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**Opportunity Costs of Providing Crop Diversity
in Organic and Conventional Farming:
Would Targeted Environmental Policies Make Economic Sense?**

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Opportunity costs of providing crop diversity in organic and conventional farming: Would targeted environmental policies make economic sense?

Abstract

Targeted environmental policies for farmlands may improve the cost-efficiency of conservation programs if one can identify the farms that produce public goods, or environmental outputs, with the least cost. We derive shadow values of producing crop diversity on conventional and organic crop farms to examine their opportunity costs of conservation. Non-parametric distance functions are estimated by applying data envelopment analysis to a sample of Finnish crop farms for the period 1994 – 2002. Our results show that there is variation in the shadow values between farms and the technologies adopted. The extent of cost heterogeneity and farms' potential for specialization in the production of environmental outputs determine whether voluntary programs such as auctions for conservation payments are economically reasonable.

JEL Classification: C21, D24, H41, Q12, Q24

Keywords: biodiversity, Shannon index, DEA, distance functions, shadow values

1. Introduction

Biodiversity conservation on farmland is increasingly recognized as an important environmental goal in agricultural policies (see Wossink and van Wenum, 2003; van Wenum et al., 2004). Nevertheless, agri-environmental policies are largely seen by the general public as subsidy programs that compensate farmers for the costs of conservation measures but have yet to provide convincing evidence that they have achieved a better environment. (Feng 2007) One of the challenges in designing environmental policies is measuring the benefits of environmental improvements. An additional concern is that, due to asymmetric information, the costs of conservation on farmland are not necessarily known by the regulator (Sheriff 2009). The rationale here is that if environmental goals are truly part of agricultural policies, it should be possible to evaluate the performance of the policies implemented.

Calls have been heard for better incentives and market-like mechanisms for conservation - such as auctions – that would improve the effectiveness and impacts of policies designed to enhance biodiversity in agriculture (e.g., Pascual and Perrings, 2007). The US Department of Agriculture has the longest experience with auctions through its Conservation Reserve Program, into which farms are accepted based on an environmental benefits index (Latacz-Lohman & Van der Hamsvoort 1997, Kirwan et al. 2005). In contrast, the European Common Agricultural Policy has focused on dictating appropriate farming practices rather than providing incentives for creating actual environmental benefits. This orientation may be changing: there is growing interest in using auctions as a means to deliver payments for environmental services in agriculture (for a review see, e.g., Latacz-Lohman and Schilizzi 2005). However, given the limited use of auctions in European agriculture, the bulk of the research evaluating such policy instruments is based on pilot studies or experiments and simulations carried out to test auction theory in alternative settings (see, e.g., Bastian et al. 2008, Glebe 2008, and Groth 2009). Owing to the hypothetical approach, the bids in experimental auctions do not necessarily reflect farmers' opportunity costs of conservation.

We analyze agricultural production within the frame of economic theory by taking crop diversity into account as a positive non-market output of farms. Trade-offs in the production of market and non-market outputs are made explicit, since the opportunity costs of conservation measures ultimately determine the costs of the agri-environmental policies implemented. To gain insight into those costs, we apply the framework provided by Färe and Grosskopf (1998) to estimate shadow values for non-market public goods such as environmental amenities. Variants of estimation methods within this framework have been used to price negative externalities, or public bads, in European agriculture (e.g., Huhtala and Marklund 2008, Piot-Lepetit and Le Moing 2007, Piot-Lepetit and Vermersch 1998); less work has been carried out on pricing the effects of agriculture on biodiversity conservation. The analysis of biodiversity most closely related to ours is an application by Färe et al. (2001) that prices the non-market characteristics of conservation land in the United States.

In our analysis, we use crop diversity as a non-market output measured by a farm-level value for the Shannon Diversity Index, which captures both the richness and evenness of the crops cultivated on the farms. The index is a typical landscape diversity indicator, one that can be seen as reflecting the esthetic value of a diverse agricultural landscape from a social point of view. On the other hand, in the literature on risk management in agriculture, crop diversity has been attributed a private value as an option whereby risk-averse farmers can hedge against uncertainty (for a discussion see, e.g., Di Falco and Perrings 2005). On these grounds, the trade-off between market output (crop yield) and non-market ecological by-products (crop diversity) can be considered relevant for farmers' decision making.

Finally, it is important to bring out how the currently implemented European agricultural policies are reflected in choices of farming practices and the corresponding (ecological) benefits. Compared to conventional farming organic production can be seen as a more restricted, or even an alternative, technology that has been promoted for environmental reasons¹. Therefore, we estimate distance functions for conventional and organic crop farms separately. The analysis provides us with efficiency scores for the farms with respect to their chosen technology, but our main interest lies in determining shadow values of crop diversity. These values can be interpreted as the opportunity costs of crop diversity in terms of crop output forgone. This information is important for policy design since it reveals whether there is heterogeneity in costs between types of farms and, accordingly, room for improving the cost-efficiency of policies that target the conservation of crop biodiversity in agriculture.

The paper is organized as follows. Section 2 introduces and discusses the crop biodiversity index applied in the empirical study. In section 3 we elaborate the fundamental approaches of the study in terms of production economics: we present models of distance functions when there are multiple outputs and, alternatively, when one of the outputs is held as a minimum constraint; and we then derive shadow values for crop diversity using these alternative models. Section 4 presents how non-parametric distance functions are estimated by applying data envelopment analysis (DEA). Section 5 presents the data for the period 1994 – 2002, obtained from cross sections of Finnish crop farms participating in the Finnish bookkeeping system, which also serves as the database for the EU's official Farm Accountancy Data Network (FADN). The empirical results are reported in section 6. The concluding section discusses several findings on variation in the shadow values between farms and between the technologies adopted.

2. Crop biodiversity

In addition to yielding marketable output such as cereals, agricultural systems may produce biodiversity as a positive by-product. Management practices may have various impacts on biodiversity due to crop rotation, application of chemical inputs and similar choices by the farmer. Biodiversity is a complex concept with several dimensions and choosing proper measures of or indicators for it poses a challenge. The availability of data on biodiversity is a major limitation for empirical analysis. Here, we rely on a relatively simple measure of diversity known as the crop diversity index, which can be described as a measure of landscape diversity. According to a classification by Callicott et al. (1999), the crop diversity index can be classified as a compositional measure of species diversity.

Species-level diversity is quantified as the number of species in a given area (richness) and how evenly balanced the abundances of each species are (evenness) (Armsworth et al., 2004). It should be noted that species-level biodiversity is only one of the measures that can be used in analyzing biodiversity. For example, community-level biodiversity describes the interactions of species in their natural habitats. The spatial scale is also important since richness increases with area. Usually a choice is made to use either an economically or an ecologically meaningful scale. We choose to study the diversity of agricultural land use at the farm level within the framework of production theory. At the farm level, we know the number of crops cultivated and the area under each crop. In their discussion of the mechanisms increasing the homogeneity of agricultural habitats, Benton et

¹ Organic farming as a method of production puts considerable emphasis on environmental protection. It avoids, or substantially reduces, the use of synthetic chemical inputs such as fertilizers, pesticides and additives. Crop production uses low-soluble fertilizers, fertilization with manure, growing legumes to bind nitrogen from the air, and composting of vegetables, as well as preventive measures to control pests and diseases. Crop rotation, mechanical weed control and the protection of beneficial organisms are also important (Organic Farming in the EU: Facts and Figures, 2005). These restrictions most likely have an impact on the production technology and economic performance of organic farms.

al. (2003) point out that a reduction in the botanical and structural variety of crops and grassland cultivated on a single farm increases the probability of larger blocks of land being under the same form of management at any given time. Jackson et al. (2007) identify the valuation of biodiversity in agricultural landscapes from socioeconomic perspectives as a critical issue requiring scientific research. In light of these findings, crop diversity becomes an appealing measure for analyzing the trade-offs and synergies involved in managing farmland for agricultural productivity as opposed to biodiversity conservation. In addition, farm-level data are already available for use by government authorities for implementing policy based on crop diversity indices. In fact, the cultivation of local crops and crop diversification have been included as a voluntary conservation measure eligible for specific support in the Finnish agri-environmental program, but the measure has not gained wide popularity among farmers. (Horisontaalinen maatalouden kehittämisohjelma 2006)

In this study, richness is measured by the number of cultivated crops, such as barley, grass silage, potato, or by the area lying fallow. Evenness refers to how uniformly the arable land area of a farm is distributed among these different crops and uses. Evenness and richness can be quantified using the Shannon Diversity Index (SHDI) (Armsworth et al., 2004). The index, which has its origin in information theory (Shannon 1948), has been applied in a number of environmental economic studies (e.g., Pacini et al., 2003; Hietala-Koivu et al., 2004; Latacz-Lohman, 2004; Miettinen et al., 2004; Di Falco and Perrings, 2005).

The SHDI is calculated using the following formula:

$$SHDI = -\sum_{i=1}^J (P_i \times \ln P_i), \quad (1)$$

where J is the number of cultivated crops, P_i denotes the proportion of the area covered by a specific crop, and \ln is the natural logarithm.² The index in equation (1) equals zero when there is only one crop, indicating no diversity. The value increases with the number of cultivated crops and when the cultivated areas under various crops become more even. The index reaches its maximum when crops are cultivated in equal shares, that is, when $P_i = 1/J$ (McGarical and Marks 1995).

In our analysis, the SHDI is used to approximate the diversity produced by farms, which is therefore modeled as a good output within the frame of production theory. Although crop diversity has usually been applied as a landscape indicator at the regional level, its use as a measure at the farm level as well can be motivated by the fact that greater crop diversity is likely to increase the number of different habitats. In conventional farming, a monoculture may be successful, whereas organic production technology requires at least some crop rotation, ruling out the possibility of cultivating a single crop only. Thus, organic farming is likely to produce higher crop diversity. In addition, numerous studies have shown that crop rotation conserves soil fertility (Riedell et al., 1998; Watson et al., 2002), improves nutrient and water use (Karlen et al., 1994), and increases yield sustainability (Struik and Bonciarelli, 1997; see also Herzog et al., 2006).

3. Production Technology

Production technology is typically described by production functions, which define output as a function of inputs. In contrast to the traditional scalar-valued production function, distance functions allow multiple outputs and multiple inputs (Shephard 1953, 1970). In principle, there are

² The Shannon Diversity Index appears in the literature under the name the Shannon-Wiener (-Weiner or -Weaver) Index. According to Keylock (2005), it belongs to the Hill family of indices (like the Simpson Diversity Index) and is based on the Boltzmann-Gibbs-Shannon entropic form. Sometimes the index is presented in the form $\exp(SHDI)$. At the maximum, this form indicates the number of species corresponding to a uniform distribution (maximum entropy).

two extreme options that may be applied: either an input or output distance function³. For any input-output combination⁴ $(x,y) \in R_+^{M+N}$ the (Shephard) output distance function $D_o(x,y)$ is such that $D_o(x,y) = \min \{ \lambda > 0: y/\lambda \in P(x) \}$, where $P(x)$ is the output (producible) set. Alternatively, the input distance function $D_i(x, y)$ can be presented as $D_i(x, y) = \max \{ \gamma > 0: x/\gamma \in V(y) \}$, where $V(y)$ is the input (requirement) set.

The output distance function calculates the largest expansion $(1/\lambda)$ of y along the ray through y as far from 0 as possible while staying in output set $(P(x))$, which means that y belongs to $P(x)$ if and only if $D_o(x, y) \leq 1$. It is also obvious that the distance function takes the value one only if the output vector belongs to the frontier of the corresponding input vector. Correspondingly, the input distance function looks for the largest contraction (γ) of inputs while remaining in the input requirement set $(V(y))$. It follows that $D_i(x, y) \geq 1$ when x belongs to $V(y)$. Therefore, the output and input distance functions completely characterize the technology, which inherits its properties from $P(x)$ and/or $V(y)$.

Distance functions possess some specific virtues with respect to a firm's behavior. Färe (1975) showed an important and widely used connection between Shephard distance functions and (Debreu)-Farrell input- and output-oriented technical efficiency measures. The Farrell (1957) measure of output- (input-) oriented technical efficiency (F_o) is the reciprocal of the value of output (input) distance function, i.e. $F_o(x,y) = (D_o(x,y))^{-1}$ (alternatively $F_i(x,y) = (D_i(x,y))^{-1}$). One desirable property of the Farrell type measure is that it is invariant with respect to the units of measurement in the inputs and outputs. In addition, the evaluation of efficiency provides equal, although reciprocal values for distance function/technical efficiency when constant returns to scale prevail.

Distance functions provide a framework for the primal approach with multiple inputs and outputs. It is sometimes claimed that no behavioral assumptions are required whenever distance functions are applied, but Färe and Primont (1995) showed that there is a dual relationship between input (output) distance functions and cost (revenue) functions. This duality can be utilized when we consider which orientation would be appropriate in our case; it is also an important property that can be used in determining shadow prices.

In addition to yielding crops that can be sold on the market, agricultural production provides other, non-market outputs as by-products. Some of these non-market outputs are desirable and others are not, a fact that has to be taken into account when production technology is modeled. Undesirable outputs have been modeled either as weakly disposable outputs or as inputs (e.g., Färe et al. 1989) or as a normal output after some transformations of data (e.g., Scheel 2001). When the two outputs are both desirable, as in our case, it is reasonable to assume a production technology of multiple desirable outputs (and multiple inputs), which are strongly disposable. This is illustrated in Figure 1, in which we have two outputs – crops and non-market crop diversity – being produced by two different technologies.

[Figure 1 about here]

³ Directional distance functions provide a more general representation of technology than the proportional distance functions discussed by Shephard. Chambers et al. (1998) have shown that the proportional distance function is a special case of directional distance functions. In spite of the generality of directional distance functions, it is problematic that the direction vector has to be defined a priori. Therefore, proportional functions are preferred as a starting point in the present case.

⁴ Input (x) and output (y) combinations consist of M non-negative inputs and N non-negative outputs.

The transformation curves show how much of the crop output has to be sacrificed to increase crop diversity, given inputs. Technologies 1 and 2 (e.g., organic vs. conventional), which allow for different production possibilities at a given input level, are illustrated by two separate transformation curves (or the outer boundaries of the producible output sets). Output distance functions are derived for the radial distances from the frontier. For example, a value of the output distance function for point *e* with respect to technology 1 (O_e/O_g) is different compared to the value with respect to technology 2 (O_e/O_f). In our illustration in Figure 1, the producible output sets of the two technologies cross⁵. Figure 1 shows that the assumption as to whether all farms have access to the same technology or whether different farm types, for example organic and conventional farms, do not have access to the same technology is critical in the measurement of the distance function if the technological frontiers differ by technology. As Dyson et al. (2001) have pointed out, a comparison of firms precludes the firms having access to a similar set of inputs. This is not the case when organic and conventional technologies are analyzed, and we therefore prefer to examine the technologies separately rather than applying a metafrontier approach, for example (Battese et al. 2004, O'Donnell et al. 2008).

The traditional output distance function approach assumes that the distance is calculated as a possibility for an equiproportionate increase in outputs, given inputs and reference units. Thus, we in principle assume that socially optimal proportions of these outputs are already being produced but that our objective is to produce more of both. This is a critical assumption in the case of non-market outputs, which do not have a market price. We might also think that society seeks to increase either crop diversity (given the inputs and traditional output) or the traditional crop output (given the inputs and crop diversity). This would be conceivable where a socially optimal level of one of the outputs is already being produced but the purpose is to evaluate the possibilities to increase the other output. This kind of directional distance function is similar to the technical subvector efficiency approach introduced by Färe et al. (1994) and applied to variable inputs by Oude Lansink et al. (2002). Figure 2 illustrates the traditional radial output distance function (solid line) and the specific directional distance functions (broken line - vertical for crop, horizontal for crop diversity⁶).

[Figure 2 about here]

Although non-market goods have no market price, the current product mix of each farm reflects the marginal rate of transformation (MRT) between crop output and crop diversity. It is possible to derive a shadow value for crop diversity from the known price of crop output and the current output mix, or the MRT between market and non-market outputs. It can be claimed that farmers do not in fact aim at producing crop diversity; rather, it is a by-product of their production process. However, there may be differences between farms in their location on the transformation curve (different shadow values), for example because of unobserved heterogeneity in resources or heterogeneous risk preferences. This variation provides an opportunity to target policy actions such that they serve the purposes of enhancing or preserving crop diversity.

4. Estimation

The two most frequently used approaches for the estimation of distance functions/efficiency scores are mathematical programming and econometric estimation of stochastic frontiers. Charnes et al.

⁵ It is of course possible that one of the technologies dominates at all output combinations.

⁶ An obvious alternative would be to think that society seeks to reduce cost/input use of production but to still preserve current output quantities. This would lead us to an input orientation that would coincide with the farm level objective of cost minimization. In addition, other directions, such as the simultaneous reduction of input use and increase in outputs, could also be analyzed using directional distance functions.

(1978) extended the piecewise linear frontier function to multiple inputs and outputs and referred to the method as data envelopment analysis (DEA). The benefits of DEA are that no functional form (except the scale, disposability and convexity properties) of the production technology or technical inefficiency has to be assumed prior to analysis and that the method can easily handle multiple inputs and outputs. One drawback is that no error component has been taken into account. Stochastic frontier analysis (SFA) requires specific assumptions about functional forms and efficiency distributions but accounts for statistical noise. Recently, non- and semi-parametric methods have been developed that are able to capture the stochastic elements with less restrictive assumptions than those in SFA (see e.g., Daraio and Simar 2007, Fried et al. 2008, Kuosmanen 2008). Kuosmanen and Johnson (2010) have shown that DEA and SFA can be seen as special cases of the more general StoNED (stochastic non-smooth envelopment of data) method.

In our case, we prefer non-parametric DEA based models because of the minimal assumptions required for the estimation. In addition, the models make it possible to derive farm-specific shadow prices for crop diversity, not just one socially optimal value for all farms. The DEA estimation is carried out using linear programming (LP) models which have to be solved for each decision-making unit (farm) separately. In the case of constant returns to scale, we define the model with m outputs, y_m , and n inputs, x_n , with k decision-making units forming the reference set and each unit, k' , being compared in turn to the reference set. In our notation below, $F_o(CRS, S)$, or ϕ , denotes technical output efficiency under constant returns to scale (CRS) and strong disposability (S) assumptions. The radial output efficiency measure (henceforth denoted by CRS_radial) can be conveniently used in the estimation, inasmuch as it is the reciprocal of the output distance function, $(D_o(x, y))^{-1}$ (Färe et al. 1994).

$$\begin{aligned}
F_o(CRS, S) &= (D_o(x, y))^{-1} = \max \phi \\
s.t. \quad \phi y_{k'm} &\leq \sum_{k=1}^K z_k y_{km}, m=1, \dots, M, \\
\sum_{k=1}^K z_k x_{kn} &\leq x_{k'n}, n=1, \dots, N, \\
z_k &\geq 0, k=1, \dots, K.
\end{aligned} \tag{2}$$

When the non-negative intensity variables z_k are not constrained, the scaling of reference units up and down is unlimited, a condition which coincides with constant returns to scale. The input orientation refers to searching for the largest equiproportionate downscaling of the input usage, subject to the reference set. In this case the model turns into a minimization problem. The CRS assumption, however, implies that the efficiency ranking of units is independent of the choice of orientation, be it input or output.

Relative shadow prices (relative weights) for inputs and outputs can be obtained from the dual (primal in Charnes et al. 1978) solutions of the above-mentioned linear equation system (equation 2). The dual form for a regular model (CRS) is as follows:

$$\begin{aligned}
F_o(CRS, S) &= \min \sum \mu_{k'n} x_{k'n} \\
s.t. \quad &\sum v_{k'm} y_{k'm} = 1 \\
&\sum v_{k'm} y_{km} - \sum \mu_{k'n} x_{kn} \leq 0 \quad \forall k \\
&v, \mu \geq 0 \quad \forall m, n.
\end{aligned} \tag{3}$$

The non-negative multipliers μ_n and v_m can be interpreted as relative shadow prices of inputs n and outputs m . As the equations show, the prices are farm (k) specific. We apply these relative shadow prices, estimated from the above dual formulation of DEA, when determining the value of crop diversity. The estimation is based on the fact that the marginal rate of transformation between two outputs can be derived as a ratio of their marginal products (the first order derivatives), and at the optimum this ratio should equal the price ratio of these outputs:

$$MRT_{y_{m1}y_{m2}} = \frac{\partial y_{m1}/\partial x}{\partial y_{m2}/\partial x} = \frac{\frac{\partial F(\bullet)}{\partial x}}{\frac{\partial F(\bullet)}{\partial y_{m2}}} \bigg/ \frac{\frac{\partial F(\bullet)}{\partial x}}{\frac{\partial F(\bullet)}{\partial y_{m1}}} = \frac{\frac{\partial F(\bullet)}{\partial y_{m2}}}{\frac{\partial F(\bullet)}{\partial y_{m1}}} = v_{m2}/v_{m1} \tag{4}$$

When we have estimates for the relative shadow prices (the slope) and know the true price of one of the outputs (crop output), we may solve for the absolute shadow value of crop diversity for each farm. Correspondingly, the derivation of shadow prices becomes possible for the input orientation.

To assess the influence on the shadow values of the chosen direction for the distance function, we introduce the LP model of subvector efficiencies with a slightly different set of constraints⁷. In particular, we assume first that only the traditional output is adjusted; crop diversity is treated as an ordinary constraint indicating that the crop diversity in the feasible solution should be at least as large as in our decision-making unit (this is the vertical direction in Figure 2; henceforth denoted by CRS_subC). The output distance function is thus only measured in relation to traditional output, given inputs and crop diversity. Second, we evaluate the output distance function with respect to crop diversity, given traditional output and inputs (the horizontal direction in Figure 2; CRS_subBD). The subvector models are formally presented in equations (A1) and (A2) in Appendix 1. The direction of the distance function changes the slope in equation (4), and changes the shadow values accordingly.

For the efficiency analysis, we have to choose the reference sets for technology, that is, organic or conventional. The small number of observations for organic farms poses a challenge for analyzing the organic technology separately. Earlier studies (e.g., Myyrä et al. 2009) have shown that technical change has been relatively slow in Finnish crop farming, whereas the variation between consecutive years has been large. Inter-annual variation is mainly explained by weather fluctuations; Schlenker (2010) has recently shown that yields are particularly sensitive to weather in cold climates such as in Finland. Therefore, we chose to pool all years into the same reference set but kept conventional and organic farms as separate technologies. In addition, in order to reduce

⁷ In practice, in the primal (output-oriented) formulation the distance/efficiency coefficient is minimized/maximized with respect to only one output. (see Färe et al. 1994).

stochastic variation at the farm level, we have estimated the distance functions on the basis of three-year averages of inputs and outputs for conventional farms (see Ruggiero 2004).

5. Data

We use a set of farm bookkeeping data which is a sample of active Finnish crop farmers from the Farm Accountancy Data Network (FADN) of the EU in the period from 1994 to 2002. The original farm data formed a balanced panel, but because of the small number of organic farms the panel was complemented by adding organic farms that participated in the bookkeeping system for at least two years. These farms, as well as panel farms changing over from other forms of production (e.g., milk production) to crop production, increased the number of observations towards the end of the study period. Farms were classified as crop farms if their animal density was less than 0.1 animal units per hectare and the share of cereals in total sales return was at least 20 percent. The first criterion was the same as that used in a previous study by Oude Lansink et al. (2002) on Finnish crop farming. The purpose of the criterion is to guarantee that the return from animal production is low but that, at the same time, the farm is allowed to have a limited amount of animal production. The second criterion eliminates farms specialized solely in sugar beet and potato cultivation from the sample. This restriction is employed because the production technology of such farms differs significantly from that of the majority of the less specialized crop farms.

The total number of observations was 78 in 1994, with this increasing to 103 by 2002⁸. The farms receiving aid for organic farming are considered as farms engaged in organic production. In the sample, the number of organic crop farms was 11 in 1994, and 20 in 2002. The data set consists of 831 observations in total (689 conventional and 142 organic), summary statistics for which are presented in Table 1.

[Table 1 about here]

We use crop returns as a proxy of the quantity of aggregate marketable crop output. Crop output is measured at constant prices of the year 2000. For both organic and conventional farms output at constant prices is obtained by dividing crop returns by the respective price indices of conventional outputs published by Statistics Finland⁹. The main reason for using only price indices for conventionally produced goods is that no reliable price index for organic products is available. In addition, we do not know the exact magnitude of the price premium – if any – for organic production. This means that we have to assume equal prices and price changes for organic and conventional products, and any price premium for organic products will increase our proxy of the output quantity. In spite of this, the average traditional crop output is considerably lower on organic than on conventional farms (see Table 1).¹⁰ All subsidies (direct payments) paid on the basis of the arable land areas of the farms are excluded.

As a measure of another positive output, or desirable environmental by-product, we use the Shannon Crop Diversity Index (SHDI), which was discussed in section 2. As Table 1 indicates, the

⁸ In total, about 1,000 farms provide their bookkeeping records to FADN in Finland. It should be noted that in FADN, the average size of farms is larger than the average in Finland. In 2000, the number of crop farms by size class was as follows: 32 farms had less than 30 ha, 42 had 30-50 ha, 36 had 50-100 ha and 15 more than 100 ha. Riepponen (2003)

⁹ In practice this results in our assuming equal prices for all farms and any quality differences end up in the output proxy.

¹⁰ The market share of organic products is at most 2 percent in Finland. Anecdotal evidence suggests that as a result price premiums have not increased over time, but, at best, the prices have followed the pattern for conventional products.

index is on average larger on organic farms.¹¹ Even though the SHDI was chosen as an indicator because it takes into account the evenness and richness of land use, there is a strong correlation between the index and the number of crops cultivated on a farm. The distribution of the number of crops in the samples of organic and conventional farms is illustrated in Figure 3. The distribution for organic farms is slightly skewed such that the share of farms having seven or more crops is larger among the organic than the conventional farms.

[Figure 3 about here]

The outputs are produced by using five inputs. Labor is measured in hours as a sum of family and hired labor input. Land is measured in hectares representing the total arable land area of the farm. Input variables accounted for at constant prices of 2000 are energy, including both fuel and electricity; other variable input, consisting of purchased fertilizers, seed, feed, etc.; and capital, including the value of buildings and machinery. The respective input price indices are obtained from Statistics Finland. The average arable land area of conventional farms is about 15 hectares larger than that of organic farms, a difference that is statistically significant (t-test statistics 4.09, p-value < 0.00001).

When comparing crop farms, we observed very low or fairly high crop output values in some cases. Low (high) output relative to inputs also yields a low (high) technical efficiency score for a farm. However, it is difficult to determine whether these observations should be regarded as outliers¹². Accordingly, no observation has been removed; instead, we complemented our study by examining three-year averages of the original farm data. The advantage of this approach, as shown by Ruggiero (2004), is that it averages out the measurement error for all the farms (decision-making units).

6. Results

6.1 Efficiency scores for conventional and organic farms

We apply DEA to separate data sets of conventional and organic farms. First, before estimating the shadow values for crop diversity, we report the Farrell-type radial technical output efficiencies, or distance functions, from a model including two outputs - crop diversity and crop output - and constant returns to scale, CRS (equation 2). The traditional output is sold on the market; crop diversity is a non-marketable good. Second, two subvector efficiency models are applied using the two directional distance functions: crop subvector efficiency (vertical direction in Figure 2) and crop diversity subvector efficiency (horizontal direction in Figure 2). The cumulative distributions of efficiency scores for the three separate directions (radial, vertical, horizontal) are reported for conventional and organic farms in Figures 4 and 5, respectively. Crop (crop diversity) subvector efficiency is denoted by CRS_subC (CRS_subBD), whereas the efficiency scores from the traditional radial output distance functions are denoted by CRS_radial.

[Figures 4 and 5 about here]

It should be underlined that the distributions of efficiency scores in Figure 4 and Figure 5 should not be compared, as these two figures represent two distinct technologies; only comparisons

¹¹ The t-test statistics for differences in output and crop diversity index were 9.13 (p-value < 0.00001) and 3.86 (p-value 0.0002), respectively.

¹² Specific methods have been proposed for identifying outliers. We applied the methods presented in Wilson (1993) and Tran et al. (2008) for this purpose. However, in the data set for organic farming, for example, there were still observations which could be classified as outliers when approximately 20 percent of observations were removed from the sample. Fox et al. (2004) have shown that their dissimilarity index and Wilson's (1993) index provided rather different identifications of outliers. Fortunately, in the present case, the distribution of shadow values was not sensitive to the removal of possible outliers.

between farms using the same technology are meaningful. Among the conventional farms, the efficiency scores are highest for the radial measure (blue line), whereas they are lowest for the crop diversity subvector efficiency (green line). Similarly, the radial efficiency scores receive the highest values for the organic farms, but the crop sub-vector efficiency gives the lowest scores (brown line). Hence, the conventional (organic) farms tend to fall further away from the efficiency frontier with respect to crop diversity (crop output). These differences in distributions by direction of the distance function are also reflected in the summary statistics for efficiency scores. For conventional farms, the mean (standard deviation) radial efficiency score is 0.647 (0.192), whereas the mean crop diversity sub-vector efficiency is 0.447 (0.249). A similar comparison among the organic farms shows that the mean radial efficiency score is 0.741 (0.192), whereas the mean crop diversity sub-vector efficiency is 0.631 (0.267).

Since we pooled all the observations from 1994-2002 in the same data set by technology, the annual variation in the data cannot be discerned. To gain some insight into the development of farm data over time, we apply DEA to all inputs and outputs averaged across time for a three-year-period such that we have three time periods to consider. According to Ruggiero (2004), this serves two purposes. The potential measurement error of the farm data and the measurement error of frontier units are averaged out. Due to the limited number of observations for organic farms, we were able to perform DEA analysis only for averaged data of conventional farms, resulting in 77 observations for the period 1994-1996, 73 for 1997-1999 and 91 for 2000-2002. The distributions of radial efficiency scores are reported in Figure 6. (For distributions of sub-vector efficiency scores for crop and crop diversity, see Appendix 2, Figures A1 and A2).

[Figure 6 about here]

For the distributions of radial efficiency scores plotted in Figure 6 for the three time periods, we have a mean (standard deviation) radial efficiency score of 0.786 (0.163) for the period 1994-1996, 0.685 (0.180) for 1997-1999, and 0.758 (0.173) for 2000-2001. As one would expect from the findings of Ruggiero (2004), the results become more consistent with a decreasing standard deviation as compared to estimates derived from data on conventional farms, which were not averaged. The efficiency scores for the period 1997-1999 are dominated by the higher scores in 1994-1996 and 2000-2002 in Figures 6, A1 and A2. Poor weather conditions in 1997-1998 explain at least partially the lower efficiency in these years.

6.2 Shadow values, or opportunity costs, of crop diversity

We apply the dual formulation of DEA to calculate shadow values for crop diversity using equations (3) and (4) (for subvectors, we use equations (A1) and (A2) in Appendix 1). It should be noted that an increase of one unit in the index is quite considerable, whereby we report the shadow prices, or marginal values, for an increase of 0.1 unit of SHDI. This is an increase that an average farm in the data set might achieve by adding one crop, for example.

Figures 7 and 8 present cumulative distributions of the shadow values based on the separate distance function estimations for organic and conventional technologies. Again, three directions for distance functions have been applied. The shadow values derived from the crop subvector (brown lines) are the lowest for both farm types as confirmed by the order of distributions in the figures.

[Figures 7 and 8 about here]

Table 2 summarizes statistics for the shadow values of a marginally increasing SHDI based on the separate efficiency estimations of organic and conventional technologies. A comparison of means

shows that the shadow values of crop diversity in the crop subvector model, or EUR 22.2/ha, are statistically significantly lower than the shadow values of crop diversity in the crop diversity subvector model, EUR 54.5/ha, (with a p-value 0.0002) for organic farms. A similar statistical difference for conventional farms holds between the means of shadow values of crop diversity derived from the crop diversity subvector model, EUR 83.9/ha, and the crop subvector model, EUR 15.6/ha (p-value 0.0004).

Since the shadow values reflect the opportunity costs to farms of increasing crop diversity, they provide important information for policy design. Therefore, it is meaningful to compare the shadow values also between the organic and conventional technologies from a policy point of view, because the shadow values - the opportunity costs - can be technology driven and, given their technological constraints, the farms supply crop diversity as a non-market output to the same “policy-driven market” of environmental outputs.

[Table 2 about here]

Interestingly, the differences in the mean shadow values between technologies do not turn out statistically significant for the pooled data sets. This holds true for all three directions of the distance function; a t-test on the difference of the mean shadow values based on the crop diversity subvector, or EUR 83.9/ha for conventional farms and EUR 54.5/ha for organic farms results in the lowest p-value, which is still as high as 0.1446.

As there is variation in the shadow values, it would be interesting to explain the variation with exogenous variables describing the farm characteristics. However, the FADN data set does not provide these types of variables (other than the inputs and outputs already used for the estimation of the shadow values). Therefore, we can only examine the correlation between the efficiency scores and the shadow values. Since the shadow values of crop diversity reflect the opportunity costs of traditional crop output forgone, one would assume that more efficient farms would have higher shadow values. Indeed, there is a positive correlation (Spearman Rank Correlation) between the efficiency scores and the shadow values for conventional farms (0.08-0.16) and organic farms (0.21-0.22) for all three alternative directional distance functions. The magnitudes of the correlations are small, but they are all statistically significant (for a two-tailed test, $\alpha=0.05$).

To relate the shadow values of the SHDI to agri-environmental policies implemented, it is interesting to know that there was a payment of EUR 13.46 per hectare for a voluntary additional measure - “crop diversification” - in 2000-2006 in the Finnish agri-environmental support system. According to Table 2, the opportunity costs are higher on average than the compensation payment provided for crop diversification. This would explain the low interest in the additional measure. Yet, because there is strong variation in the shadow values (as indicated by Figures 7 and 8), it is important to identify the shadow values of the least-cost farms to see how large a proportion of each sample they represent. Therefore, we order the farm observations (given their land area) by the estimated shadow values, or opportunity costs (per hectare), of increasing crop diversity (SHDI) by marginal value of 0.1 unit. The opportunity costs ordered from lowest to highest in Figures 9 and 10 can be interpreted as supply curves for crop diversity given that the samples can be considered representative for active farms in Finland. The least-cost farms are the most promising candidates for receiving conservation payments if auctions and competitive bidding were used in the conservation of crop diversity on farmland.

[Figures 9 and 10 about here]

Figures 9 and 10 show that shadow values derived from the crop diversity subvector model give the highest estimates (green lines), and these shadow values are systematically higher for conventional than organic farms. The shadow values derived from the traditional radial distance function (blue lines in Figures 9 and 10) are higher for conventional than organic farms up to 50 percent of their least-cost farming area, or up to the shadow value of about EUR 10/ha. Thereafter, the opportunity costs (derived for radial direction, blue lines) increase more rapidly on organic than conventional farms.

Finally, comparing the shadow values in Figures 9 and 10 with the actual agri-environmental payment of EUR 13.46/ha, it can be seen that about 15 percent of the land area of conventional farms and about 45 percent of the land area of organic farms have an opportunity cost of roughly EUR 13/ha or less when we use the highest or most conservative opportunity cost estimates (green lines). For these farms, the agri-environmental payment for crop diversification would have covered our estimated opportunity costs. Yet, fewer than 1 percent of farms adopted crop diversification in reality. This low rate could be explained by the bureaucracy related to the adoption of this measure and the corresponding transaction costs rather than by the high opportunity costs of the farms. Another explanation is that other voluntary additional measures, such as more accurate fertilization on arable crops, which had more financially rewarding compensation payments than those provided for crop diversification appealed more to the farmers.

From a policy point of view, the findings on opportunity costs are interesting. The average opportunity costs of conservation do not reflect the variation in the costs between farms, and may bias the design of environmental policies. In addition to the absolute magnitudes of our shadow value estimates, it is interesting to recognize the heterogeneity between the farms with respect to these costs. There seems to be room for tailored policies to attract more farms to adopt crop diversification. Yet, identification of low-cost farms using auctions for conservation payments should not increase the administrative, or transaction costs of voluntary programs.

7. Conclusions

Consideration of the concrete environmental benefits to be achieved is important for the design of agri-environmental policies. The present study integrates such benefits into the production process as a desirable output and compares conventional and organic technologies using the Shannon Crop Diversity Index. The index takes into account both richness and evenness, but one could focus on richness only and use number of crops as an ecological indicator.

In our sample, organic farms had on average slightly higher crop diversity than did conventional farms. A difference regarding crop diversity was also recognized in the analysis of directional distance functions and efficiency scores. Among the conventional farms, the efficiency scores were lowest for the crop diversity sub-vector efficiency (measured in the direction of increasing crop diversity for a given crop output of the farm), whereas for the organic farms, the crop sub-vector efficiency (measured in the direction of increasing crop output for a given crop diversity of the farm) gave the lowest scores. The opportunity costs of crop diversity are on average higher for conventional than organic farms; yet, it is important to recognize the heterogeneity in the costs between the farms using the same technology, as the variation in the shadow values is strong. In general, there is a positive correlation between the efficiency scores and the shadow values.

In the long run, crop diversity may provide economic benefits as well as other benefits that are not related to agricultural productivity. Even though our approach is only a first step towards analyzing the economic and environmental impacts of alternative farming technologies simultaneously, the thrust of our analysis is clear. Normally, there is a trade-off between several outputs, whereby

multiple outputs, including environmental impacts, should be accounted for. It is important to identify the heterogeneity of farms in producing environmental benefits if tailored agri-environmental policies are to lead to cost efficiency and savings in the use of taxpayers' money.

Further research is needed on elaborating other environmental benefit indices that can be calculated on the basis of the farm accountancy data available to regulators. In our analysis, we have concentrated on the variation in diversity at the farm level. If landscape values are evaluated, the scale of analysis should be extended beyond the borders of farm units. Studies incorporating aggregation over farms and time would enable better informed policy assessments.

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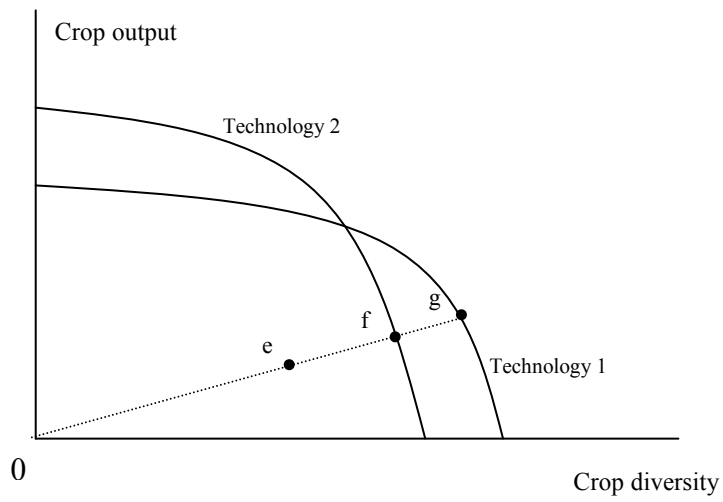


Figure 1. Technical output efficiency in the case of crop output and crop diversity.

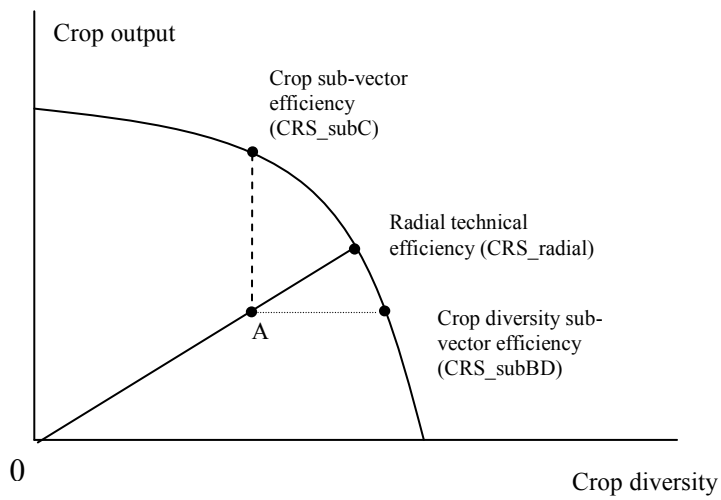


Figure 2. Traditional (radial) and sub-vector (crop and crop diversity) technical efficiencies.

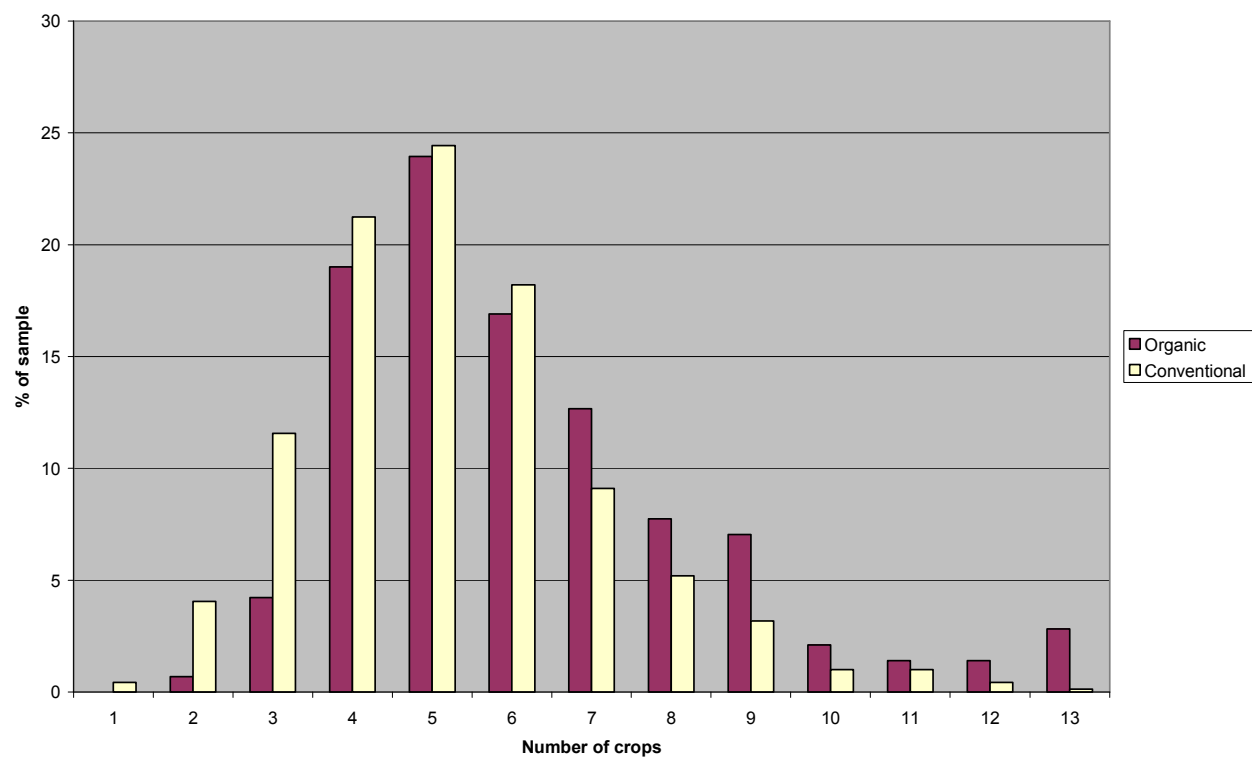


Figure 3. Distribution of number of crops in the samples of organic (red) and conventional (yellow) farms .

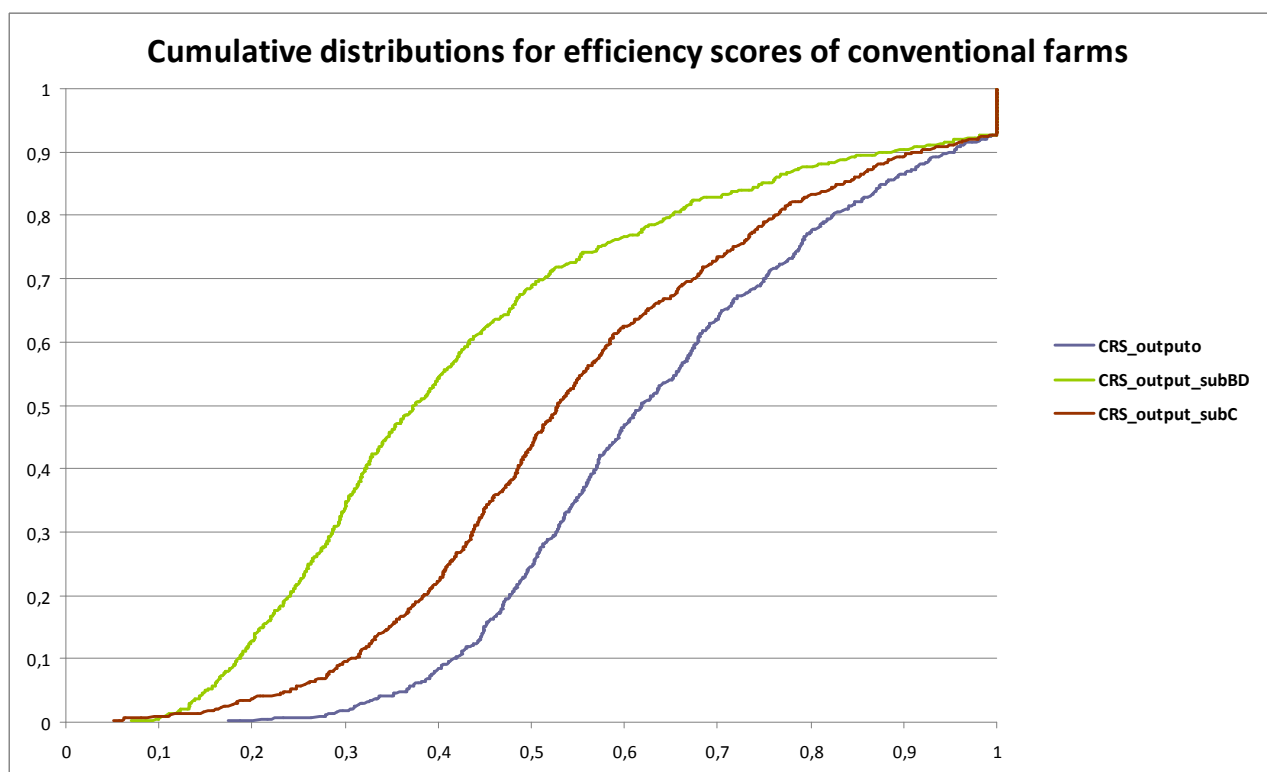


Figure 4. Cumulative distributions for efficiency scores of conventional farms.

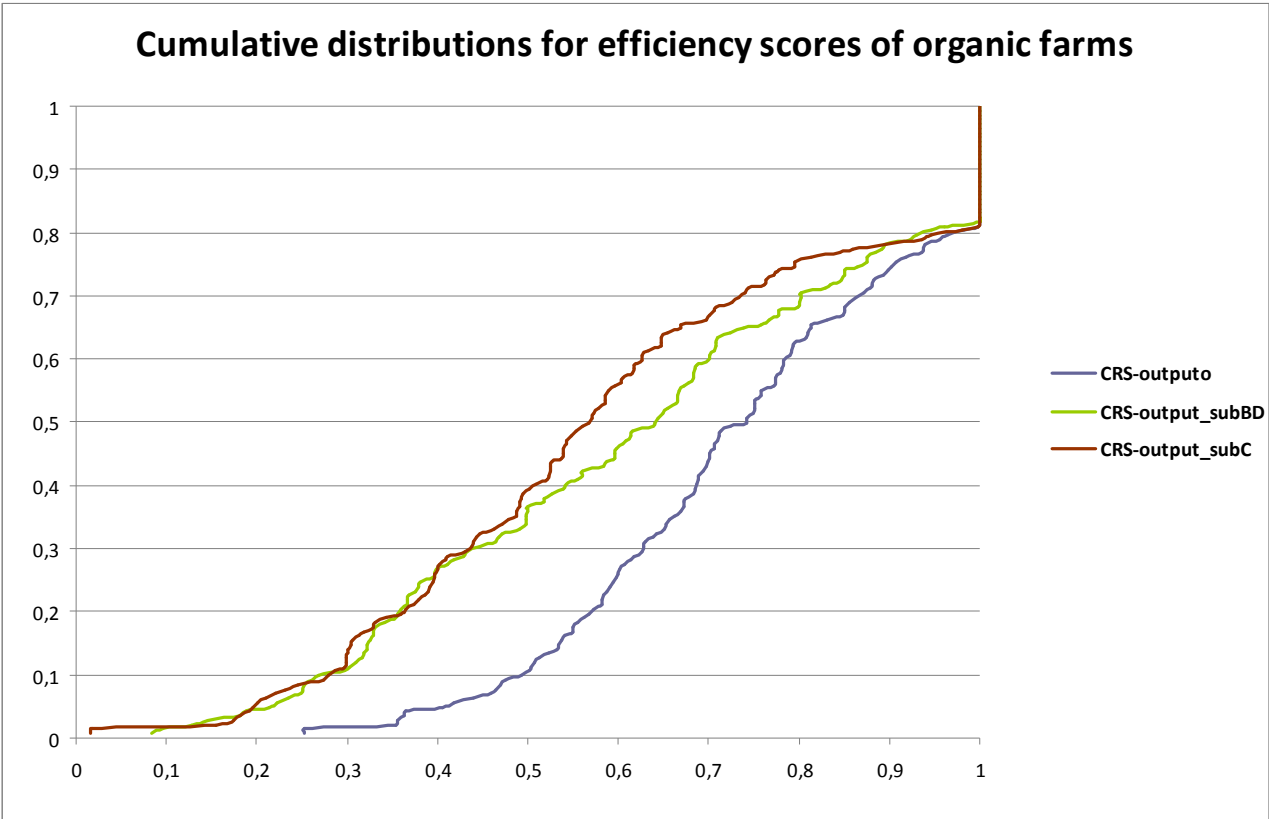


Figure 5. Cumulative distributions for efficiency scores of organic farms.

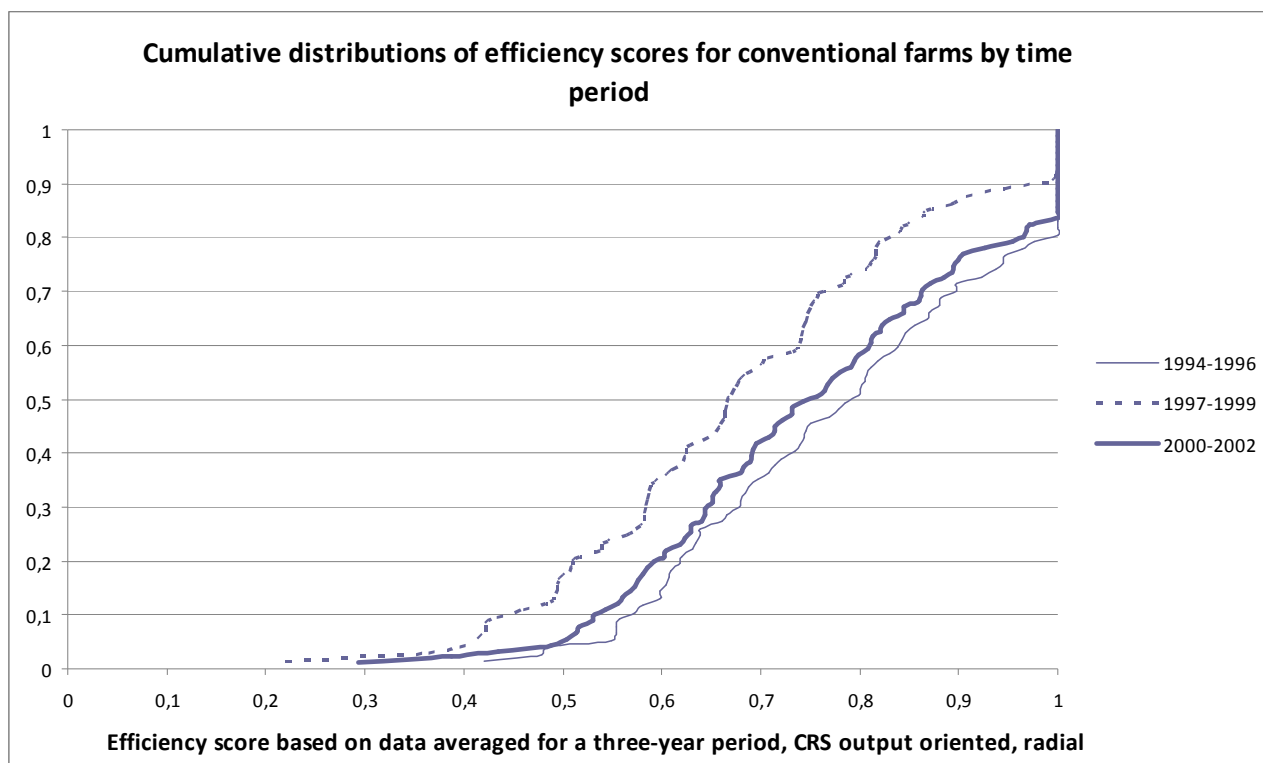


Figure 6. Cumulative distributions of efficiency scores for conventional farms by time period.

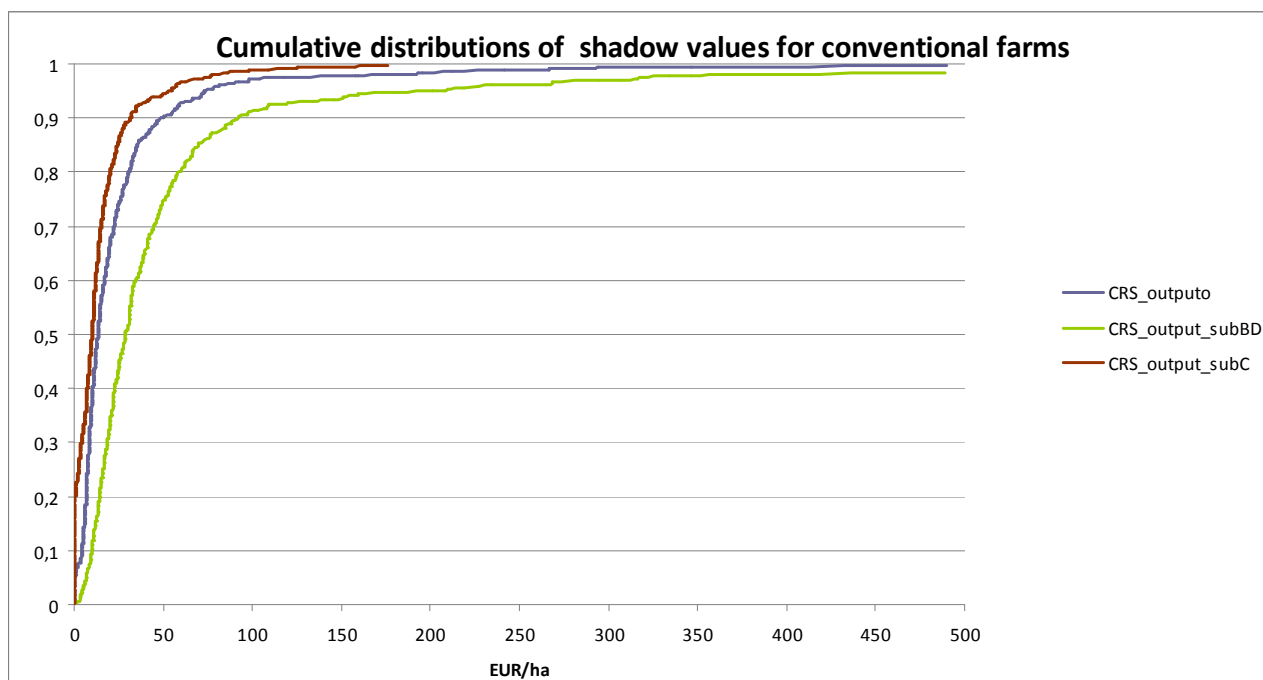


Figure 7. Cumulative distributions of shadow values for conventional farms by direction of distance function (radial, crop sub-vector and crop diversity sub-vector).

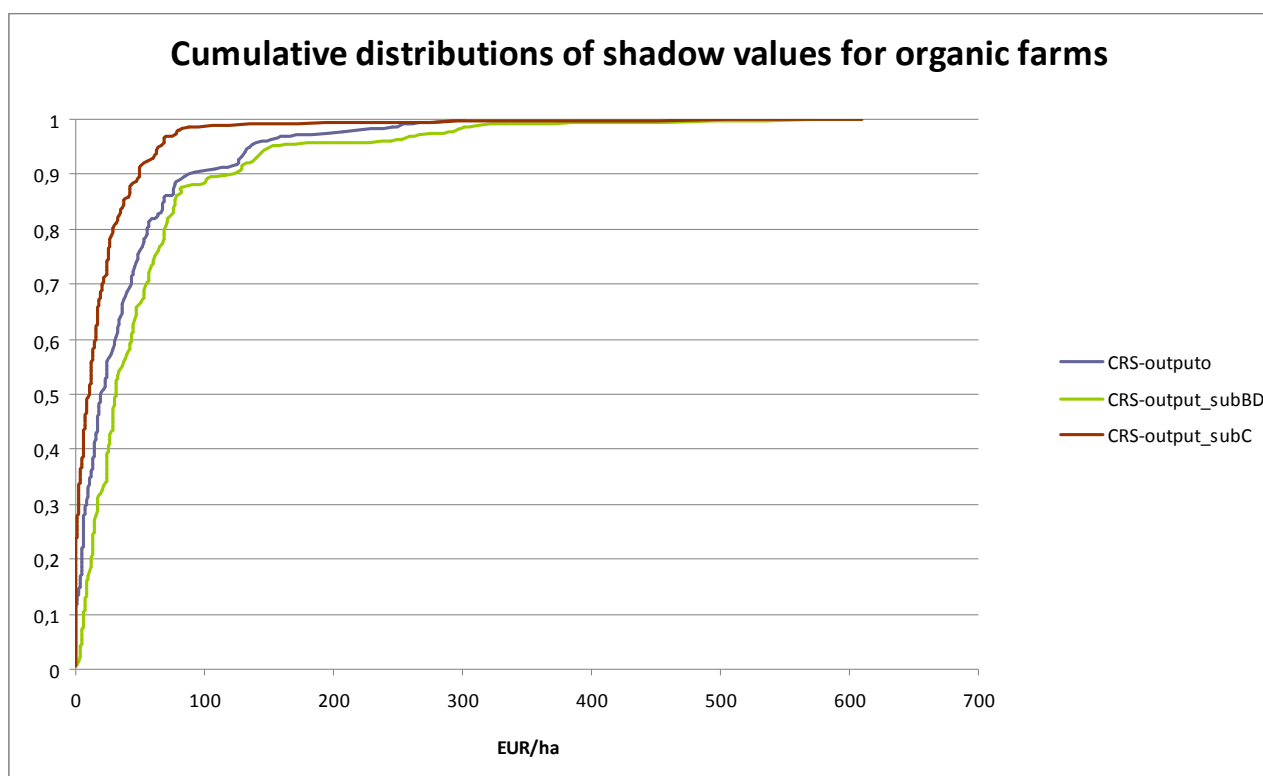


Figure 8. Cumulative distributions of shadow values for organic farms by direction of distance function (radial, crop sub-vector and crop diversity sub-vector).

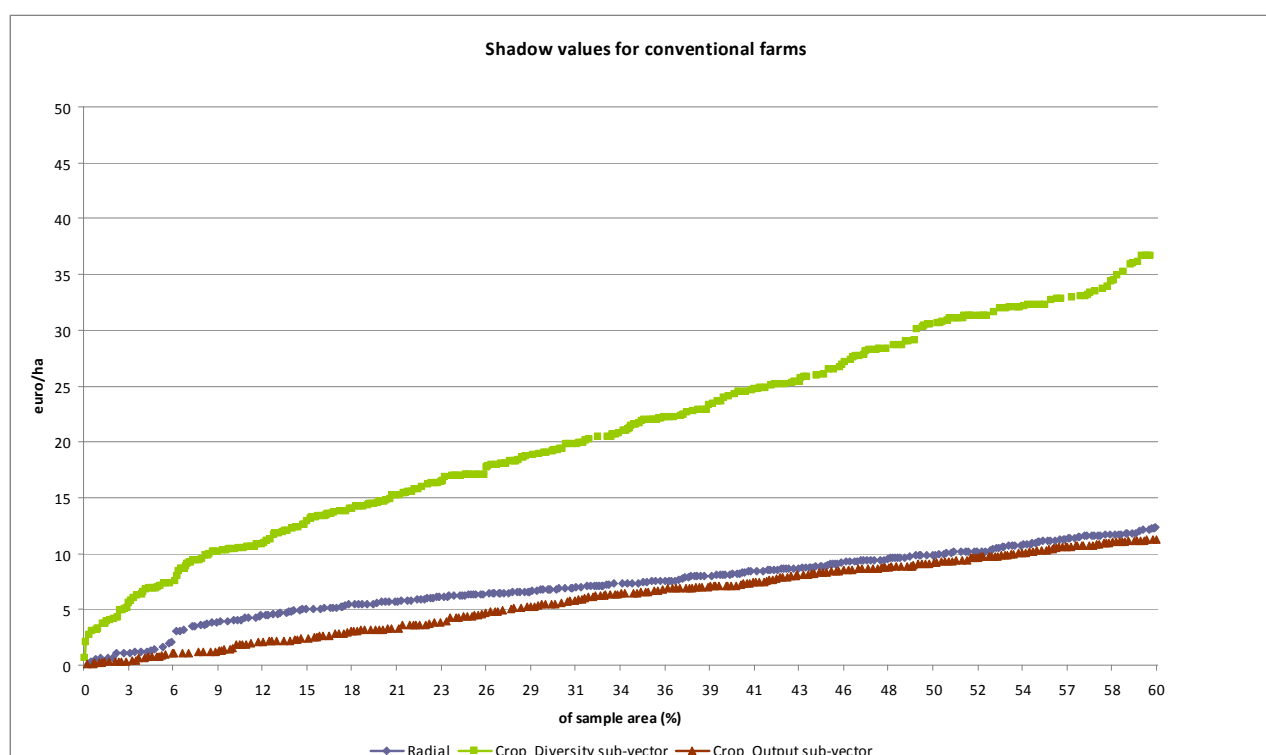


Figure 9.

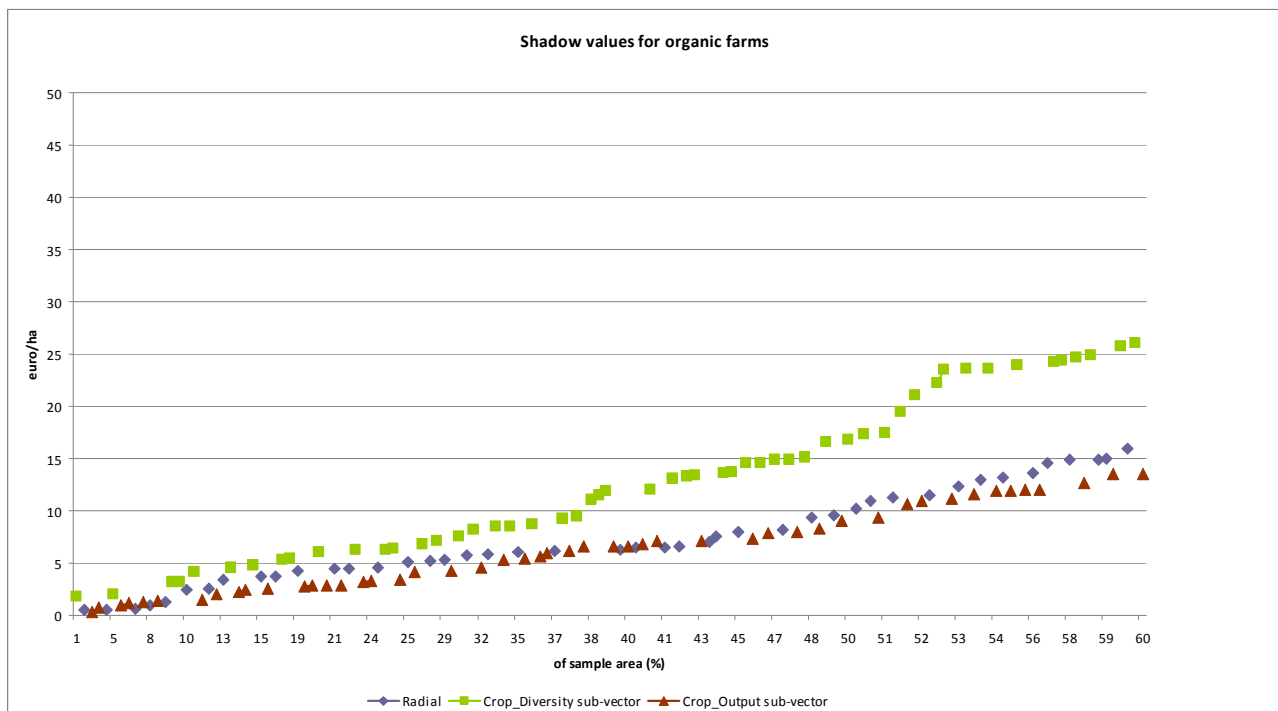


Figure 10.