlorpyrifos	6	2	72.55
Diuron	20	8.5	50.9
MSMA	8	5	41
DCPA	9	4	33.3
Benefin	9	4	39
TOTAL	**15.65**	**6.68**	**55.31**

a. Derived from: Kiely et al. (2004).
b. EIQ scores were obtained from the Integrated Pest Management Program, Cornell University 2013).

Third step: The redistributed base values for external costs on each component (Table 5B.6) were divided by their respective average EIQ scores (total values in Table 5B.7) to obtain an external cost per unit of EIQ.

Table 5B.8 External cost per unit of EIQ on each component.

	2011 US $/EIQ
EIQ Environment	0.05
EIQ Farm worker	0.86
EIQ Consumer	0.11

Fourth step: To estimate the shadow price for pesticide toxicity the estimated external costs per unit of EIQ on each component were adjusted to reflect the differences in socio-economic conditions in Vietnam. Hence, the external cost per unit of EIQ on each component was multiplied by the factor 0.12, which represents the ratio of the GDP per capita of Vietnam to the average GDP per capita of the USA, Germany and the UK (source the World Bank 2015). In addition, the external cost unit for the farm worker component was adjusted by the factor 28.8, which represents the difference between the share of agricultural employment in Vietnam and the average share of agricultural employment in the USA, Germany, and the UK (derived from The World Bank (2015).

Table 5B.9 Adjusted external cost unit estimates for the Vietnamese context and shadow price for the externality pesticide toxicity.

	2009 US $/EIQ
EIQ Environment	0.01
EIQ Farm worker	0.10
EIQ Consumer	0.35
Shadow price pesticide toxicity	0.15

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CHAPTER 6

General Discussion

Introduction

The overall objective of this dissertation was to perform integrated assessments of relative sustainability performance of (stages of) agri-food supply chains. As described in Chapter 1, the overall objective was split into four sub-objectives that were addressed in Chapters 2-5.

Chapter 2 developed a framework for benchmarking agri-food supply chains in terms of their relative sustainability performance. Depending on the aggregation method that is used to combine sustainability issues, two integrated indicators were proposed, i.e. the Social Profit indicator (also called Adjusted Profit indicator) and the Technical Inefficiency indicator. In this framework sustainability issues are operationalized by expressing them as outputs, inputs and externalities (hereafter, the expressions "outputs, inputs and externalities" and "variables" are used interchangeably). Key aspects for the implementation of the indicators such as data availability, the selection of sustainability issues, and sustainability standards and targets were discussed. Chapter 3 assessed the relative sustainability performance of two Brazilian soybean meal chains using the Social Profit indicator. Differences in the sustainability performance of both chains were assessed by means of the Bennet Total Factor Productivity (TFP) and Total Price Recovery (TPR) indicators. Based on the outcomes of this assessment, potential areas for improving the sustainability performance of each chain were highlighted. Chapter 4 assessed the relative sustainability performance (economic and environmental) of specialized potato farms in Germany and the Netherlands using the Social Profit indicator and the Technical Inefficiency indicator. Based on the decomposition of each indicator, the areas for improving the sustainability performance in each country were identified. In addition, the advantages and limitations of each indicator for the sustainability assessments were discussed. In Chapter 5, a third approach, the Nerlovian Social Profit Inefficiency indicator was used to assess the relative sustainability performance of coffee farms in Vietnam. Also, the impact of socio-economic characteristics and management practices on the estimated relative sustainability was assessed.

This concluding chapter synthesizes the results of the four research chapters, discusses the implications of the results for policy makers and business stakeholders, outlines directions for future research and finally, it provides the main conclusions of the dissertation.

Synthesis of results

Each of the three integrated indicators partially overcome the main weaknesses of the single and composite indicators/indexes that are currently used in sustainability assessments, i.e. incommensurability, subjectivity, comparability, multi-dimensionality (see Chapter 1, section 'Problem Statement'). First, the proposed indicators reduce the incommensurability problem in decision-making that arises with indicators that cover two or more dimensions of sustainability. This is possible by aggregating the set of outputs, inputs and externalities, into a single metric of relative sustainability performance by using one of two aggregation methods: prices or distance functions. Second, the aggregation of outputs, inputs and externalities using either prices or distance functions reduces the subjectivity that is implicit in composite indicators/indexes when aggregation is performed by using the practitioner's own weighing factors. These two points are detailed in subsection 'Aggregation method'. Third, the three integrated indicators allow a consistent comparison between the relative sustainability performance of (stages of) agri-food supply chains. In the case of the Technical Inefficiency indicator and the Nerlovian Social Profit Inefficiency, Data Envelopment Analysis (DEA) is used to construct the performance frontier which reveals the relative performance of (stages of) chains. In the case of the Social Profit indicator, consistent comparison between (stages of) chains is performed by means of the Bennet TFP indicator and the Bennet TPR indicator. This point is explained in more detail in the following subsections. And fourth, the indicators allow for the inclusion of social implications of food production. However, as discussed in next subsections, which sustainability issues and thus, which outputs, inputs and externalities can be incorporated depends on data availability.

The three indicators were implemented in Chapter 3, Chapter 4 and Chapter 5. Results in these chapters show that the indicators differ in terms of the scope to incorporate outputs, inputs and externalities, in the data requirements and in the information provided for improving relative sustainability. Also, their implementation provided insights in the importance of selecting the most important sustainability issues. Each of these points, along with a discussion of the advantages of these indicators over existing indicators, is discussed below (subsections 'Aggregation method' to Improvement options') in the light of their empirical implementation.

Aggregation method

Outputs, inputs and externalities were aggregated into a single measure of relative sustainability using prices (Chapter 3 and Chapter 4) or distance functions (Chapter 4 and Chapter 5). In the Social Profit indicator these variables were aggregated using prices. Observed prices were used for the outputs and the inputs that are traded in well-defined markets. As there is not a well-defined market for most of the externalities, shadow prices were obtained from the literature and were adjusted to the context of the country under investigation. In this aggregation method, the (shadow) prices serve as social weights for the outputs, inputs and externalities, in the construction of the Social Profit indicator. In this respect, a high price for an output, input or externality indicates high Willingness to Pay (WTP) for an additional unit of a product or scarce resource used in production, or high WTP to reduce the impacts caused by the (negative) externality. It was assumed that prices adequately reflect the tradeoffs between economic, environmental and social issues in the relative sustainability assessment.

The aggregation of outputs, inputs and externalities using distance functions did not require *a priori* weights regarding their relative importance. As shown in Chapter 4 and Chapter 5, the computation of the distance functions in the Technical Inefficiency and the Nerlovian Social Profit Inefficiency indicators using DEA, generates weights that are determined directly from the quantity data of outputs, inputs and externalities. DEA assigns weights to each output, each input and each externality for a given chain (stage), in such a way that its ratio of weighted outputs to weighted inputs and externalities is maximized subject to constraints (Cooper et al. 2002; Fried et al. 2007). The dual values of the constraints in the DEA models in Chapter 4 and Chapter 5 are the weights assigned to outputs, inputs and externalities. Thus, in these two chapters, these dual values reflect the input tradeoffs, the output tradeoffs, the externality tradeoffs and the output-input-externality tradeoffs that a farm gives to each variable. This implicitly gives information on how high each output, input and externality is valued by a farmer.

The aggregation of outputs, inputs and externalities using distance functions has some advantages over prices. First, (shadow) prices are not always available and their estimation can be costly and time consuming. Second, market prices can be distorted due to tariffs, taxation, subsidies and market failures (Kuosmanen et al. 2004). In spite of these two main advantages, the aggregation of outputs, inputs and externalities using distance functions has the drawback that data-derived weights are not presented explicitly. Hence, the distance function method may work as a black box tool for decision makers (Chapter 4).

Notwithstanding the advantages and limitations of each aggregation method, in Chapter 4 it was shown that the implementation of the Social Profit indicator and the Technical Inefficiency indicator yields similar outcomes in terms of best-worst sustainability performers. This result suggests that the weights used in the computation of both indicators indicate similar levels of relative importance for each of the outputs, inputs and externalities that were included in the assessment. Although an empirical comparison between the Social Profit indicator and the Nerlovian Social Profit Inefficiency indicator was not performed, I hold the view that the ranking of chains/farms in terms of their sustainability performance would be similar. This is due to the fact that chains/farms with the highest social profit are commonly the ones with the lowest inefficiency in social profit.

Valuation and monetization of externalities

A broad set of economic valuation methods exists for deriving shadow prices for the externalities. Methods include stated preference methods (e.g. Contingent Valuation and the Choice Experiment), revealed preference methods (e.g. Replacement Cost, Travel Cost, Avoided Cost and Hedonic Pricing) and the benefit transfer method (de Groot 2006; Kuosmanen and Kortelainen 2004; TEEB 2010). In Chapter 3, Chapter 4 and Chapter 5, the benefit transfer method was used to obtain the shadow prices. In this way, first, shadow prices for the same externalities selected in these chapters were obtained from valuation studies that were found in the scientific literature. Next, as the shadow prices coming from these valuation studies were generally estimated in another location and context, these prices were adjusted to the prevailing socio-economic conditions of the study site in which these were applied. Although shadow prices were adjusted based on the socio-economic characteristics of the study site, a lower accuracy is expected for those externalities such as pesticide toxicity and eutrophication (Chapter 3 and Chapter 5) and nitrate pollution (Chapter 5) with impacts that are highly determined by specific environmental conditions (e.g. soil types, vegetation cover and climatic conditions). The WTP for the reduction of these externalities could have varied depending on the severity of the environmental and social problems. While stated or revealed preference methods can be preferred to derive shadow prices, the benefit transfer method is a practical way of getting weights in the situation of poor data availability.

Regarding the valuation of externalities, two issues deserve special attention. First, although economic valuation methods have had considerable progress in recent years (Dalal-Clayton and Sadler 2014), there is still a lack of knowledge about the environmental and socio-economic consequences caused by some externalities and about the time-spans at which they operate. This knowledge gap limits the extent to which all external costs can be accounted for in the valuation exercise. For example, in Chapter 3 and Chapter 5 the external costs associated to acute and chronic pesticide poisoning of humans and the environment and synergetic and multiplicative effects of the use of pesticides (Pretty 2005) were not considered in the estimation of the shadow price for pesticide toxicity. Also, in Chapter 3 and Chapter 5, the shadow price for eutrophication and nitrate pollution did not take into account long-term effects of pollution in water bodies and soils in Brazil and Vietnam, nor were the potential impacts on biodiversity taken into account. Moreover, in Chapter 5, the external costs that might result from the over-irrigation of coffee plantations, such as the reduction in the availability of groundwater, salinity and the loss of biodiversity (D'haeze et al. 2005; Lindskog et al. 2005), were not considered in the price of water. The second issue that deserves special attention is how to deal with the intergenerational equity in the valuation of externalities. Thus, to which extent the future external costs should be discounted to estimate an optimal intergenerational shadow price, an issue which is currently subject to lively debate (Atkinson and Mourato 2008; Freeman and Groom 2013). A notable example is the use of different discount rates to discount future external costs of global warming in different climate economic models (see for example Ackerman 2007 and the controversy following the publication of the Stern report (Stern 2007).

The sensitivity of the Social Profit indicator and the Nerlovian Social Profit indicator to changes in (shadow) prices of outputs, inputs and externalities was computed in Chapter 3 and Chapter 5. Also, in Chapter 3 the social profit of the average non-GM and GM soybean meal chains was calculated under two alternative shadow prices for eutrophication (a higher and a lower shadow price as compared with the shadow price used in the study). Results show that under the two shadow price alternatives the social profit of the average non-GM soybean meal chain and the GM chain did not vary considerably. Therefore, the conclusions that were drawn from the relative sustainability assessment did not change. In Chapter 5, the impact of changes in the price of coffee, labor and water on the computed observed and maximum social profit for coffee farms in Vietnam was evaluated. The observed profit would have been considerably reduced by higher input prices, or by a lower coffee price. Consequently, the maximum attainable social profit would be also reduced. Nevertheless, the social profit inefficiency that was estimated for each coffee farm in our sample would not differ substantially (especially under the first two price changes), because the ratio of maximum to observed social profit would be similar.

Number of variables that can be incorporated in the relative sustainability assessment

The Technical Inefficiency indicator and the Nerlovian Social Profit Inefficiency indicator have less scope for including outputs, inputs and externalities than the Social Profit indicator. The probability that all observations operate at the efficient frontier increases with increasing number of outputs, inputs and externalities in the model (Dyson et al. 2001; Hughes and Yaisawarng 2004). Therefore, in Chapter 4 and Chapter 5, the number of variables that were included in the computation of the Technical Inefficiency indicator and in the Nerlovian Social Profit Inefficiency indicator was limited to eight. Reducing the number of outputs, inputs and externalities can be problematic because it might lead to the omission of important issues for the sustainability of agri-food supply chains. Hence, applying the Technical Inefficiency indicator and the Nerlovian Social Profit Inefficiency indicator would require tradeoffs between sustainability issues to select the most important variables for the assessment (this issue is discussed in more detail in subsection 'Selection of sustainability issues'). On the contrary, the implementation of the Social Profit indicator shows that all considered important variables can be included if there is data available to quantify them and information to estimate the corresponding (shadow) prices. This is due to the additive nature of this indicator. In comparison, the computation of the Social Profit indicator in Chapter 3 included 26 variables.

Data requirements of each indicator and quality of the data sources

Implementation of the Social Profit indicator in Chapter 3 and Chapter 4, the Technical Inefficiency indicator in Chapter 4 and, the Nerlovian Social Profit Inefficiency indicator in Chapter 5, demonstrate that the three approaches are sufficiently flexible to assess the relative sustainability performance in a variety of socio-economic contexts: non-GM and GM soybean meal production in Brazil, potato production in North-Western Europe and coffee production in Vietnam. The implementation of these indicators in each chapter provides insights into the suitability of each indicator for assessing the relative sustainability performance at the chain level and, on the impact of the data source on the quality of results.

The Social Profit indicator was found to be more suitable than the Technical Inefficiency and Nerlovian Social Profit Inefficiency for implementation at the chain level. As shown in Chapter 3, the Social Profit indicator can be implemented at the chain level as long as there is data on quantities and prices for at least two chains. In Chapter 3 the Social Profit indicator was used to assess the relative sustainability performance of non-GM and GM soybean meal chains. In contrast, in Chapter 4 and in Chapter 5 the Technical Inefficiency indicator and the Nerlovian Social Profit Inefficiency indicator only could be estimated at the farm level. This is due to the fact that the construction of the benchmarking frontier in the computation of these two indicators requires a large sample of observations. Due to the common lack of data for post-farm stages (processing, retailing), a large sample of chains with the related information on quantities for outputs, inputs and externalities is generally not available.

Although the sustainability assessment was performed at the chain level in Chapter 3, the precision of the results might be affected by the quality of the data. At the agricultural stage, farm-specific data was not available in Brazil. Hence, for this stage, average quantities of outputs and inputs across non-GM and GM soybean farms at the municipality level were used. This data was obtained from the Brazilian Agricultural Research Corporation (EMBRAPA). The quantities of the externalities were computed based on the average quantities of inputs in non-GM and GM soybean production. Averaging quantities of outputs, inputs and externalities at the municipality level could result in a bias of the Social Profit indicator. This bias could arise from the potential existence of outliers and from differences in the way the data was collected at each farm. In addition, data was not available for soybean post-farm stages. To estimate the quantities of outputs, inputs and externalities for these stages, secondary data sources were used and several assumptions were made. Given these data issues, the results of Chapter 3 may be less precise than the results of Chapter 4 and Chapter 5, in which farm-specific data was used.

Although the farm-specific data may have higher quality than the municipality data, the quality of farm-specific data in each chapter is different. In Chapter 4, data was obtained from the European Farm Accountancy Data Network (FADN). The dataset consisted of output and input data for 205 specialized potato farms expressed in terms of annual revenues (Euros) and annual expenditures (Euros). Hence, output and input quantities were not available in physical terms. Equally important is that input data was not very detailed in terms of purchased inputs, e.g. type of pesticide product and type of fertilizer product. Although much more detailed data is collected by the FADN agencies, this data was not available for this research. For these reasons, and given that for the quantification of externalities physical quantities of each type of input is needed, in Chapter 4 only one externality was incorporated. Other important externalities could have been included in the assessment, taking into account the limitation in the number of variables that can be incorporated in the Technical Inefficiency indicator (subsection 'Number of variables that can be incorporated in the relative sustainability assessment'), if disaggregated quantities for inputs had been available.

In contrast to the data used in Chapter 4, the farm-specific quantity data that was used to estimate the Nerlovian Social Profit Inefficiency indicator was very detailed by type of input and product. Likewise, the data was directly collected by farmers who were previously trained in data recording. Therefore, the data was checked by the farmers for potential errors. In this way, a more comprehensive quantification of the externalities arising from coffee production was possible. Although this method of data collection allows for a more detailed representation of outputs, inputs and externalities, this method is costly in terms of time and economic resources.

Selection of sustainability issues

In this thesis, two approaches were used to select the main sustainability issues and the corresponding outputs, inputs and externalities in the sustainability assessments. In Chapter 4 and Chapter 5, the issues and the variables were selected based on reported economic and environmental impacts of potato production in North-Western Europe and the reported impacts of coffee production in Vietnam. In Chapter 3, the main sustainability issues and variables were selected in three steps. First, a preliminary list of sustainability issues was made based on literature review on the impacts of soybean meal production. Second, once the list was defined, a diverse group of stakeholders was consulted to select, based on their opinion, the most important issues associated with soybean meal production. Stakeholders included academic researchers, representative of NGO's, certifying organizations and firms in the agri-food sector. Third, for all the selected issues a set of output, input and externality variables was defined. A specific issue was represented by one variable or by a set of variables. The second approach is preferred for sustainability assessments that serve as input for decision making, because the involvement of relevant stakeholders can improve the quality and transparency of the outcomes of the sustainability assessments (Gibson 2006).

Nevertheless, it should be noted that not all selected main sustainability issues in Chapter 3, Chapter 4 and Chapter 5 were included in the assessments. As previously mentioned in subsection 'Data requirements of each indicator and quality of the data sources', the final issues that were selected in each chapter depended on the availability of the data. Product responsibility and health in potato production and soil and biodiversity in coffee production are of utmost importance for the sustainability of these production systems (Haase and Haverkort, 2006; Spiertz et al., 1996; D'haeze et al. 2005; Lindskog et al. 2005). Nevertheless, these issues were not considered in the assessments. Similarly, in Chapter 3, the consulted stakeholders gave high importance to issues that reflect labor rights, biodiversity and water (Chapter 3, Table 3.1). Also, due to lack of data, these issues were not accounted for in the relative sustainability assessment of soybean meal chains in Brazil.

Improvement options

Differences in relative sustainability performance between chain/farms (social profit differences in Chapter 3 and Chapter 4) were assessed using the Bennet indicator. This assessment provided information on the social profit differences that are caused by higher (lower) aggregate productivity (TFP component) and, the social profit differences that are caused by higher (lower) total price recovery (TPR component). In Chapter 3, higher sustainability performance of the non-GM soybean meal chain relative to the GM soybean meal chain was mainly caused by higher total price recovery. The main factor driving the difference in the price recovery between the two chains is the higher selling price for the non-GM soybean meal. This might reflect consumer preferences for non-genetically modified products. To a lower extent, higher sustainability performance of the non-GM soybean meal was also the result of a better productivity in the use of inputs, especially herbicides, insecticides, and fungicides that are used at the agricultural stage. The decomposition of the social profit differences between the two soybean meal chains provided insights, not only into each chain's overall performance, but also into the contribution of individual stages to the performance of the entire chain.

In Chapter 4, the decomposition of the Social profit indicator was used to assess the social profit differences at the farm level. In this case, the results show that specialized potato farms in the Netherlands perform more sustainably than German farms (higher social profit). Although Dutch farms have a lower partial productivity for some inputs and lower partial price recovery than German farms, the overall productivity of Dutch farms is higher. Higher overall productivity of Dutch farms was mainly driven by higher yields in potato production and renders Dutch farms socially more profitable.
Both in the relative sustainability assessment of soybean meal chains and in the assessment of potato farms, the decomposition of the social profit differences in monetary terms gives a clear link between potential sustainability investments and, expected private and social returns.

Chapter 4 also used the Technical Inefficiency indicator to assess the relative sustainability of specialized potato farms. Although the ranking of farms in terms of best-worst performers was similar to the ranking obtained by the Social Profit indicator, the Technical Inefficiency indicator provided different insights into the potential improvements of the performance in each country. The decomposition of the performance scores obtained in the Technical Inefficiency indicator show that the sources of technical inefficiency in the Netherlands and Germany are mainly driven by pure technical inefficiencies rather than technology gap inefficiencies and scale inefficiencies. This suggests that in both countries there is a poor or inadequate use of the existing production potential. Although in this assessment the technology gap between the production frontier of each country and the meta-frontier and, the inefficiency in scale were small compared to the pure technical inefficiency, these two components still provide useful information for sustainability improvements. The technology gap component shows to which extent the differences in sustainability performance between the observations of two or more regions are the result of differences in the production technology. Also, this source of inefficiency shows in which regions the production of a given product would be a priori more sustainable due to more favorable production conditions. This can lead to setting up macro-policies and strategies that might be implemented by governments towards a better allocation of production across regions.

The scale inefficiency component, on the other hand (also computed in the decomposition of the Nerlovian Social Profit Inefficiency indicator), shows whether farmers have potential for improving their performance by adjusting the scale at which they operate. Based on the outcome of the scale inefficiency component, it can be decided whether to procure new resources to expand the size of the operations or whether to reduce it, to achieve an optimal size. In contrast to the Social Profit indicator, which implicitly assumes that chains/farms operate under a production technology that is characterized by constant returns to scale (CRS), this source of inefficiency provides additional information for sustainability performance improvements.

In Chapter 5, the Nerlovian Social Profit Inefficiency indicator provided information about the extent to which coffee farms are maximizing the benefits to society. Results of Chapter 5 show that coffee farms in Vietnam, on average, can significantly increase their social profit given the existing production technology, land and the current (shadow) prices. The decomposition of inefficiency in social profit revealed that by choosing a better combination of inputs and coffee (allocative inefficiency component) and by improving operation managerial practices (pure technical inefficiency component), significant improvements in the sustainability performance could be achieved. Although the pure technical inefficiency and the scale inefficiency components are similar in the Technical Inefficiency indicator (Chapter 4), in the Nerlovian Social Profit indicator these two components were computed using the radial directional distance function. Consequently, output-specific, input-specific and externality-specific pure technical and scale inefficiencies provided by the Technical Inefficiency indicator (Chapter 4) were not estimated. Only an overall score for each of these components on each farm was obtained. Compared to the sources of low sustainability performance derived from the decomposition of the other two indicators, the decomposition of the Nerlovian Social Profit Inefficiency indicator provides additional information about the allocation of resources and about the optimum levels of pollution. This information can help deciding on the proper use of scarce resources and might help to set up strategies to reduce most expensive costs to society.

Finally, in the efficiency literature, low performance has been associated with specific socio-economic characteristics, institutional deficiencies and poor management practices of farmers (Balcombe et al. 2008). To investigate the extent to which the relative sustainability performance of coffee farms is influenced by external factors, in Chapter 5 a bootstrap truncated regression was performed. Results show that with increasing values for the socio-economic characteristics such as the distance of the farm to the closest town/center and the distance to the closest coffee factory/traders, the social profit inefficiency increases. An increase in the social profit inefficiency was also associated with an increase in the frequency of management activities such as spraying of chemical pesticides. On the other hand, a decrease in the social profit inefficiency was found to be associated with an increasing value for characteristics such as the share of hired labor, the ethnic group and the frequency of fertilizing and pruning.

Policy and business implications

The three indicators facilitate relative sustainability assessment of agri-food supply chains. Below I mention some possible application areas that are relevant to businesses stakeholders and policy makers. First, the indicators can be the basis of sustainability certification schemes, standards and labels, which in turn can be useful in resolving trade disputes on sustainability issues. Second, indicators can be used by governments as tools to internalize the negative externalities of production into public policy frameworks such as subsidies and taxes. Third, stakeholders along the chain can use the indicators to increase the sustainability of their own businesses by considering the sustainability of inputs along with other factors when buying inputs. Fourth, the indicators can be used by retailers to differentiate themselves from their competitors by communicating the environmental and social impacts of food products. Finally, the indicators could potentially be used for each stage of agri-food supply chains to identify opportunities to improve the relative sustainability performance.

Application requires involvement of all relevant business stakeholders and policy makers in further development and implementation of the indicators. Wide acceptance of the indicators can only be achieved when consensus is reached on which sustainability issues should be included, and when standards to collect quantitative information of outputs, inputs and externalities have been adopted and implemented. Definitions and perceptions of sustainability might vary among the different stakeholders involved in food production (policy makers, business stakeholders, NGOs). Therefore, international harmonization will require bringing together the most important stakeholders to reach a consensus about a common set of sustainability issues and variables that should be included in any sustainability assessment. Multilateral organizations such as the OECD could play an important role in facilitating the required interaction and in stimulating discussions between these stakeholders.

Apart from harmonization of sustainability issues and variables, agreements on implementation aspects will have to be reached before the indicators can be used widely. First, agreement about what data will be used and who will be responsible for the collection of this data is needed. Second, further agreement on the method of analysis of the data and the computation of the indicators is needed, e.g. the quantification of externalities and aggregation method. Third, discussions are needed with regard to how the policies and measures will be implemented based on the outcome of the indicators. Thus, for example, how governments can use the results to give market access preferences or to impose green tariffs. And fourth, discussions are needed on the ways the outcome of the indicators can be communicated by governments and retailers to consumers to raise awareness about the impact of their purchasing behavior. In the case of the Social Profit indicator and the Nerlovian Social Profit Inefficiency indicator, the ground-level implementation would also require the development of a database of robust and transferable estimates of shadow prices at the regional and country level.

At a lower scale, the harmonization of sustainability issues and variables could be coupled to the selection of the indicators that are used for public payment schemes, such as agri-environmental programs. Instead of making payment conditional on adherence to prescriptive standards, the payments could be related to the farmer's performance. For example, as a function of the performance of each farm/chain relative to the sustainable production frontier. Additionally, national governmental institutions could set standards for the production of different externalities or make recommendations on the maximum amounts of inputs that would yield the best sustainability performance scores. These standards can be derived on the basis of the observed input use and externality level of the best performers. On the production side, the decomposition of the indicators in Chapter 3, Chapter 4 and Chapter 5 provide information to producers about the potential sustainability improvement that can result from adoption of better management and practices. Improvement options provided by the indicators have a clear link with efficiency gains, productivity gains, or profit gains.

Future Research

This dissertation developed tools and generated insights that help in assessing the relative sustainability of (stages) of agri-food supply chains in different socio-economic and environmental contexts. There are, however, further research areas that could be explored to improve the conclusions that are drawn from these assessments. In the case of aggregating outputs, inputs and externalities using distance functions, the DEA models account for substitution possibilities between the different variables without requiring subjective weighting (Kuosmanen and Kortelainen 2005). In these models, the flexibility of substitution between the variables highly depends on the way the production process is modelled in the presence of externalities. However, a scientifically unique model of the production process in the presence of externalities does not exist. Some authors have proposed modelling the externalities as strongly disposable inputs (e.g. Hailu and Veeman 2001; Yang and Pollitt 2009). Others have suggested treating the externalities as weakly disposable bad outputs (Färe and Grosskopf 2005). More recently, it has been proposed to divide the production process in two sub-technologies, i.e. a by-production approach. A first sub-technology that models the production of intended outputs and a second sub-technology for externalities (Dakpo 2015; Førsund 2009; Murty et al. 2012). As an illustration, Annex 6A shows how the results of the pure technical inefficiency component for coffee farms in Vietnam (Chapter 5) changes when applying alternative models of the production process based on the by-production approach. Results of Annex 6A show that the pure technical inefficiency of coffee farms in Vietnam increases considerably when using the by-production approach. Modelling the production process using two sub-technologies allows for more flexibility in the substitution of the outputs, inputs and externalities. Therefore, different conclusions from this assessment could be drawn. Further research might explore adequate ways of modelling pollution-generating technologies in performance benchmarking. Developments on this area of research can be incorporated afterwards in the Technical Inefficiency and Nerlovian Social Profit Inefficiency indicators. In the case of the Nerlovian indicator, additional work would be required to establish the duality between the profit function and the directional distance function in an alternative production technology such as the by-production approach.

Our three indicators are based on the assumption that a good performance in any of the three dimensions of sustainability and at any stage of the agri-food supply chain can compensate lower performance in the any other dimension and stage, as long as the overall chain's performance is maintained. Complete substitution between or within some of the components of each dimension, however, could be ethically and morally unacceptable. For example the substitution of adult labor by child and slave labor can be inconceivable, even if the profitability obtained from agricultural production is higher. Another example is the deforestation of the Amazon forest at the expense of higher agricultural economic returns. Consequently, further work needs to be done to identify the critical components of the natural and social capital that must be maintained at minimum quantity and quality levels (cannot be substituted), as a prerequisite for long-term sustainability.

It is also recommended to undertake participatory workshops for further use and development of the indicators. In these workshops, stakeholders can be guided about how the indicators can be used in practice and, it can be explained, openly and transparently, the assumptions and weighting factors that are used in the construction and estimation of the indicators. By providing information to the diverse stakeholders involved in food production and by stimulating debate between them, the exchange of perceptions and ideas will allow adjusting the indicators based on common sustainability concerns. This participatory approach will enhance the uptake of the concepts by the stakeholders. Furthermore, it will help in generating indicators that are acceptable by end users. This process can follow the participatory approach of initiatives such as the Global Reporting Initiative (GRI). In the GRI initiative, guidelines for sustainability reporting at the company level are created in a collaborative participation process between international working groups. These working groups include members representing business, civil society, organizations, consultancy and academic institutions and experts on diverse sustainability issues (GRI 2006). Once sustainability guidelines are proposed, these are put into consideration of society to get feedback on their interests with regard to sustainability.

Finally, the relative sustainability assessments performed in this dissertation only included negative externalities such as green-house gas emission, nitrate pollution and pesticide toxicity, among others. Future implementation of the three indicators should also include positive externalities originating from food production such as carbon sequestration by agricultural plantations, landscape beauty, and creation of employment at any stage of the chain. This would allow making a more complete assessment of the social costs and benefits derived from agri-food supply chains.

Main conclusions

The main conclusions of this dissertation are:

- The multi-dimensional nature of relative sustainability can be captured into a single metric using prices or distance functions as aggregation methods (Chapter 2-5).
- The integrated indicators developed in this dissertation partially overcome the limitations of the single-issue and the composite indicators that are commonly used in sustainability assessments: incommensurability, subjectivity, comparability and multi-dimensionality (Chapter 2-6).
- The integrated indicators of relative sustainability performance can be used in different socio-economic and environmental contexts (Chapter 3-5).
- The Social Profit indicator is more suitable for conducting a relative sustainability assessment of agri-food supply chains than the Technical Inefficiency and Nerlovian Social Profit Inefficiency indicators, due to lower data requirements (number of observations) and a larger scope to include a diverse set of sustainability issues (Chapter 3-5).
- The Brazilian non-GM soybean meal chain performs overall more sustainably than the GM chain because of higher TFP and higher TPR (Chapter 3).

- Specialized potato farms in the Netherlands have higher social profit per hectare than German specialized potato farms. Dutch farms are also environmentally and technically more efficient than German farms (Chapter 4).
- German farms are slightly more technically and environmentally inefficient than Dutch farms due to higher pure technical inefficiencies and technology gap inefficiencies (Chapter 4).
- The differences in the rankings of specialized potato farms produced by the Social Profit indicator (economic and environmental performance) and the Technical Inefficiency indicator (technical and environmental performance) is statistically not significant (Chapter 4).
- Social profit in Vietnamese coffee farms can be increased threefold if farmers choose a better combination of inputs and levels of coffee production at given prices (allocative efficiency) and if the production potential is fully used (pure technical efficiency) (Chapter 5).
- Larger distances from the coffee farm to the closest town/city center and to the closest coffee factory/traders, increase social profit inefficiency of coffee farms in Vietnam. (Chapter 5).
- Coffee producers belonging to the ethnic group JoRai and increasing values for socio-economic characteristics such as the share of hired labor, reduce social profit inefficiency (Chapter 5).
- Increasing the frequency of farm management practices such as spraying increases social profit inefficiency of coffee farms in Vietnam, whereas increasing the frequency of fertilizing and pruning reduces social profit inefficiency (Chapter 5).

Annex 6A.

Pure Technical Inefficiency under a by-production polluting technology

The way the production process is modelled in the presence of externalities has implications on the results regarding the technical inefficiency of coffee farms. In Chapter 5, the production technology of coffee farms was modelled following a standard neoclassical technology and assuming that externalities behave as strongly disposable inputs (see Chapter 5, subsection 'Nerlovian social profit inefficiency (*NI*) indicator', for the definition of the production technology *T*). An alternative approach to the one used in this Chapter proposes modelling the production process using two independent sub-technologies, i.e. the production technology that describes how inputs are transformed into intended outputs (T_1) and, a technology that reflects the relationship between externalities and the inputs that cause those externalities (T_2) (For details see Murty et al. 2012).

Suppose there are *k = 1,...K* DMUs (farms) using *N* inputs and *D* fixed inputs to produce *M* outputs. In the production process, *J* negative externalities are produced. Let vectors $y = (y_1, y_2, \dots y_M) \in \Re_+^M$, $x = (x_1, x_2, \dots x_N) \in \Re_+^N$, $(f_1, f_2, \dots f_D) \in \Re_+^D$, and $b = \left(b_1, b_2, \dots b_J\right) \in \Re_+^J$ represent the outputs, inputs, fixed inputs, and negative externalities, respectively.

Under the by-production approach, the two technologies are given by:

$$T_1 = \left[(y, x_1, x_2, f, b) \in \mathbb{R}_+^{M,N,D,J} \middle| h(y, x_1, x_2, f) \leq 0\right],$$

$$T_2 = \left[(y, x_1, x_2, f, b) \in \mathbb{R}_+^{M,N,D,J} \middle| b \geq u(x_2)\right] ,$$

Where the total N input vector that enter in the production process is partitioned into two sub-input vectors: the first S sub-vector of inputs that do not cause pollution x_1 = (1,...,S) and, the remaining (N-S) sub-vector of inputs causing pollution $x_2 = (S + 1, \dots N)$. h and u are both continuously and differentiable functions. The set T_1 is a standard technology set that is independent of pollution. The set T_2 reflects the externality-generating mechanism (Murty 2010).

The overall production technology is represented as:

$$T = T_1 \cap T_2,$$

Based on the by production technology, two inefficiency scores can be computed for each DMU. A technical inefficiency score related to the intended production technology or operational inefficiency (analogous to the technical inefficiency score computed in Chapter 5) and, an environmental inefficiency score related to the residual generation technology. The overall inefficiency score is given by the weighted average of the two inefficiency scores.

The DDF defined on the by-production polluting technology and computed using linear programming techniques is defined for DMU k' as:

$$\vec{D}(y, x, f, b; g_y, g_x, g_b) = max\frac{1}{2}(\beta 1 + \beta 2)$$

s.t.

$$\sum_{k=1}^{K} \alpha^k y_m^k \geq y_m^{k'} + \beta 1 g_y, \quad m = 1, \dots., M$$

$$\sum_{k=1}^{K} \alpha^k x_n^k \leq x_n^{k'} - \beta 1 g_n, \quad n = 1, \dots, N$$

$$\sum_{k=1}^{K} \alpha^k f_d^k \leq f_d^{k'}, \quad d = 1,2, \dots, D$$

$$\sum_{k=1}^{K} \alpha_k = 1; \quad \beta 1 \geq 0$$

$$\sum_{k=1}^{K} \xi^k b_j^k \leq b_j^{k'} - \beta 2 g_b, \quad j = 1, \dots, J$$

$$\sum_{k=1}^{K} \xi^k x_{2n}^k \geq x_{2n}^{k'} - \beta 2 g_{x2}\,, \quad n = s+1, \dots, N$$

$$\sum_{k=1}^{K} \xi_k = 1; \qquad \beta 2 \geq 0;$$

Where $\sum_{k=1}^{K} \xi^k x_{2n}^k \geq x_{2n}^{k'}$ reflects the cost disposability of pollution causing inputs and $\sum_{k=1}^{K} \xi^k b_j^k \leq b_j^{k'}$ the cost disposability of the bad output. α and ξ represent the two different set of intensity variables of each sub-technology. The model has two sets of non-negative intensity variables α_k and ξ_k that are restricted to be equal to one, implying an intended production technology and a residual generation technology that exhibit variable returns to scale (VRS). As presented the by-production approach offers the advantage of separating the operational inefficiency ($\beta 1$) and the environmental inefficiency ($\beta 2$).

The by-production approach proposed by Murty et al. (2012) assumes independence between the two sub-technologies. Dakpo (2015) developed an extension of the Murty et al. (2012) by-production model by augmenting the model with a dependence constraint relative to the pollution generating inputs. The constraint is defined as:

$$\sum_{k=1}^{K} \alpha_k x_{n2k} = \sum_{k=1}^{K} \xi_k x_{n2k}\,,$$

To show how results of the Pure technical inefficiency component in Chapter 5 would differ under a by-production approach, the by-production model with independency of the two sub-technologies (Model B) and the by-production model with the interdependence constraint (Model C) were computed for our sample of coffee farms in Vietnam. Afterwards, the results were compared to the outcome of the Pure technical inefficiency component that was computed using Eq. 5.8 (see Chapter 5, subsection 'Sources of farm sustainability'). Table 6A.1 shows the outcomes of the three models.

Table 6A.1 Inefficiency scores (mean values for the whole sample of coffee farms N= 361).

	Standard	Murty	Dakpo
Operational inefficiency	N/A	0.27	0.26
Environmental inefficiency	N/A	0.93	0.89
Overall technical inefficiency	**0.26**	**0.60**	**0.57**

Standard = Standard neoclassical production technology (mean value of the *PTI* component. See Chapter 5, subsection 'Results'); Murty = By-production model independent technologies; Dakpo = By-production model with inter-dependence constraint

Results show that the substitution possibilities are bigger in the two by-production models as compared with a standard neoclassical production technology. The operational inefficiency in the Murty and Dakpo models is similar to the value of the pure technical inefficiency computed based on the standard technology, which indicates that externalities do not have a large effect in the standard model. It can be explained by the fact that the level of externalities is related to the level of inputs (polluting inputs). A reduction in the polluting inputs will automatically reduce the amount of externalities. Nevertheless, when dividing the production process in two sub-technologies, the environmental inefficiency component shows that even though the Pure technical inefficiency component in the standard model indicates that coffee farms can reduce by 26% the externalities, these farms could even have bigger reductions at least up to 93% and 89%, by adopting clean technologies or clean practices that could be currently be used by best coffee farm performers. Hence, the flexibility in the by-production technology allows for further reduction as externalities are not constrained by the outputs and the non-polluting inputs.

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SUMMARY

Summary

Increasing food production is crucial to meet the expected growing demand for food in the coming decades. However, increasing production may lead to undesirable social and environmental impacts such as land degradation, deforestation, depletion of water, health problems, and deterioration of labor conditions, among others. Scholars, planners, producers, policy-makers, and other stakeholders have pointed out the need to examine ways to ensure sustainable food production. Ensuring sustainability in food production requires increasing our knowledge about the economic, environmental and social performance of the various stages along the agri-food supply chains. In this respect, there is a need for integrated indicators that can provide synthetized information about the extent to which food products are sustainably produced. Such information would provide valuable insights that can help business stakeholders in identifying areas of intervention and would help policy makers to set up policies and strategies to encourage sustainable food production. In the light of the foregoing, the overall objective of this thesis was to perform integrated assessments of relative sustainability performance of (stages of) agri-food supply chains using different integrated indicators.

Chapter 2 developed a framework for the integrated analysis of the relative sustainability performance of (stages of) agri-food supply chains. To operationalize the concept of sustainability, agri-food supply chains are characterized and defined in terms of outputs, inputs and externalities, which reflect the economic, environmental and social implications of production. The outputs, inputs and externalities are aggregated into two different integrated indicators of relative sustainability performance using either prices, i.e. the Social Profit indicator or distance functions, i.e. the Technical Inefficiency indicator. This thesis proposes the Bennet Total Factor Productivity (TFP) indicator and the Bennet Total Price Recovery (TPR) indicator for a consistent comparison of the score of the Social Profit indicator between (stages of) agri-food chains. On the other hand, the comparison of the Technical Inefficiency indicator score between (stages of) chains uses a production frontier, which represents the best practice in terms of sustainability performance. The chapter is finalized with a discussion about some of the key issues for implementation of both indicators including data availability, the selection of variables, and the selection of sustainability standards and targets.

Chapter 3 assessed the relative sustainability performance of two Brazilian conventional soybean meal chains, non-genetically modified (non-GM) and genetically modified (GM) chains, using the Social Profit indicator. Sustainability issues included in the assessment were profitability, global warming potential, eutrophication potential, environmental toxicity, farmworker toxicity, consumer toxicity, deforestation, and loss of employment. Social profit differences between both chains were assessed using the Bennet Total Factor Productivity (TFP) indicator and the Total Price Recovery (TPR) indicator. Results show that the non-GM soybean meal chain has higher social profit and thus, performs more sustainable than the GM chain. Main reasons for higher sustainability performance include higher productivity of biocides, i.e. pesticides, fungicides, and herbicides (TFP component) and higher price premium paid per ton of non-GM soybean meal (TPR component). By contrast, the GM soybean meal chain has a lower emission of greenhouse gases at the transport to port stage. Although the non-GM soybean meal chain performs more sustainably than the GM chain, both chains could further improve their sustainability. Efforts should focus on providing technical and high quality assistance to reduce biocide use in GM soybean production, whereas in non-GM soybean production strategies should be designed for reducing the emission of greenhouse gases that are caused in the transportation of soybeans.

Chapter 4 assessed the relative economic and environmental performance of specialized potato farms in Germany and the Netherlands using the Social Profit indicator and the Technical Inefficiency indicator. Afterwards, cross-country differences in Social Profit and Technical Inefficiency were assessed to identify opportunities for improving the performance of potato production. Cross-country differences in Social Profit were assessed by computing the Bennet TFP indicator and the Bennet TPR indicator whereas cross-country differences in Technical Inefficiency were assessed by identifying three components: pure technical inefficiency, scale inefficiency and technology gap inefficiency. Results of both indicators show that Dutch farms overall perform slightly better than German farms. The Dutch farms generate higher social profit and are technically and environmentally more efficient. Higher social profits of Dutch farms relative to German farms are mainly the result of higher aggregated productivity (TFP component), which is mainly driven by higher revenues in potato production. Nevertheless, German farms overall have higher partial productivities for inputs such as capital and variable inputs and a higher Total

Price Recovery component. On the other hand, the main source of Technical Inefficiency in both countries is pure technical inefficiencies rather than technology gap inefficiencies and scale inefficiencies. This suggests that in both countries, there is a poor or inadequate use of the existing production potential. Differences in the outcome of each indicator suggest that both countries could improve substantially their performance by improving the pure managerial operations of the farms. This could be achieved by providing recommendations on economically optimal output combinations and technical advice on the use of inputs. Also, German farms can reduce substantially the greenhouse gas emissions. Such recommendations, however, should be specific for each group of performers in each country and should be subject to the available technology and to the environmental conditions.

Chapter 5 assessed the relative sustainability performance of coffee farms in Vietnam using the Nerlovian Social Profit Inefficiency indicator. To determine the sources of social profit inefficiency, the farm-specific social profit inefficiency scores were decomposed into three components: pure technical inefficiency, allocative inefficiency and, scale inefficiency. This decomposition allowed the identification of opportunities for increasing the social profit of coffee farms to the maximum attainable levels. As a second objective, this study assessed the impact of a set of socio-economic characteristics and management practices on the social profit inefficiency of coffee farms. The results show that coffee farms, on average, could increase their social profits threefold at given prices and given the current production technology. The main sources of social profit inefficiency are associated with the sub-optimal allocation of resources and levels of production and technical inefficiency. The sub-optimal allocation of resources is due to under-utilization of inputs and the under-production of coffee. The assessment of the external determinants of social profit inefficiency shows that larger distances from the coffee farm to the town/city center and to the traders, and higher frequency of spraying, increase the inefficiency in social profit. Management practices of the ethnic group JoRai and increasing values for hired labor and for the frequency of fertilizing and pruning activities reduce social profit inefficiency. The improvement of the relative sustainability performance of coffee farms in Vietnam would require corrective actions to ensure the efficient use of inputs and an adjustment of the frequency of management activities that were found to affect negatively the level of Social Profit inefficiency. At the regional level, policies should be focused on the provision of technical assistance by extension services. Finally, it is recommended to perform an in-depth study on the management of coffee farms by the JoRai ethnic group. It could allow identifying best management practices which extension services can then disseminate to other ethnic groups to reduce the Social Profit inefficiency of coffee production in Vietnam.

Finally, in Chapter 6 the advantages of the proposed three indicators over existing approaches are discussed and the results of the research chapters are synthetized. The synthesis of results comprises issues regarding: (1) the scope of each indicator to incorporate outputs, inputs and externalities; (2) the data requirements; (3) the improvement options and; (4) the selection of sustainability issues. Subsequently, the chapter provides the implications of the results for policy makers and business stakeholders, and finalizes by outlying possible directions for future research.

From this dissertation the following conclusions were drawn:

- The multi-dimensional nature of relative sustainability can be captured into a single metric using prices or distance functions as aggregation methods (Chapter 2-5).
- The integrated indicators developed in this dissertation partially overcome the limitations of the single-issue and the composite indicators that are commonly used in sustainability assessments: incommensurability, subjectivity, comparability and multi-dimensionality (Chapter 2-6).
- The integrated indicators of relative sustainability performance can be used in different socio-economic and environmental contexts (Chapter 3-5).
- The Social Profit indicator is more suitable for conducting a relative sustainability assessment of agri-food supply chains than the Technical Inefficiency and Nerlovian Social Profit Inefficiency indicators, due to lower data requirements (number of observations) and a larger scope to include a diverse set of sustainability issues (Chapter 3-5).
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- Social profit in Vietnamese coffee farms can be increased threefold if farmers choose a better combination of inputs and levels of coffee production at given prices (allocative efficiency) and if the production potential is fully used (pure technical efficiency) (Chapter 5).
- Larger distances from the coffee farm to the closest town/city center and to the closest coffee factory/traders, increase social profit inefficiency of coffee farms in Vietnam. (Chapter 5).
- Coffee producers belonging to the ethnic group JoRai and increasing values for socio-economic characteristics such as the share of hired labor, reduce social profit inefficiency (Chapter 5).
- Increasing the frequency of farm management practices such as spraying increases social profit inefficiency of coffee farms in Vietnam, whereas increasing the frequency of fertilizing and pruning reduces social profit inefficiency (Chapter 5).

About the author

Curriculum Vitae

Publications

Training and Supervision Plan

About the author

Daniel Gaitán Cremaschi was born in Bogotá, Colombia, on January 30, 1982. He graduated in Ecology at the Pontificia Universidad Javeriana, Colombia, in 2006. In 2007, he worked at the General Secretariat of the Town Hall of Bogotá supervising the implementation of international standards on environmental management. From 2009 till 2011 he completed with distinction (Cum Laude) his Master studies in Environmental Sciences at Wageningen University, the Netherlands. In 2012, he started his PhD research at the Business Economics Group of Wageningen University . In this capacity, he developed sustainability metrics for evaluating the sustainability level of agri-food supply chains as a key step towards international harmonization of certification schemes and corporate social responsibility reporting. His project was financed by the Ministry of Economic Affairs of the Netherlands. During his PhD research, he followed his education programme at the Wageningen School of Social Sciences (WASS). He followed various courses in the field of economics and econometrics.

Along his academic career, he has developed a strong multi-disciplinary background specialized in productivity and efficiency analysis, ecosystem service accounting and valuation, multi-functionality of natural and semi-natural systems and implementation of economic and market-based instruments.

List of publications

Gaitán-Cremaschi D, Meuwissen MPM, Oude Lansink AG.J.M (2015). Total Factor Productivity: a framework for measuring sustainability performance of agri-food supply chains. *Applied Economic Perspectives and Policy*. DOI: 10.1093/aepp/ppw008.

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Gaitán-Cremaschi D, Lasco RD, Delfino JP (2012). Payments for watershed protection services: emerging lessons from the Philippines. *Journal of Sustainable Development* 6: 90–103.

Contributions to conferences and seminars

Gaitán-Cremaschi D, Meuwissen MPM, Oude Lansink AGJM, van Evert FK (2015). Benchmarking the sustainability of soybean meal production in Brazil using a Total Factor Productivity approach. Poster presented at the International Conference of Agricultural Economists (ICAE), Milan, Italia, 8-14 August 2015 (Best poster, honorable mention).

Gaitán-Cremaschi D, Meuwissen PM, Oude Lansink AGJM, Jansen DM, van Evert FK, Bosch R, van de Pol, M (2014). Total Factor Productivity a measure of sustainability. Invited talk at the OECD workshop “Sustainable Biomass Drives the Next Bio-economy: A New Industrial Revolution?”, OECD Headquarters, Paris, France, *10-11* June 2014.

Gaitán-Cremaschi D, Meuwissen MPM, Oude Lansink AGJM, van Evert FK (2014). Bennet measure for performance analysis of agri-food supply chain sustainability. Article presented at the International conference WICaNeM, Capri, Italy, 4-6 June 2014.

Gaitán-Cremaschi D, Meuwissen MPM, Oude Lansink AGJM (2013). Total factor productivity: a framework for measuring food supply chain sustainability. Article presented at the International Symposium Productivity and Its Impacts on Global Trade, International Agricultural Trade Research Consortium (IATRC), Seville, Spain, 2-4 June 2013.

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Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Writing research proposal	BEC/WUR	2012	6
Economic Models (AEP 30806)	WUR	2012	6
Advanced Econometrics (AEP 60306)	WUR	2012	6
Theory and Practice of efficiency & productivity measurement: Static and dynamic analysis	WASS	2012	3
Cost-Benefit analysis and environmental valuation (DEC 31306)	WUR	2013	6
B) General research related competences			
WASS Introduction course	WASS	2012	1
'Measuring Food Supply Chain Performance'	IATRC symposium, Seville Spain	2013	1
'A novel index approach for measuring biomass sustainability'	OECD workshop, Paris France	2014	1
'Measuring the sustainability performance of agri-food supply chains: a TFP approach'	WICaNeM conference, Capri Italy	2014	1
'Benchmarking the sustainability of soybean meal production in Brazil using a Total Factor Productivity approach'	ICAE conference, Milan Italy	2015	1
C) Career related competences/personal development			
Teaching and supervision of students	BEC, WUR	2014-2015	2
Participation PhD meetings	BEC, WUR	2012-2016	2
Total			**36**

*One credit according to ECTS is on average equivalent to 28 hours of study load.

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