DE GRUYTER OPEN

RURAL SUSTAINABILITY RESEARCH 37(332), 2017
ISSN – 2256-0939

http://www.llu.lv/en/

The Comparative Efficiency Analysis of EU Members Agriculture Sectors

*Eligijus Laurinavičius, Daiva Rimkuvienė
Aleksandras Stulginskis University, Universiteto Street 10, Akademija, Kaunas region, LT-53361, Lithuania

Abstract. Production economics forms a very important part of an enormous range of economic theory. Agricultural production is no exception. When evaluating the competitiveness of the multifunctional agriculture, it is necessary to use the measure of efficiency instead of productivity. The conception of the efficiency is explained and the methods for measurement are provided. The authors discuss the methods of Stochastic Frontier Approach (SFA), Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA) that are particularly useful for multi-criterial evaluation of multifunctional processes. Those methods assign an efficiency score to each Decision Making Unit (DMU) based on how well it transforms a given set of inputs into outputs. Most studies have only focused on application of DEA method for assesment of the efficiency of agriculture farms. There is still a need on applications for sectors. This paper provides an examination of the applicability of DEA method to agriculture sectors efficiency measurement. By applying mathematical models, which are based on the DEA, the efficiency of agriculture in each EU country was evaluated.
Keywords: agriculture, data envelopment analysis, efficiency, productivity.

Introduction

The role that agriculture should play on economic development has been recognized for years. For agriculture industry, where tax and subsidy systems are applied, competitive forces may not be sufficient to penalise firms that are inefficient. Where differences in efficiency are significant – which they often are – measuring relative efficiency becomes an extremely important issue. The assessment of efficiency in agricultural sector is of high importance when making strategic decisions at any management level. Increase in efficiency leads to increase in competitiveness of production. Comparative efficiency analysis is increasingly recognised as a useful tool for benchmarking and incentive regulation. It can help managers to identify under performance and to encourage efficiency.

DMU. Any production activity (agriculture is not an exception) is conditioned by the inputs, which should be minimised, and outputs which should be maximised. The organisations or units being examined in the study are called Decision Making Units. These units may not be commercial or profit-making entities. DMU's are units, which use the same set of inputs to produce the same set of outputs. Thus, we have five sets with 28 DMU or one set with 140 DMU.

Production process. Production is any process that converts a set of inputs into a set of outputs (Figure 1). For any process taking a set of inputs to produce certain outputs can be viewed in the following way.

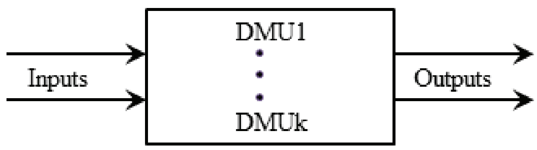

Figure 1. Production process.

In production processes, the conversion of inputs into outputs does not generally follow a known functional. This means that it is not possible to know exactly what the maximum output obtainable from the given inputs is. The maximum output has to be estimated from the observed data. This is the difference between an engineering definition of efficiency and the relative efficiency estimated in production theory.

Inputs. In line with the literature we selected three inputs and two outputs. The inputs determine the amounts of material and financial resources – factors

* Corresponding Author's email:
eligijus.laurinavicius@asu.lt

DOI:10.1515/plua-2017-0002

of production – employed in production process. X1 – total labour input expressed in AWU (annual work unit, i. e. 1000 full-time person equivalent) quantifies labour input. X2 – total Utilised Agricultural Area (UAA, million hectares) resembles land input and describes the area used for farming. It includes the land categories: arable land, permanent grassland, permanent crops and other agricultural land even if they only represent small areas of total UAA. The term does not include unused agricultural land, woodland and land occupied by buildings, farm yards, tracks, ponds, etc. X3 – Intermediate Consuption (IC, million EUR) – an accounting flow which consists of the total monetary value of goods and services consumed or used up as inputs in production by DMUs, including raw materials, services and various other operating expenses.

Outputs. The outputs describe the results of agriculture sector's activity. Y1 – crop production (million EUR) – total crop output is valued at basic prices. The basic price is defined as the price received by the producer after deduction of all taxes on products, but including all subsidies on products. The concept of output comprises sales, changes in stocks, and crop products used as animal feeding stuffs, for processing and own final use by the producers. Y2 – livestock production (million EUR) – outputs from livestock production vary by species: direct consumption outputs, multiple use consumption outputs and sale goods.

Productivity. The productivity is defined as the ratio of the output(s) that it produces to the input(s) that it uses. Productivity = outputs/inputs. When the production process involves a single input and a single output, this calculation is a trivial matter. However, when there is more than one input (which is often the case), then a method for aggregating these inputs into a single index of inputs must be used to obtain a ratio measure of productivity. Simple weighted method is often used method to aggregate inputs (and/or outputs) for the construction of productivity measures. Productivity of the *r*-th DMU:

$$P_r = \frac{\sum_{j=1}^{m} \beta_j \cdot y_j}{\sum_{i=1}^{n} \alpha_i \cdot x_i} \qquad (1)$$

x_i ; y_j – used amounts of inputs (resources) and produced amounts of outputs (products) respectively; α_i ; β_j – weights of inputs (resources) and outputs (products) respectively, *n,m* – number of inputs and outputs respectively. Weights indicate the importance attached to each factor (input/ output) in the analysis.

Efficiency. The terms, productivity and efficiency, are often used interchangeably, but they are not precisely the same things. The efficiency is the ratio of DMUs and the best productivity in certain circumstances, so the efficiency score is always a relative measure. The production (efficiency) frontier is the frontier (envelope) representing 'best performance' and is made up of the units in the data set, which are most efficient in transforming their inputs into outputs. Empirical production function, empirical production envelope and envelopment surface are all terms, which are analogous to efficient frontier. The production frontier represents the maximum output attainable from each input level. DMUs in this production process operate either on that frontier if they are technically efficient or beneath the frontier if they are not technically efficient.

Measurement techniques. There are two main approaches to estimate relative efficiency: the parametric (statistical) and non-parametric. The main difference between these two approaches is that the former specifies a particular functional form for the production or cost function while the latter does not. The parametric approach relies on econometric techniques and includes simple regression analysis and SFA. Whilst simple regression analysis typically seeks to estimate a production or cost function, SFA is an extension of regression analysis methodology to estimate the 'frontier' of a set of functions with different underlying levels of efficiency. The non-parametric approaches FDH and DEA use linear programming techniques, which help to construct 'frontier' – linear segmented surface – without any assumptions about a true production function.

The analysis carried out here suggests that frontier methodology in agriculture is a robustly developing branch of science. Both DEA and SFA are important instruments for estimating productivity efficiency. The literature regarding efficiency of agricultural sectors is rather limited. Agricultural sector as a producer requires analysis of its efficiency, however, is not sufficiently analysed by the means of the frontier techniques. Such kind of analysis could help to discover possible ways for improvement in performance.

Purposes. Linear programming is the underlaying methodology that makes DEA a particularly powerful tool compared with alternative productivity management tools. DEA has since been proven to locate ways to improve performance not visible with other technics. Sadly, managers have not widely adopted DEA to improve organization performance, in part, because most DEA publications are in academic journals or books requiring the ability to understand linear programming and supporting mathematical notation.

The purposes of this paper are to: 1) present some of the different techniques that can be used to measure relative efficiency; 2) declare their possibilities as well as give a guidance which technique is more appropriate in different circumstances; 3) present DEA as a very powerful benchmarking technique in more friendly form to agricultural researches; 4) estimate and analyse the efficiency of EU Member states agricultural sectors.

Literature Review

The value of DEA lies in its capability to evaluate the performance of a DMU within a target group of agriculture industry. Agricultural industry practically adopt DEA for a variety of reasons. As Golany & Roll (1989) pointed out that it can be applied to: identify sources of inefficiency, rank the DMUs, evaluate management, evaluate the effectiveness of programs or policies, create a quantitative basis for reallocating resources, etc.

A brief scientometric analysis based on data of database Web of Science has been performed by Liu *et al*. (2013) to identify the current trends of agriculture efficiency assessment. The number of publications has been growing throughout the analysed period 2007–2011 on average 14 publications per year and reached 120 publications per annum in 2011. The number of citations is 190 and 1400 respectively.

Productive efficiency of agricultural sector is extensively analysed across the Central and East European states where agriculture is relatively important economic activity (Gorton & Davidova, 2004). A number of studies have been attempted to investigate the issues of efficiency by using widely applied frontier methods. Asmild & Hougaard (2006) analysed the influence of environmental improvement potencial to efficiency of Danish pig farms. Davidova & Latruffe (2007) related the Czech farm efficiency to financial management. Vasiliev *et al*. (2008) employed the DEA method to analyse the efficiency of Estonian grain farms after Estonia's transition to the market economy and during the accession period to the European Union (EU). Rasmussen (2010) used SFA in the form of input distance functions to estimate efficiency of Danish crop, dairy and pig farms. Bojnec and Latruffe *(*2011*)* analysed the relationships between size and efficiency of Slovenian farms.

Some branches of the Lithuanian agricultural sector received an attention in this scientific area. Tamošaitienė *et al*. (2010) analysed the significance of comparative financial indicators by evaluation of financial conditions and results of farm activities. The paper by Rimkuvienė, Laurinavičienė, & Laurinavičius (2010) addressed the issue to estimate the farming efficiency using DEA and FDH – the two non-parametric methods. The authors suggest that methods provide viable options and are useful for multi-criteria evaluation of multifunctional processes. Baležentis & A. Baležentis (2011) proposed a new framework using MULTIMOORA and DEA methods for multi-criteria assessment and comparison of farming efficiency. Baležentis & Kriščiukaitienė (2012) also analysed dynamics of productive efficiency across different farming types in Lithuania by applying statistical and DEA methods. Baležentis, Li, & Baležentis (2015) analysed the trends in efficiency of Lithuanian dairy farms applying the semiparametric approach based on nonparametric regression and SFA method.

Materials and Methods

The efficiency of agriculture sectors was evaluated across the 28 EU Member States on a basis of data from European Commission database Eurostat. The data cover the five years period 2010–2014. http://ec.europa.eu/eurostat/data/database.

Efficiency measure. Farrell (1957) laid the foundation on how to define efficiency and productivity, and how to calculate efficiency measures. The basis for this measure is connecting inefficient observed points with virtual (unobserved) reference points on the production frontier. The efficiency frontier can be established by employing different assumptions and computation techniques, which can be classified into parametric and non-parametric methods (Murillo-Zamorano, 2004). Parametric methods estimate the frontier with statistical methods and impose an explicit functional form for both the frontier and deviations from it that is inefficiency. Nonparametric methods, in contrast, rely on linear programming to calculate piecewise linear segments of the efficient frontier and do neither impose any assumptions about functional form of the frontier nor any distributional assumptions about inefficiency.

Estimation methods. Two classes of methods, namely, DEA (Charnes, Cooper, & Rhodes, 1978), FDH (Deprins, Simar, & Tulkens, 1984) and SFA (Aigner, Lovell, & Schmidt, 1977; Meeusen, & van den Broeck, 1977; Battese & Corra, 1977) were developed for estimating the efficiency of DMU. DEA is a non-parametric approach. This method gives efficiency relative to the best practice DMUs. The parametric SFA approach, on the other hand, uses observed input-output correspondences to estimate an underlying relationship between the inputs and outputs. This function is then used as the frontier against which to measure the efficiencies.

Preferences. Currently, the choice of which method to use is often dependent upon which one is seen as the easiest to implement. This leads to DEA often being chosen in preference to SFA methods (although there are other reasons for preferring DEA including the fact that the results can be easier to analyse). Since the performances of these methods are highly dependent upon the data set, which is being analysed, there is no easy answer as to which of the two approaches performs better. DEA and FDH are the two widely renowned nonparametric deterministic models.

DEA method. DEA is a linear programming methodology to measure the efficiency of multiple DMUs when the production process presents a structure of multiple inputs and outputs. Objective of a DEA assessment: a) comparison of performance of homogeneous DMUs that use multiple inputs for the production of multiple outputs; b) the efficiency measure compares the ratio output/input of the DMU assessed with the value of this ratio observed in the other DMUs analysed.

Returns to scale assumptions: constant returns to scale (CRS) – if output increases by that same proportional change as all inputs change, otherwise there are variable returns to scale (VRS) (Figure 2). As for VRS, two cases are possible: if output increases by less than that proportional change in inputs, there are decreasing returns to scale (DRS), and if output increases by more than that proportional change in inputs, there are increasing returns to scale (IRS). Production function could exhibit different types of returns to scale in different ranges of output.

DEA can perform output or input oriented analysis. Input oriented efficiency indicates by how much input quantities can be proportionally reduced holding output constant. Output oriented efficiency indicates by how much output quantities can be proportionally increased holding input constant.

In addition to the efficiency value of each DMU, DEA also provides benchmarking information, which can be used to improve the efficiency of the DMU (Bogetoft & Otto, 2011). This benchmarking information gives DEA a distinct advantage over other efficiency methodologies. These two kinds of information, the efficiency level and the benchmarking information, are inseparable. The efficiency is measured based on the distance between the observed DMU and the reference DMU, which serves as a benchmarking target (Figure 2). DMUs 3 and 4 are benchmarks for DMU A on the direction of input decreasing. Also, DMUs 4 and 5 are benchmarks for DMU A on the direction of output increasing.

The advantages of DEA are the following: no need to explicitly specify a mathematical form for the production function, capable of handling multiple inputs and outputs, capable of being used with any input-output measurement, the sources of inefficiency can be analysed and quantified for every evaluated unit. The disadvantages of DEA are as follow: results are sensitive to the selection of inputs and outputs (Berg, 2010); the number of efficient DMUs on the

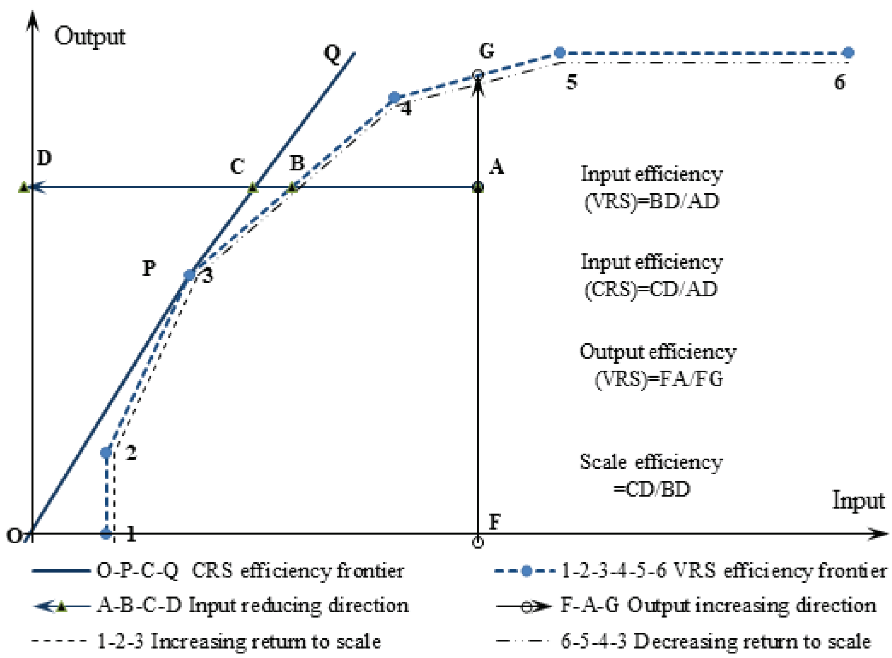

Figure 2. Graphical demonstration of DEA concepts.

Input Oriented CCR (CRS model)	Input Oriented BCC (VRS (I) model)	Output Oriented BCC (VRS (O) model)
$\max_{\mu,\nu} w_o = \mu^T Y_o$	$\max_{\mu,\nu,u_o} w_o = \mu^T Y_o + u_o$	$\min_{\mu,\nu,\nu_o} q_o = \nu^T X_o + \nu_o$
$s.t.\quad \nu^T X_o = 1$	$s.t.\quad \nu^T X_o = 1$	$s.t.\quad \mu^T Y_o = 1$
$\mu^T Y - \nu^T X \le 0$	$\mu^T Y - \nu^T X + u_o \cdot \vec{1} \le 0$	$-\mu^T Y + \nu^T X + \nu_o \cdot \vec{1} \ge 0$
$-\mu^T \le -\varepsilon \cdot \vec{1}$	$-\mu^T \le -\varepsilon \cdot \vec{1}$	$\mu^T \ge \varepsilon \cdot \vec{1}$
$-\nu^T \le -\varepsilon \cdot \vec{1}$	$-\nu^T \le -\varepsilon \cdot \vec{1}$	$\nu^T \le \varepsilon \cdot \vec{1}$
	u_o *free*	ν_o *free*

frontier tends to increase with the number of inputs and output variables.

DEA models. Charnes, Cooper & Rhodes (1978) coined the term *data envelopment analysis* (DEA). Proposed an input orientation CRS model was abbreviated to CCR model by their creators. Banker, Charnes & Cooper (1984) proposed VRS models also were abbreviated to BCC models. The models presented below Cooper *et al*. (2004) have been used for EU Member states agriculture sectors efficiency evaluation.

All three models express mathematically the circumstances of evaluation of DMU weighted productivity (Equation (1)): (i) the type of surface used as reference – whether it is only linear (CRS) or partially linear (VRS); (ii) the direction of productivity evaluation - is the weighted resource being reduced, while weighted product is being maintained constant, or is the weighted product being increased, while maintaining weighted resource constant. The software created by authors in Fortran and Pascal algorithmic languages was used. DMU technical efficiency assessment scores in input and output oriented cases are equal. They are obtained by means of CRS model using the maximal productivity envelope–frontier, i.e. TEI(A)=TEO(A)=CD/AD (Figure 2). VRS (I) model implements an input oriented evaluation of technical efficiency TEI(A)=BD/AD, while VRS (O) model is used for the output oriented evaluation of technical efficiency TEO(A)=AF/GF (Figure 2).

Results and Discussion

Preliminary statistical analysis has shown that it is not correct to depict production process by an often-used Coub-Douglas function. For the application of SFA method deeper investigation of statistical relationships between inputs and outputs are needed. Therefore, it was refused to use the SFA method. Also, it was decided not to use FDH method, because in this FDH frontier convexity requirement is not being raised, thus the resulting steppet surface is not a natural expression of production function. The advantage of FDH method, however, is that it provides the possibility for the DMU which is being estimated to define a closer benchmark DMU as compared to the one defined by DEA method.

Example. Efficiency assessment of EU Member states agricultural sectors was carried out by using DEA method. For demonstration purposes Figure 3 depicts technical efficiency measuring using DEA method in one input-one output case. The efficiency was assessed for all 140 DMU in respect of the 2011-2014 time period data envelope. We used different the period and annual envelopes. The abbreviations used in this paper stand for the country and year of data. For example, Malta agricultural sector 2010 year data, abbreviated as MT10, Ireland 2013 year data – IE13 and so on. DEA VRS frontier (dashed broken line) is formed containing MT10, IE13, UK14, DE13, DE14 and FR14 DMUs. DEA CRS frontier (solid line) is formed containing MT10, IE13 DMUs. The technical input and output efficiencies of point B are calculated as follows:

$$TEI(B)_{VRS} = \frac{RP}{BP},\ TEI(B)_{CRS} = \frac{QP}{BP},$$

$$TEO(B)_{VRS} = \frac{AB}{AC},\ TEO(B)_{CRS} = \frac{AB}{AD}.$$

DEA method forms a permissible linear segment, connecting MT10–UK14 DMUs for input efficiency evaluation and UK14–DE13 DMUs for output efficiency evaluation. The coordinate of virtual points R and C are calculated from the data of above mentioned segments.

Feature. The assessments of both input and output oriented technical efficiency for Swedish (SE), Finnish (FI), Estonian (EE), Latvian (LV) and Lithuanian (LT) agriculture sectors would be calculated with respect to the same segment MT10–IE14 (Figure 3).

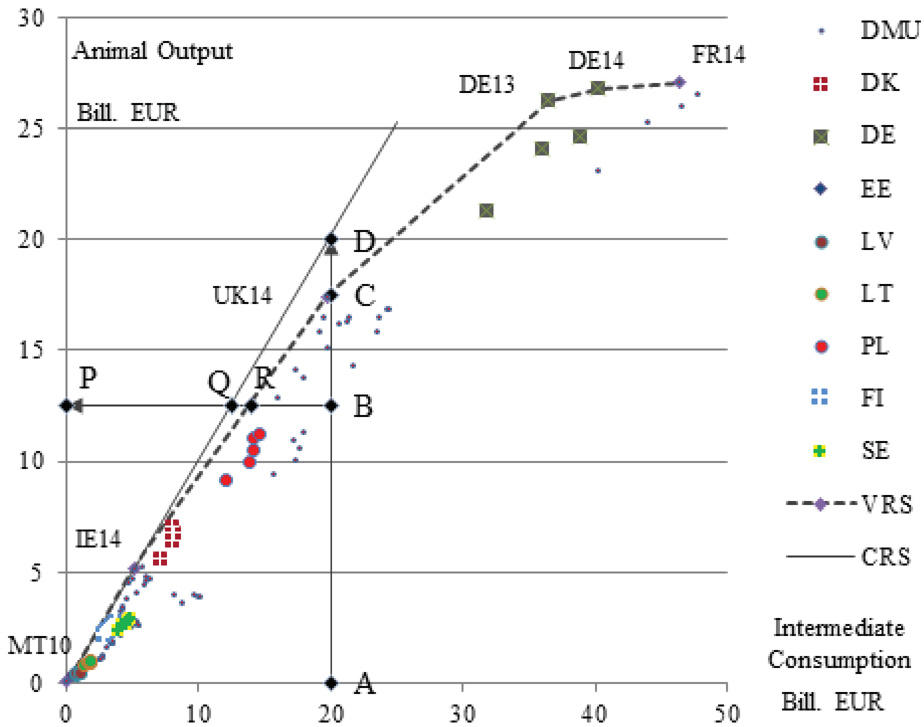

Figure 3. Measuring technical efficiency (DEA method).

Descriptive analysis of inputs and outputs has shown a fairly strong correlating relationship. For instance, $r(X1,Y1)$=0.88, $r(X1,Y2)$=0,86, $r(X3,Y1)$=0.98, $r(X3,Y2)$=0.98. This allows raising a hypothesis about slightly bent linear surface in the common 3×2 measurement space. Furthermore, both input and output oriented VRS assessments namely *TEI, TEO* almost for all DMU are very close, i.e. correlation coefficient of the relationship between them $r(TEI,TEO)$=0.96. Such a strong correlation was unexpected and is rarely observed in applications of DEA method. Therefore, variants of modified VRS models were used in order to obtain additional information. It turned out that such results were determined by two factors: 1) the envelope of the whole period includes a segment containing the axes of small countries Malta and Luxembourg as well as big countries Germany, Spain, France or Italy; 2) the data-points for Malta or Luxembourg are very close to the origin. The efficiencies measured with respect of these segments almost fulfil the condition for triangle similarity, thus the evaluations obtained by VRS (I) and VRS (O) models are almost identical. Only for big countries Germany (DE), Spain (ES), France (FR), Poland (PL) above-mentioned evaluations are noticeably different.

Efficiency scores. For this reason the efficiency assessments, shown in Table 1, are common according to VRS model, because the difference in input and output oriented case is small. It must be noted that values obtained by CRS model are always lower than obtained by VRS model.

Efficiency dynamics. A glimpse into Baltic Sea surrounding EU Member States technical efficiency dynamics (Figure 4) allows making a clearer view. The efficiency of agriculture sectors in Germany, Denmark during the time period of 2010–2014 was high with the tendency to increase. In Poland, Sweden and Lithuania a fair level of efficiency was maintained, which corresponds to the efficiency increase trend between EU countries of its rank (small and medium-size). Efficiencies of Finnish and Latvian agriculture sectors have declined over the observed period. Such efficiency dynamics would be difficult to notice if the DEA method would be applied on the DMUs of each year separately. As the envelope of the whole period is composed of the best practices of the whole period, and is the ideal variant of the practice, the annual envelope will never be above the envelope of the whole period. For this reason, efficiency evaluations calculated in respect with the annual envelope are not lower as compared with the ones obtained in respect of the period envelope. The annual envelope, in turn, is closer to the present moment, and may be useful in calculating the improvement trajectories of production efficiency.

Peers. As Table 2 suggests, there were 13 cases of efficient farming in 2010-2014 among DMU, namely

Table 1

Technical efficiency (%) of EU Member States according to DEA (by 2010–2014 data envelope)

State code	Output oriented TE (VRS)					CRS model				
	2010	2011	2012	2013	2014	2010	2011	2012	2013	2014
BE	96.6	95.6	**100**	97.8	97.4	95.4	95.3	**100**	97.7	97.2
BG	66.2	67.7	68.3	69.4	71.4	65.8	67.3	68	69.1	71
CZ	65.5	70.1	68.9	70.1	71.4	65.3	69.7	68.6	69.7	71
DK	92.1	92.1	**100**	96.5	97.5	92.1	92.1	**100**	96.5	97.5
DE	90.3	96.1	95.1	**100**	**100**	84.8	90.8	85.1	94.4	87.7
EE	82.3	86.5	84.5	86.2	87.1	79.4	85.4	84.1	85.7	86.7
IE	86.4	95.5	93.2	93.7	**100**	85.4	94.8	93	93.2	**100**
EL	90.9	83.5	84.9	82.2	83.2	90.6	83.3	84.7	82	83.1
ES	**100**	98.7	**100**	99.3	98.6	99.8	97.1	97.8	98.1	97.3
FR	98	99.5	**100**	98.7	**100**	91.9	92.3	92.7	88.3	91.8
HR	86.7	84.5	77.9	78.3	82	85.4	83.1	77.1	78.2	81.5
IT	94.7	95.9	98.9	**100**	98.7	94.6	95.4	97	**100**	97.8
CY	99.4	98.3	99.2	**100**	**100**	93.7	92.9	93.6	94	94.1
LV	65	62.7	59.2	59.1	59.2	63.3	61.5	59.2	57.9	57.7
LT	70.8	69.7	71.1	71.1	70.6	69	69.4	71.1	71.1	70.6
LU	**100**	**100**	**100**	97.4	**100**	81.4	82.9	90.7	82.4	84.6
HU	67.3	70.1	69.4	71.3	74.7	66.8	70.1	68.6	70.9	74.5
MT	**100**	**100**	**100**	**100**	99.5	**100**	99.3	98.3	**100**	99.2
NL	**100**	94.6	96.6	**100**	**100**	**100**	94.6	96.6	**100**	**100**
AT	91.3	93.6	93.5	93.9	93.4	90.8	93.1	92.9	93.1	92.6
PL	88.7	85.8	87.8	90.6	89.2	82	80	80.9	83	80.5
PT	81.7	76.3	76.2	79.1	81.7	78.8	72.8	72.2	75.7	77.4
RO	74.7	77.2	74.7	74.5	73.7	74.5	77	74.5	74.3	73.6
SI	82.1	84.4	80.1	82.3	85.4	78	80.1	75.3	77.4	81.2
SK	63.6	64.4	66.5	67.5	66.9	63.4	64	66.4	66.9	66.1
FI	89.8	87.6	88.2	83.6	78.1	89.1	87.1	87.8	83	77.5
SE	81.7	83.2	83.6	81.7	83.2	81.3	82.8	83.3	81.4	82.9
UK	91	94	94.8	96.5	**100**	90.8	93.9	94.6	96.4	**100**

for IT13, MT10, ES10, IE14, DK12, UK14, CY14, LU12, NL10, DE13, NL13, FR12, NL14. They had 100% VRS efficiency and thus became peers for other states; MT10, IE14, CY14, LU12 for small countries, DK12, UK14, NL10, NL13 for medium countries and IT13, ES10, DE13, FR12 for big countries. Hence, technical rather than scale efficiency was peculiar for the EU farming. In order to rank them according to DEA approach, we counted how many times each of efficient states acted as peers for other states. Countries with higher number of such occurences, therefore, were attributed with highers ranks. Countries, the peer count of which were less then 6, were accepted as the surface edge DMUs.

Partial efficiencies. In DEA efficiency measurement, there are two types of measures, namely, radial (i.e. Farrell measure) and non-radial (i.e. Russell measure). Radial measures are the models that adjust all inputs or alternatively all outputs of a DMU by the same proportion. A non-radial DEA measure allows for non-proportional reductions in each positive input or augmentations in each positive output. Multi-directional efficiency analysis (MEA), like DEA, is a non-parametric method, differing from

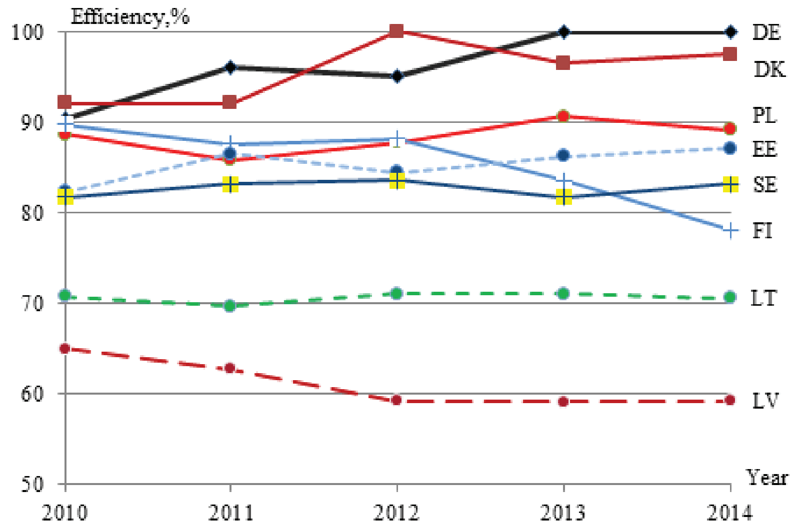

Figure 4. Baltic Sea surrounding EU Members States technical efficiency dynamics.

DEA in the way in which efficiency is measured. MEA has the advantage that it allows for a more substantive analysis of the effect of external variables on the ineffciency scores.

In this work, we applied the iterative calculation procedure implementing only the initial phase of MEA method, which, similarly to the case of partial derivatives in the multiple variable' function, separately evaluates partial efficiency of each resiurce or product. A partial technical efficiency shows the level of input or output compared to real or virtual practically best DMU on the each input or output direction when other inputs and outputs are keeping constant. Table 3 presents partial and total efficiencies of ineffective agriculture sectors within Baltic states in 2014. It can be stated that the total efficiency of inputs TEI is determined by the intermediate consumption efficiency of input X3. Other inputs, namely, X1–AWU (annual work unit) and X2–UAA (utilised agriculture area) contribute only weakly to the total

Table 2

Technical efficiency and ranking of EU Member States according to DEA

Peers	IT13	MT10	ES10	IE14	DK12	UK14	CY14	LU12	NL10	DE13	NL13	FR12	NL14
Peer count	103	76	58	54	44	41	24	17	16	13	13	11	11
Rank	1	2	3	4	5	6	7	8	9	10	11	12	13

Table 3

Partial technical efficiencies (%), by 2014 year data envelope

State	TEI(X1)	TEI(X2)	TEI(X3)	TEI	TEO(Y1)	TEO(Y2)	TEO
Estonia	10.5	47.3	87.6	88.4	80.6	80.1	88.3
Latvia	4.6	4.2	60.3	60.7	54.8	48.4	60.3
Lithuania	6.6	12.3	72.9	73.1	69.8	56.9	72.9
Poland	44.4	8.6	89.8	90.1	77.1	85.6	89.8
Finland	24.5	28.4	76.7	79.3	70.1	73.9	79.3
Sweden	15.5	51.2	82.1	84.4	82.9	69.1	84.5

efficiency of inputs. In case of Estonia and Sweden, TEI is slightly increased by TEI(X2), in case of Poland - TEI(X1), in case of Finland - TEI(X1) and TEX(2). Concerning total output efficiency–TEO, partial of the crop production output efficiency–TEO(Y1) and livestock production output efficiency–TEO(Y2) had an almost equally important influence. TEO(Y1) was slightly more important in case of Lithuania and Sweden, while TEO(Y2)–in case of Poland.

Conclusions

The technical efficiencies agriculture sectors were evaluated across the EU Member States on a basis of data from European Commission database Eurostat. The five indicators have been chosen as main factors of agriculture sectors efficiency. Three of them identify inputs and the remaining two – outputs. The input indicators identify material and financial resources, but output indicators describe results of production activity.

DEA is a potentially powerful approach to the evaluation comparing the efficiency of different agriculture sectors performance. We applied the iterative calculation procedure, which separately evaluates partial efficiency of each resource or product. A partial technical efficiency shows the level of input or output compared to real or virtual practically best DMU on the each input or output direction when other inputs and outputs are keeping constant.

The efficient EU Member States were ranked according to peer count of DEA method. Hence, the Italy, Malta, Spain, Ireland, United Kingdom, Denmark, Netherlands, Germany can be considered as states peculiar with the most relatively efficient agricultural sectors. As for 2014, Poland held the rank of 14, whereas the Baltic States remained beneath. Estonia (ranked 15th) was first among the remaining Baltic neighbours; Lithuania and Latvia were attributed with ranks of 26 and 28, respectively. The results show that agriculture of new EU countries, including Lithuania and Latvia, is still poorly effective, even though the efficiency tends to increase. The main factors that could increase the agricultural efficiency in Lithuania and Latvia are the use of cheap labour force and sophisticated agriculture machinery. Evaluating the results of the conducted research, we can propose to the Baltic countries (Estonia, Latvia, and Lithuania) to find ways of decreasing the AWU (maybe by lowering the manual labour); the Baltic countries should consider the opportunities of decreasing the UAA (maybe by better exploiting more efficient agricultural technologies).

References

1. Aigner, D.J., Lovell, C.A.K., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, Vol. 6, No 1, 21–37.
2. Asmild, M., & Hougaard, JL. (2006). Economic Versus Environmental Improvement Potentials of Danish Pig Farms. *Agricultural Economics* 35(2), 171–181.
3. Baležentis, T., Li, T., & Baležentis, A. (2015). The trends in efficiency of Lithuanian dairy farms: a semiparametric approach. *Management Theory and Studies for Rural Business and Infrastructure Development*. Vol. 37. No. 2, 167–178.
4. Baležentis, T., & Baležentis, A. (2011). A multi-criteria assessment of relative farming efficiency in the European Union Member States. Žemės ūkio mokslai, Vol. 18, No 3, 125–135.
5. Baležentis, T., & Kriščiukaitienė, I. (2012). Family farm efficiency across farming types in Lithuania and its managerial implications – data envelopment analysis. *Management Theory and Studies for Rural Business and Infrastructure Development*, No. 1(30), 22–30.
6. Banker, R., Charnes A., & Cooper W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30, 1078–1092.
7. Battese, J. E., & Corra, G. S. (1977). Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics,* 21 (3), 169–179.
8. Berg, S. (2010). *Water Utility Benchmarking: Measurement, Methodology, and Performance Incentives*. London: IWA Publishing.
9. Bogetoft, P., & Otto, L. (2010). *Benchmarking with DEA, SFA, and R*. New York: Springer Science+Business Media B.V. (International Series in Operations Research & Management Science, No. 157). DOI: 10.1007/978-1-4419-7961-2.
10. Bojnec, S., & Latruffe, L. (2011). Farm Size and Efficiency during Transition: Insights from Slovenian Farms. *Transformations in Business and Economics*, 10(3), 104-116.
11. Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, Vol. 2, No 6, 429–444.
12. Cooper,W.W., Seiford,L.M., & Zhu, J. (2004). *Handbook on Data Envelopment Analysis*, XIV, 593. Springer US.

13. Davidova, S., & Latruffe, L. (2007). Relationships betwen technical efficiency and Financial Management for Czech Republic farms. *Journal of Agricultural Economics*, 58(2), 269–288.
14. Deprins, D., L. Simar, & Tulkens, H. (1984). *Measuring Labor-Efficiency in Post Offices. The Performance of Public Enterprises: Concepts and measurements*. 243–67. Amsterdam, North-Holland: Elsevier Science Publishers.
15. Farrell, M.J. (1957). The measurement of technical efficiency. *Journal of the Royal Statistical Society*, Series A, General, Vol. 120, No 3, 253–281.
16. Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega* 1(3), 237–250.
17. Gorton, M., & Davidova, S. (2004). Farm productivity and efficiency in the CEE applicant countries: a synthesis of results. *Agricultural economics*. Volume 30, Issue 1, Pages 1–16.
18. Liu, J. S., Lu, L. Y. Y., Lu, W. M. & Lin, B. J. T. (2013). A survey of DEA applications. *Omega*, 41(5), 893-902.
19. Meeusen, W., & van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, Vol. 18, No 2, 435–444.
20. Murillo-Zamorano, L.R. (2004). Economic Efficiency and Frontier Techniques. *Journal of Economic Surveys*, Vol. 18, No 1, 33–45.
21. Rasmussen, S. (2010). Scale efficiency in Danish agriculture: an input distance-function approach. *European Review of Agricultural Economics,* Vol. 37 (3), 335–367.
22. Rimkuvienė, D., Laurinavičienė, N., & Laurinavičius, J. (2010). ES šalių žemės ūkio efektyvumo įvertinimas (Evaluation of agricultural efficiency in the EU countries). *LŽŪU mokslo darbai*, Vol. 87, No 40, 81–89.
23. Tamošaitienė, A., Juškevičienė, D., Kriščiukaitienė, I., & Galnaitytė, A. (2010). Ūkininkų ūkių verslo stabilumo vertinimas naudojant finansinės analizės santykinius rodiklius (Farmers Farms Business Stability Assessment using Financial Analysis of Comparative Indicators). *Management Theory and Studies for Rural Business and Infrastructure Development*, Nr. 5(24), 173–185.
24. Vasiliev, N., Astover, A., Mõtte, M. Noormets, M., Reintam, E., & Roostalu, H. (2008). Efficiency of Estonian grain farms in 2000–2004. *Agricultural and Food Science*, Vol.17, pp. 1–40.

Acknowledgements

This research was done in the framework of the Nordplus Higher Education 2016 project NPHE-2016/10342 'Raising awareness about the role of math skills in building specialists competence for the sustainable development of society'.