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Energy-related CO_2 emission in European Union agriculture: Driving forces and possibilities for reduction

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HIGHLIGHTS

- The research focuses on agricultural sectors of the eighteen European countries.
- The main drivers of energy-related CO_2 emission are quantified by means of IDA.
- The slack-based DEA model is applied to gauge the environmental efficiency.
- Shadow prices of carbon emission are analysed.
- Energy efficiency remains the primary means for increasing environmental efficiency.

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ABSTRACT

Climate change mitigation is a key issue in formulating global environmental policies. Energy production and consumption are the main sources of greenhouse gas (GHG) emissions in Europe. Energy consumption and energy-related GHG emissions from agriculture are an important concern for policymakers, as the agricultural activities should meet food security goals along with proper economic, environmental, and social impacts. Carbon dioxide (CO_2) emission is the most significant among energy-related GHG emissions. This paper analyses the main drivers behind energy-related CO_2 emission across agricultural sectors of European countries. The analysis is based on aggregate data from the World Input-Output Database. The research explores two main directions. Firstly, Index Decomposition Analysis (IDA), facilitated by the Shapley index, is used to identify the main drivers of CO_2 emission. Secondly, the Slack-based Model (SBM) is applied to gauge the environmental efficiency of European agricultural sectors. By applying frontier techniques, we also derive the measures of environmental efficiency and shadow prices, thereby contributing to a discussion on CO_2 emission mitigation in agriculture. Therefore, the paper devises an integrated approach towards analysis of CO_2 emission based upon advanced decomposition and efficiency analysis models. The research covers eighteen European countries and the applied methodology decomposes contributions to CO_2 emission across of regions and factors. Results of IDA suggest that decreasing energy intensity is the main factor behind declines in CO_2 emission. According to the SBM, the lowest carbon shadow prices are observed in France, Finland, Sweden, Denmark, the Netherlands, Poland, and Belgium. These countries thus have the highest potential for reduction in CO_2 emission. The results imply that measures to increase energy efficiency are a more effective means to reduce CO_2 emissions than are changes in the fuel-mix.

1. Introduction

The increasing worldwide concerns regarding climate change mitigation call for deeper analysis into environmental performance of global and regional economies[1]. One of the key questions in this area is CO_2 (carbon dioxide) emission. Indeed, CO_2 is the main contributor to overall greenhouse gas (GHG) emission. A proper understanding of the main drivers behind the changes in CO_2 emission is

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[1] There have been important reports on GHG emission prepared by various international bodies [1–8].

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necessary to deliver sound policy implications and ensure sustainable development of various economic systems [9–11]. Energy production and consumption are the main sources of GHG emissions in Europe. Energy consumption by and GHG emissions from agriculture are an important concern for policymakers, because agricultural activities – the cultivation of crops and livestock husbandry – themselves significantly contribute to GHG emissions. Therefore, there is considerable pressure on this sector to identify the most efficient climate change mitigation policies and measures. This has also been acknowledged by both policy-makers and researchers in the European Union [12]. The present paper, hence, attempts to analyse the CO_2 emission performance of agricultural sectors of the EU Member States.

Essentially, there are two principal ways to reduce GHG emissions arising from energy consumption in agriculture: increase energy efficiency and increase the use of renewable energy sources. Accordingly, there is a need for integrated analysis of economic activities, environmental pressures, and the dynamics thereof. Moreover, another important issue is the potential for reducing environmental pressures, including CO_2 emissions. The literature has suggested a number of quantitative techniques for analysis of the aforementioned problems and environmental pressures in general [13–18]. Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA) are widely applied for analysis of changes in CO_2 emissions with respect to multiple factors. As regards the gaps in the CO_2 emission performance, frontier techniques appear as a primal tool for efficiency analysis. Among the frontier techniques, the non-parametric Data Envelopment Analysis (DEA) and the parametric Stochastic Frontier Analysis (SFA) constitute the main strands of methods.

Analysis of the earlier literature suggests that there have been analyses on energy and/or carbon efficiency involving multiple countries. Only a handful of them have addressed these issues within a specific sector of economy. Furthermore, IDA and efficiency analysis have not been applied in an integrated manner, even though the directions for reductions in carbon emission can be quantified by means of efficiency analysis (e.g., DEA). Methodologically, this paper addresses the latter gap and demonstrates the possibilities for interaction among the two approaches. Indeed, the agricultural sector receives substantial public financial support in the European Union (EU) under the Common Agricultural Policy. Furthermore, other structural measures can be taken to improve energy sustainability in rural areas as well. Accordingly, there is a need to identify the key factors contributing to changes in CO_2 emission as well as targets for its reduction. Noteworthy, regional disparities are also important in order to deliver appropriate policy guidelines. However, the recent literature on the EU agriculture has only been focused on application of IDA in this context [19]. From empirical viewpoint, this paper seeks to analyse the main drivers along with performance gaps for energy-related CO_2 emission across agricultural sectors of European countries thereby filling yet another gap in the literature. By applying frontier techniques, we also derive measures of environmental efficiency and shadow prices. This enables us to identify performance gaps and possible ways for furthering reductions in CO_2 emission. Therefore, this paper contributes to the empirical discussion regarding management of energy-related CO_2 emission in the EU agricultural sectors.

The research framework comprises the two main techniques. The Shapley/Sun index is applied for IDA. This allows us to quantify the impacts of different factors on the overall change in CO_2 emission. Subsequently, DEA is applied to identify gaps in emission performance. By applying the Slack-based Model (SBM), as proposed by Cooper et al. [20], we obtain both the measures of efficiency and shadow prices of CO_2 emission. The research relies on the World Input-Output Database [7].

The paper is organized as follows: Section 2 presents a survey on analysis of CO_2 emission by means of decomposition analysis and frontier techniques. Section 3 presents the techniques employed for the analysis as well as the dataset. Section 4 discusses the results obtained, namely the factors of change in CO_2 emission, environmental efficiency, and shadow prices. Finally, Section 5 presents our conclusions and offers directions for further research.

2. Literature survey

Policy making for mitigation of CO_2 emission (and many other environmental pressures, too) requires information on the two key issues: (1) the driving factors of the emission, and (2) the extent to which the emission could be reduced. In this section, a survey of the literature on the aforementioned issues is presented[2].

Changes in CO_2 emission can be factorized by means of decomposition analysis. In this approach, the main idea is to break down the overall change in emission by attributing it to the underlying factors (e.g., the level of economic activity, carbon factor, energy intensity, structure of the economy). Such a setting for decomposition of CO_2 emissions allows one to track the progress achieved by implementing specific climate change mitigation policies and measures (e.g., energy efficiency improvements, increased usage of renewables in final energy consumption) aimed at reducing the carbon intensity of energy consumption.

In general, two strands of decomposition analysis are available, namely SDA and IDA; see Hoekstra and van der Bergh [21] for a detailed discussion. These approaches differ in that SDA relies on input-output analysis [22–24], whereas IDA requires no information about inter-sectoral linkages. Ang [25], Ang [26] and Xu and Ang [13] presented the main methodological issues for IDA. Indeed, following Ang et al. [27], one can identify two groups of IDA methods, namely techniques linked to the Divisia index and techniques linked to the Laspeyres index. Choi and Ang [28] proposed decomposing the changes in energy intensity into real intensity change and structural effects. Ang et al. [29] presented an IDA for a multi-country setting.

IDA has been extensively used for CO_2 emission analysis at various levels of aggregation [30–34]. Brizga et al. [35] employed IDA to decompose CO_2 emissions in countries of the former Soviet Union, whereas Brizga et al. [36] applied SDA for analysis of GHG emissions in the same localities. Voigt et al. [37] addressed a related topic – energy intensity – in multiple countries by utilising the logarithmic mean Divisia index (LMDI). Kaivo-oja et al. [38] applied IDA to identify trends in CO_2 emission in the main world economies. González et al. [39], González et al. [40] analysed CO_2 emissions across the European Union Member States by means of IDA. Ang and Su [41] applied IDA to analyse CO_2 emission resulting from electricity production worldwide. Kang et al. [42], Yu et al. [43], and Zhang et al. [44] applied different IDA techniques to analyse CO_2 emission across Chinese provinces. Shao et al. [45] looked into GHG emission from primary aluminium production by applying generalized Divisia index approach [46]. Robaina Alves and Moutinho [47] analysed CO_2 emission across economic sectors in Portugal by means of the Shapley index. Robaina-Alves et al. [48] analysed CO_2 emission in the Portuguese tourism sector by using IDA. Lin and Lei [49] proposed guidelines for reductions in CO_2 emission from Chinese food industry on the basis of IDA. Fan et al. [50] investigated CO_2 emission in Shanghai by applying IDA. Similarly, Kang et al. [51] and Zhang et al. [52] addressed

[2] The techniques this study focuses on can be applied for sub-national, national, or international analysis. However, a wider range of techniques is available for farm-level analysis [12].

the same topic with IDA in Tianjin and Beijing, respectively. IDA has also been applied to CO_2 emissions from the agricultural sector: Robaina-Alves and Moutinho [19] focused on European Union countries, whereas Li et al. [53] analysed Chinese agriculture. Therefore, the IDA can be specific with the following features: (i) it can be international, national, or sub-national in scope; (ii) it can cover a single sector of the economy or the whole economy; (iii) it can apply different techniques.

Besides identifying the key factors behind CO_2 emission, it is also important to try to foresee possible means for their reduction. Environmental efficiency measures [54,55] are useful tools in this regard. Indeed, these measures enable identification of performance gaps (or room for improvement) and derivation of shadow prices of non-marketable outputs (e.g., CO_2 emission). Murty et al. [56] proposed the by-production approach for measurement of environmental performance. Efficiency measures can be applied to calculate changes in total factor productivity [57]. Shadow prices can be used when constructing marginal abatement curves [58]. Various techniques and measures can be employed for shadow price analysis [14,59]. Furthermore, efficiency models can be used for emission allocation [60,61].

In regards to estimation techniques, both parametric and non-parametric approaches can be used. The parametric approach involves specification of the functional form of the distance function describing the underlying technology. Parametric techniques can be applied in a deterministic setting by means of linear programming [62–65]. Similarly, econometric techniques allow estimation of the environmental frontier by accounting for random noise [66–68]. In contrast, the non-parametric approach does not require assumptions regarding the functional form of the representation of the underlying technology[3]. In the latter case, Data Envelopment Analysis (DEA) is employed to estimate the production frontier as well as the distance functions [56,69,70]. Stochastic errors can be included in the non-parametric analysis by means of stochastic DEA [71]. Similarly to the case of decomposition analysis, efficiency analysis can also focus on the whole economy [70,72] or particular economic activities [73,74].

Wei et al. [75] pointed out that the well-established approaches relying on directional distance functions still feature certain shortcomings. Specifically, the setting of directional distance function analysis requires imposition of a directional vector. Therefore, the analysis focuses on a particular direction. Furthermore, the conventional measures do not account for slacks. In the present paper, we therefore apply a non-oriented, non-radial and non-parametric measure of environmental efficiency, i.e., SBM, as proposed by Cooper et al. [20]. Even though SBM has been applied for analysis of environmental performance [75], here we combine it with IDA to produce a more integrated perspective for policy making.

3. Methods

This section provides an overview of the main techniques we employed in the research as well as the data we used. In particular, we employed the Shapley/Sun index for IDA, and the slack-based DEA model to measure environmental efficiency and shadow prices of CO_2 emission in European agriculture. Finally, we discuss the dataset based on the World Input-Output Database.

3.1. Shapley/Sun index

The Shapley/Sun index belongs to the group of indices linked to the Laspeyres index. The Shapley/Sun index does not suffer from path dependency, i.e., the results are independent on the exact order the factors come into analysis. Alongside the latter property, the index also features other desirable properties of perfect decomposition, time reversal etc. Sun [76] and Albrecht et al. [77] were the first to propose and employ the Shapley value as a tool for IDA. Subsequently, Ang et al. [78] argued that both of the aforementioned studies had actually employed the same technique, namely the Shapley/Sun index. The Shapley/Sun index has since been applied in various studies on CO_2 emission [43,44,79].

Assume that a certain variable of interest, V, is factorized in terms of the three components, x_1, x_2, x_3. Let the two time periods be denoted by 0 and T. Then, the following relationship holds [78]:

$$\Delta V = V^T - V^0 = x_1^T x_2^T x_3^T - x_1^0 x_2^0 x_3^0 = \Delta V_{x_1} + \Delta V_{x_2} + \Delta V_{x_3}, \tag{1}$$

where ΔV is the absolute change in V, and ΔV_{x_i} are the effects associated with factors x_i, $i = 1, 2, 3$.

The Shapley value [80] is then used to estimate the effects of factors. In a three-factor model, we have:

$$\Delta V_{x_i} = \sum_{s=1}^{3} \frac{(s-1)!(3-s)!}{3!} \sum_{S: x_j \in S, |S|=s} (V(S) - V(S \setminus x_i)), \tag{2}$$

where S is a set of factors, with each factor obtaining values of period T, i.e., $V(S) = \prod_{j\in S} x_j^T \prod_{j \notin S} x_j^0$, for $j \subseteq i$. Specifically, ΔV_{x_1} is estimated via:

$$\Delta V_{x_1} = \frac{1}{3}\left(x_1^T x_2^0 x_3^0 - x_1^0 x_2^0 x_3^0\right) + \frac{1}{6}\left(x_1^T x_2^T x_3^0 - x_1^0 x_2^T x_3^0\right) + \frac{1}{6}\left(x_1^T x_2^0 x_3^T - x_1^0 x_2^0 x_3^T\right) + \frac{1}{3}\left(x_1^T x_2^T x_3^T - x_1^0 x_2^T x_3^T\right). \tag{3}$$

In order to factorize the CO_2 emission, the following terms are considered: carbon emission factor (t CO_2 eq per joule), energy intensity (joule per Purchasing Power Standard – PPS) and Gross Value Added (GVA) in PPS. Therefore, the three variables are taken into analysis: (i) CO_2 emission in tonnes, (ii) emission-relevant energy consumption in joules, (iii) GVA in PPS (base year 1995). The data come from the WIOD database.

The following three-factor model is therefore established[4]:

$$C_t = \frac{C_t}{E_t} \frac{E_t}{GVA_t} GVA_t = F_t I_t Q_t, \tag{4}$$

where C_t is carbon emission, F_t indicates a carbon factor, I_t is an energy intensity factor, and Q_t is an economic growth factor during period t. The Shapley/Sun technique is then employed to quantify the impacts of changes in the aforementioned factors:

$$\Delta C_t = \Delta F_t + \Delta I_t + \Delta Q_t, \tag{5}$$

The effects of the three factors given in Eq. (5) are then estimated by applying Eq. (2).

The analysis is carried out in a chain-linked manner, i.e., two-year periods are considered for each country. We then aggregate the results across years or countries if needed.

3.2. Slack-based measure of efficiency

Initially, neoclassical production technology did not include undesirable outputs as these cannot be priced [75]. Färe et al. [82] presented a weak-disposability technology to model the productive technology with externalities. Kuosmanen and Matin [83] and Leleu [84] presented the relevant models for pricing of undesirable outputs in a non-parametric framework.

[3] The interested reader is referred to a special issue of *Mathematical and Computer Modelling*, Volume 58 (2013), entitled *The Measurement of Undesirable Outputs: Models Development and Empirical Analyses.*

[4] In this paper, we limit the IDA model to the three factors. However, one can consider such additional factors as the share of fossil fuels, see Robaina Alves and Moutinho [79]. Furthermore, multi-country comparisons can be facilitated by extending the decomposition model [29]. In cases of multiple economic activities, one can also account for structural effects [81].

The present paper applies SBM to measure environmental efficiency and derive shadow prices of undesirable outputs. The model was proposed by Cooper et al. [20] and rests on the following technology set:

$$T = \left\{ (x, y, u) | x \geqslant \sum_{k=1}^{K} \lambda^k x^k, \; y \leqslant \sum_{k=1}^{K} \lambda^k y^k, \; u \geqslant \sum_{k=1}^{K} \lambda^k u^k, \right.$$
$$\left. \lambda^k \geqslant 0, \; k = 1, 2, \ldots, K \right\}, \tag{6}$$

where $x = (x_1, x_2, \ldots, x_I) \in \Re_+^I$ is a vector of inputs, $y = (y_1, y_2, \ldots, y_J) \in \Re_+^J$ is a vector of desirable outputs, $u = (u_1, u_2, \ldots, u_L) \in \Re_+^L$ is a vector of undesirable outputs, λ^k is an intensity variable, and $k = 1, 2, \ldots, K$ is the index of decision making units (countries). Note that Eq. (6) defines a constant-returns-to-scale technology.

The following SBM accounts for both desirable and undesirable outputs and measures the efficiency of a certain decision making unit (country) in terms of slacks in inputs and outputs:

$$\begin{aligned} \rho_t = & \min_{s_i^x, s_j^y, s_l^u} \frac{1 - \frac{1}{I} \sum_{i=1}^{I} \frac{s_i^x}{x_i^t}}{1 + \frac{1}{J+L} \left(\sum_{j=1}^{J} \frac{s_j^y}{y_j^t} + \sum_{l=1}^{L} \frac{s_l^u}{u_l^t} \right)} \\ & \text{s.t.} \\ & \sum_{k=1}^{K} \lambda_k x_i^k + s_i^x = x_i^t, \quad i = 1, 2, \ldots, I; \\ & \sum_{k=1}^{K} \lambda_k y_j^k - s_j^y = y_j^t, \quad j = 1, 2, \ldots, J; \\ & \sum_{k=1}^{K} \lambda_k u_l^k + s_l^u = u_l^t, \quad l = 1, 2, \ldots, L; \\ & \lambda_k \geqslant 0, \quad k = 1, 2, \ldots, K; \\ & s_i^x, s_j^y, s_l^u \geqslant 0 \end{aligned} \tag{7}$$

where $t = 1, 2, \ldots, K$ and $0 < \rho_t \leqslant 1$ with $\rho_t = 1$ indicating full efficiency. Eq. (7) presents the underlying idea of the SBM: the t-th observation, as represented by the input-output vector (x_i^t, y_i^t, u_i^t), is projected onto the production frontier at the point $(x_i^t - s_i^{x^*}, y_j^t + s_j^{t^*}, u_l^t - s_l^{t^*})$, where $s_i^{x^*}$, $s_j^{y^*}$, and $s_l^{u^*}$ are the optimal values of s_i^x, s_j^y, and s_l^u, respectively. The objective function is normalised so that the efficiency scores can be compared across the observations. However, Eq. (7) defines a non-linear model. It can be linearized as follows:

$$\begin{aligned} \tau_t = & \min_{h, s_i^x, s_j^y, s_l^u} h - \frac{1}{I} \sum_{i=1}^{I} \frac{s_i^x}{x_i^t} \\ & \text{s.t.} \\ & 1 = h + \frac{1}{J+L} \left(\sum_{j=1}^{J} \frac{s_j^y}{y_j^t} + \sum_{l=1}^{L} \frac{s_l^u}{u_l^t} \right) \\ & \sum_{k=1}^{K} \lambda_k x_i^k + s_i^x = h x_i^t, \quad i = 1, 2, \ldots, I; \\ & \sum_{k=1}^{K} \lambda_k y_j^k - s_j^y = h y_j^t, \quad j = 1, 2, \ldots, J; \\ & \sum_{k=1}^{K} \lambda_k u_l^k + s_l^u = h u_l^t, \quad l = 1, 2, \ldots, L; \\ & \lambda_k \geqslant 0, \quad k = 1, 2, \ldots, K; \\ & s_i^x, s_j^y, s_l^u \geqslant 0; \\ & h > 0. \end{aligned} \tag{8}$$

Indeed, the efficiency scores rendered by Eqs. (7) and (8) are the same: $\rho_t = \tau_t$.

The shadow prices of undesirable outputs can be derived by employing the multiplier model, which is dual to Eq. (8):

$$\begin{aligned} \varepsilon_t = & \max_{\varepsilon, \pi_i^x, \pi_j^y, \pi_l^u} \varepsilon \\ & \text{s.t.} \\ & \varepsilon + \sum_{i=1}^{I} \pi_i^x x_i^t - \sum_{j=1}^{J} \pi_j^y g_{y,j} + \sum_{l=1}^{L} \pi_l^u g_{u,l} = 1 \\ & \sum_{j=1}^{J} \pi_j^y y_j^k - \sum_{l=1}^{L} \pi_l^u u_l^k - \sum_{i=1}^{I} \pi_i^x x_i^k \leqslant 0, k = 1, 2, \ldots, K; \\ & \pi_i^x \geqslant \frac{1}{I} (1/x_i^t), \quad i = 1, 2, \ldots, I; \\ & \pi_j^y \geqslant \frac{1}{J+L} (1/y_j^t), \quad j = 1, 2, \ldots, J; \\ & \pi_l^u \geqslant \frac{1}{J+L} (1/u_l^t), \quad l = 1, 2, \ldots, L \end{aligned} \tag{9}$$

where π^x, π^y, and π^u are the virtual prices of inputs, outputs, and undesirable outputs, respectively. The constraints in Eq. (9) ensure that the virtual profit is maximised for the t-th observation subject to the condition that no positive profits are observed for all the observations. This is done by manipulating virtual prices of inputs and outputs. In the optimal case, the virtual profit equals zero and, thus, $\varepsilon_t = 1$.

Following Lee et al. [69] and Wei et al. [75], the virtual prices yielded by Eq. (9) can be employed to derive the shadow price of an undesirable output:

$$p_l = p_j \pi_l^u / \pi_j^y, \tag{10}$$

where p_j is the market price of the j-th output. In our case, we use GVA as the "numeraire" output. Accordingly, the market price of the latter output is equal to unity, i.e., the absolute and relative shadow prices of an undesirable output are equal. The shadow price is a marginal abatement cost [58,62,75] and shows the trade-off between a desirable output and an undesirable output. The SBM was implemented in the General Algebraic Modeling System (GAMS) environment.

3.3. Data sources

The research applies a dataset retrieved from the World Input-Output Database [7]. The research period spans the years 1995–2009. Specifically, the research focuses on the data series for the Agriculture, Hunting, Forestry and Fishing sector (NACE 1.1 sectors A-B). To ensure a meaningful international comparison, the GVA and real fixed capital stock are deflated by the respective price indices available in the World Input-Output Database (base year 1995), thereby constructing the implicit quantity indices. Furthermore, purchasing power parities of 1995 based on the EU-28 Gross Domestic Product are used. Therefore, the monetary terms used in this study are expressed in purchasing power standards (PPS) of 1995, which are devoid of price and exchange rate differences that would otherwise have existed among the analysed states. To model the production process, we also include total hours worked by employees, emission relevant energy use (in terajoules), and CO_2 emissions (in kilotonnes). The latter variable is treated as an undesirable output. GVA is a desirable output. The remaining variables are input ones.

We do not cover all the European Union Member States as some countries have rather different output structures. Therefore, we look at a subset of European countries, thus supplementing and extending research such as that by Robaina-Alves and Moutinho

[19]. The following countries are covered: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany Hungary, Latvia, Lithuania, the Netherlands, Poland, Romania, Slovakia, Slovenia, and Sweden. These countries face similar climatic conditions in general and, therefore, may follow similar agricultural practices. Furthermore, agricultural producers operating in these countries are able to generate similar levels of value added per land area unit due to similar output mix. As a result, even though such countries as Romania and Bulgaria might not face exactly the same climatic conditions, it is meaningful to include them in the same sample due to their specialisation.

4. Results and discussion

The analysis focuses on agricultural sectors of the 18 EU Member States. The analysed countries are rather similar in their farming conditions and/or output structure. The present section comprises the two parts dedicated to the changes in CO_2 emission (i.e., application of IDA) and efficiency analysis (i.e., application of DEA).

4.1. The trends in and decomposition of carbon emission from agriculture

First of all, we look at the dynamics of absolute and relative indicators related to CO_2 emission. Then, an IDA is performed by means of the Shapley/Sun index. Note that this sub-section presents the trends in different variables for both the whole sample and individual states.

4.1.1. The dynamics in absolute indicators

As the dynamics in CO_2 emission is explained in terms of economic activity and energy use, the three absolute indicators can be analysed in the first stage: GVA captures the changes in overall economic activity, the energy use indicator quantifies the energy input, and the carbon emission indicator represents the environmental pressure arising from the processes described by the former two indicators.

Fig. 1 below presents the changes in the absolute indicators for the whole sample. A general observation is that absolute decoupling has occurred between the economic activity and energy use/CO_2 emission during the research period. Furthermore, the change in economic performance was rather meagre during 1995–2003. The subsequent period of 2004–2009 experienced an increase in GVA but with certain short-term declines mainly due to unfavourable climatic conditions (prolonged cold periods, droughts or flooding; cf. [85]. A serious increase in energy consumption during 1996 can be attributed to a prolonged winter period (as indicated by an increase in the number of heating degree days), which rendered a sharp upswing in energy consumption in the Netherlands–a country highly engaged in greenhouse farming. However, no decoupling has been achieved between energy use and CO_2 emission as they stood at 73% and 80% of their initial levels, respectively, at the end of the research period.

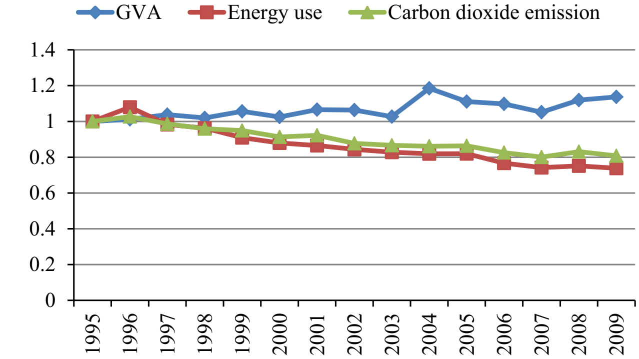

Fig. 1. Carbon emission and related indicators for the group of selected EU countries, 1995–2009. Notes: *GVA* stands for Gross Value Added. The data cover the 18 countries as described in Section 3.3.

Energy use and CO_2 emission followed a negative trend for the entire research period (with a minor exception for energy use in 1996). Obviously, the reduction in CO_2 emission was lower than that in energy use. Specifically, energy use decreased by some 26%, whereas CO_2 emission fell by slightly less than 20%. Therefore, multiple factors have affected the developments in the volume of CO_2 emission in different directions.

Looking at particular countries, one can note that the highest variance in agricultural GVA (as measured in PPS) was observed for Slovakia, Hungary, Bulgaria, Estonia, Latvia, and Sweden (Table 1). Slovakia showed the highest growth rate, 103%. Lower yet still vibrant growth rates of over 60% were observed for Estonia and Hungary. Sweden experienced a growth rate of 34%, whereas Bulgaria's was 3% during the period 1995–2009. A declining GVA was observed for Austria (−7%), Czech Republic (−7%), Romania (−21%), and Slovenia (−1%). Therefore, the general trend prevailing among the analysed EU countries was that of increasing activity of the agricultural sectors.

Most of the analysed countries also showed a reduction in energy use. However, Estonia, Finland, and Slovenia featured an opposite trend, with increases in energy use of 1–12%. As regards to the other countries, these can be grouped into high- and low-decrease nations. High-decrease countries featured growth rates of less than −30%. The latter group comprises Bulgaria, Czech Republic, Germany, Hungary, Lithuania, the Netherlands, Romania, and Slovakia. Low-decrease countries underwent a decrease of more than −30%. These countries are Austria, Belgium, Denmark, France, Latvia, Poland, and Sweden. Indeed, Slovakia and Czech Republic saw the steepest reductions, −53% and −54%, respectively.

Divergence from the prevailing trend in CO_2 emission change was observed in Bulgaria, Estonia, Slovakia, and Sweden. For larger emitters, namely Bulgaria and Sweden, the rates of growth in CO_2 emission were 15% and 22%, respectively. Smaller emitters, namely Estonia and Slovakia, saw increases of 56% and 62%, respectively. The steepest reduction in CO_2 emission was observed for Romanian agriculture (−77%), whereas Germany, Hungary, and Lithuania featured rates of decrease of 38–39%. Therefore, further analysis is needed to reveal the underlying factors behind differences in CO_2 emission across the investigated European countries.

4.1.2. The dynamics in relative indicators

The two relative indicators, namely energy intensity and carbon factor, can further shed light on the observed changes in CO_2 emission (Fig. 2). The results indicate that energy saving technologies have contributed to a reduction in energy intensity, yet changes in fuel-mix have driven up CO_2 emission. The first period of reduction in energy intensity spans over years 1995–2001. Given the output level remained virtually constant throughout the latter period, the reduction in energy intensity was solely due to savings in energy consumption. A closer look at the data[5] for 1995–2001 suggests that the major savings in energy consumption (and, hence, energy intensity) were achieved in Germany, Czech Republic, Poland, and Romania—the countries that had experienced demise of the planned economy and, in certain cases, de-collectivisation. Transition to the market economy rendered technological (modern

[5] See the electronic supplementary material for the initial data set.

Table 1
Rates of growth (%) in key variables for agricultural sectors of selected EU countries, 1995–2009.

	Gross Value Added			Emission relevant energy use			Carbon emissions			Emission intensity			Carbon factor		
	Mean (million 1995 PPS)	Growth (%)	CV	Mean (TJ)	Growth (%)	CV	Mean (kt)	Growth (%)	CV	Mean (million J/ PPS)	Growth (%)	CV	Mean (g/ million J)	Growth (%)	CV
Austria	3463	−6.7	0.05	25,766	−0.3	0.08	1033	−19.0	0.07	7.3	6.9	0.09	40.2	−18.8	0.08
Belgium	2723	1.7	0.04	38,325	−25.1	0.19	2825	−20.4	0.07	13.7	−26.4	0.18	76.2	6.3	0.15
Bulgaria	6675	2.8	0.13	18,813	−35.8	0.16	1018	15.4	0.08	2.7	−37.6	0.17	58.2	79.8	0.19
Czech Republic	4893	−6.7	0.09	30,288	−53.5	0.24	2804	−22.7	0.13	6.1	−50.2	0.24	95.1	66.4	0.15
Germany	19,648	14.4	0.08	169,601	−35.7	0.23	8750	−37.9	0.19	8.4	−43.8	0.27	52.0	−3.4	0.11
Denmark	3240	29.1	0.08	50,286	−3.6	0.04	2523	−15.7	0.06	15.3	−25.3	0.10	49.7	−12.6	0.05
Estonia	553	60.0	0.15	4381	5.1	0.16	185	56.4	0.32	7.7	−34.3	0.18	42.3	48.8	0.20
Finland	3167	18.1	0.09	37,941	12.3	0.06	2104	−16.8	0.07	12.0	−5.0	0.10	54.7	−25.9	0.11
France	32,889	16.5	0.05	190,700	−3.5	0.03	13,989	−7.6	0.03	5.8	−17.1	0.07	73.3	−4.3	0.02
Hungary	6675	66.6	0.23	30,398	−30.8	0.13	1498	−39.0	0.17	4.6	−58.5	0.33	48.7	−11.9	0.07
Lithuania	2102	27.1	0.08	8239	−36.1	0.16	348	−37.6	0.24	3.8	−49.7	0.18	41.9	−2.3	0.11
Latvia	710	35.1	0.13	7756	−26.1	0.11	465	−17.2	0.10	10.6	−45.3	0.18	60.4	12.0	0.06
Netherlands	9379	22.9	0.07	241,818	−35.8	0.20	10,268	−6.4	0.08	24.4	−47.7	0.22	45.2	45.7	0.16
Poland	18,445	21.1	0.06	215,392	−26.5	0.13	15,101	−24.2	0.12	11.4	−39.3	0.19	70.6	3.2	0.03
Romania	17,377	−20.7	0.10	34,955	−39.5	0.30	652	−76.8	0.67	2.0	−23.7	0.26	16.1	−61.7	0.36
Slovakia	2646	102.9	0.27	9686	−52.8	0.30	102	62.0	0.31	3.7	−76.7	0.52	12.3	243.2	0.40
Slovenia	857	−0.7	0.05	5043	0.5	0.26	233	−15.0	0.04	5.8	1.1	0.25	48.7	−15.4	0.18
Sweden	4706	33.5	0.12	35,450	−13.1	0.08	2439	21.5	0.09	7.4	−34.9	0.18	70.5	39.8	0.12

Notes: The data are based on the World Input-Output Database [7]. *CV* stands for coefficient of variation.

machinery featuring higher energy efficiency, improved agricultural practices), economic (market integration and optimisation of agricultural activities), and institutional (family farming) changes, which, in turn, resulted in the reduced energy consumption and intensity. Noteworthy, similar trends prevailed in other sectors of transitional economies [86]. Subsequent decline of energy intensity can be mainly attributed to technological progress (improved machinery). Indeed, modern farming practices were encouraged by the EU funds (e.g., European Agricultural Fund for Rural Development). Especially, investment support has been available for the new EU Member States which acceded in 2004. Besides investments into fixed assets, biogas and biomass production was also encouraged under different measures. Finally, increasing human capital and labour productivity, changes in cropping patterns, farm consolidation all contributed to reduce in energy intensity [12]. In any event, the increase in CO_2 emission due to an increasing carbon factor is not that significant (relative to energy intensity) given the slope of the carbon factor trend is much lower than that of energy intensity. Indeed, this might indicate that economic costs related to changes in fuel-mix are higher than the costs of improving the sector's energy efficiency (as there are virtually no tangible gains from reduction in CO_2 emission). As regards the EU Member States covered by this research, the increase in carbon factor was mainly induced by substitution of gasoil and other carbon-intensive fuels for natural gas. This was influenced by both fluctuations in fuel prices and support policies.

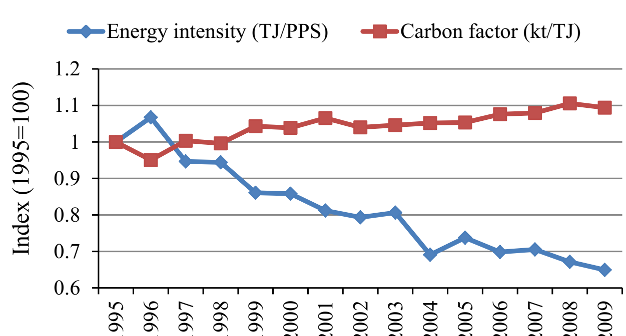

Fig. 2. Energy intensity and carbon factor for the group of selected EU countries, 1995–2009. Notes: *TJ* stands for terajoules, *PPS* – Purchasing Power Standards, *kt* – kilotonne. The data cover the 18 countries as described in Section 3.3.

Only Austria and Slovenia exhibited increases in energy intensity, of 7% and 1%, respectively (Table 1). At the other end of spectrum, the most significant decreases were observed in Hungary and Slovakia, namely −68% and −77%, respectively. The highest mean energy intensity was observed in the Netherlands (24 kJ/PPS). Denmark featured the second highest mean energy intensity of 15 kJ/PPS. The countries with higher values of mean energy intensity differed in terms of rates of decrease in the latter indicator. Belgium, Denmark, and Finland showed mean energy intensities of 12–15 kJ/PPS coupled with a decrease of some 5–25%. In contrast, the Netherlands and Poland (mean energy intensities of 24 kJ/PPS and 12 kJ/PPS, respectively) experienced rates of decrease of 48% and 39%, respectively. All in all, the analysed countries seem to be successful in reducing energy intensity in the agriculture sector during 1995–2009.

The changes in carbon factor are more diverse across the analysed countries as opposed to changes in energy intensity. Specifically, nine countries showed an increase in carbon factors. The highest increase in carbon factor was observed for Slovakia (more than 240%). The growth rates ranged between 40% and 80% for Bulgaria, Czech Republic, Estonia, the Netherlands, and Sweden. Latvia, Belgium, and Poland experienced much lower rates of growth, namely 3–12%. The highest mean carbon factor was observed in Czech Republic (95 t CO_2/GJ). Furthermore, Belgium, France, Poland, and Sweden exhibited significant increases in carbon factor, with growth rates exceeding 70%.

Coefficients of variation (CV) for the two relative indicators (Fig. 3) suggest that no serious improvements in convergence were achieved, as the values of the CVs remained rather stable throughout the research period. Obviously, variation in carbon factors is much higher than in energy intensities. Therefore, relatively higher variation in carbon factors implies the analysed countries utilise rather different fuel-mixes. This implies that further research on mitigating CO_2 emission via changes in fuel-mix is rather important. As regards the carbon factor, one can notice a downward trend in the CV for the period 2002 and onwards. However, the latter plunge did not offset a previous increase and, therefore, the

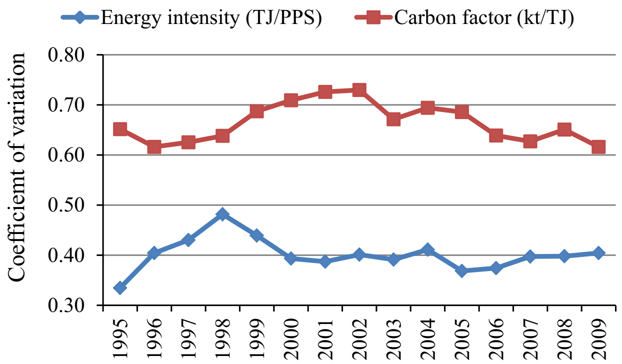

Fig. 3. Coefficients of variation for energy intensity and carbon factor, 1995–2009. Notes: *TJ* stands for terajoules, *PPS* – Purchasing Power Standards, *kt* – kilotonnes. The data cover the 18 countries as described in Section 3.3.

value of CV for carbon factor remained at the same level for the two endpoints of the time series for 1995–2009. CV for energy intensity fluctuated during 1995–2000 and subsequently increased as compared to year 1995. Afterwards, it remained stable, indicating no convergence in energy intensity in agriculture among the European countries. All in all, the spread of energy-efficient technologies and promotion of renewables remain the key means for reducing the (persistent) gaps in energy intensities and carbon factors. In the following sub-section we apply IDA to quantify the contributions of different factors to the change in CO_2 emission.

4.1.3. The results of IDA

IDA allows quantification of the contributions of different factors to the overall change in CO_2 emission. The results in absolute terms are presented in Fig. 4. The analysis was carried out in a chain-linked manner and the results were aggregated for the whole research period.

The absolute contractions in CO_2 emission exceeded 1000 kt in Germany, Poland, Romania, and France. IDA shows (see Fig. 4) that France and Germany are similar in their decomposition profiles, as both carbon factor and energy intensity contribute to a decrease in CO_2 emission, whereas increased economic activity has the opposite effect. Romania deviates from the latter pattern in that it experienced a decreasing agricultural output. For Poland, an increasing carbon factor caused a rise in CO_2 emission by 439 kt, yet this change was offset by improvements in energy efficiency, as suggested by a negative contribution of intensity effect (−7296 kt).

The second group of countries comprises Czech Republic, the Netherlands, Hungary, Belgium, Denmark, and Finland, where CO_2 emission decreased by 383–757 kt during 1995–2009. Notably, the Netherlands saw a large reduction in CO_2 emission (6441 kt) due to decreasing energy intensity. However, changes in fuel-mix (i.e., carbon factor change) and an increasing output (i.e., activity effect) pushed CO_2 emission up by 3610 kt and 2107 kt, respectively. Therefore, the overall change in CO_2 emission was rather meagre there as compared to countries with similar emission volumes. Czech Republic experienced a similar absolute reduction to that of the Netherlands due to a decreasing agricultural output and, more importantly, a decreasing energy intensity. In Belgium, CO_2 emission decreased due to an increase in energy efficiency (as represented by energy intensity effect) by 907 kt, whereas carbon factor and activity effects caused increases of 212 kt and 67 kt, respectively. In Hungary, Denmark, and Finland, CO_2 emission in those countries was reduced due to decreasing carbon factors and energy intensity. The effect of energy intensity was rather low in Finland (a decrease of 59 kt in CO_2 emission), suggesting a need for further energy efficiency measures in that country.

Countries with small absolute contractions in CO_2 emission are rather diverse in their decomposition patterns. The latter group comprises Lithuania, Austria, Latvia, and Slovenia, which, indeed, are mainly small emitters. Lithuania and Latvia experienced similar reductions in CO_2 emission caused by an energy intensity effect (272 kt). However, carbon factor caused an increase of 47 kt in Latvia. In addition, an activity effect was more evident in the latter country. Therefore, Latvia showed the total reduction of 90 kt, whereas Lithuania had a 192 kt reduction. This finding implies that fuel-mix could be adjusted in Latvia in order to curb the emissions. Austria and Slovenia share the same pattern of decomposition, namely a negative carbon factor effect, a positive energy intensity effect, and a negative activity effect. Note that the activity effect is

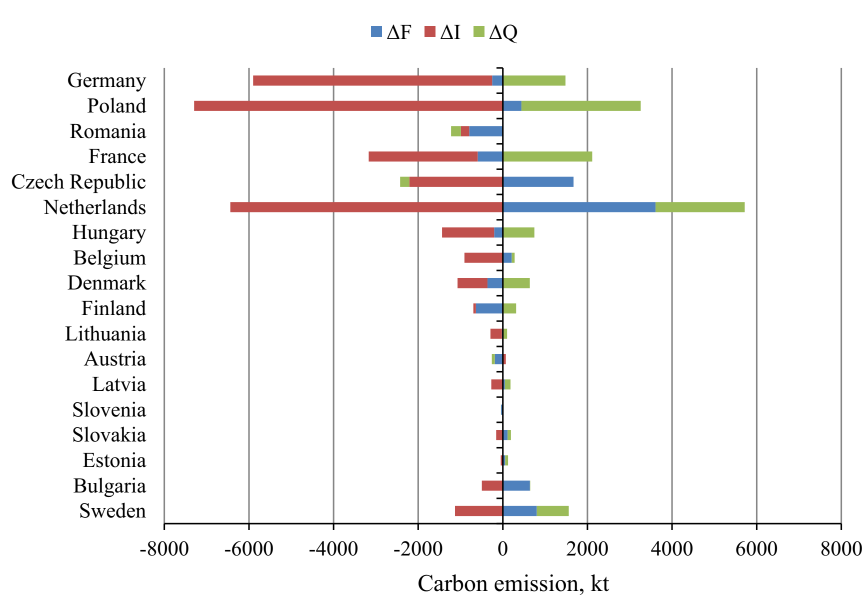

Fig. 4. Decomposition of change in CO_2 emission across the analysed countries, 1995–2009 (absolute terms). Note: ΔF, ΔI, and ΔQ stand for carbon factor, energy intensity, and activity effects, respectively.

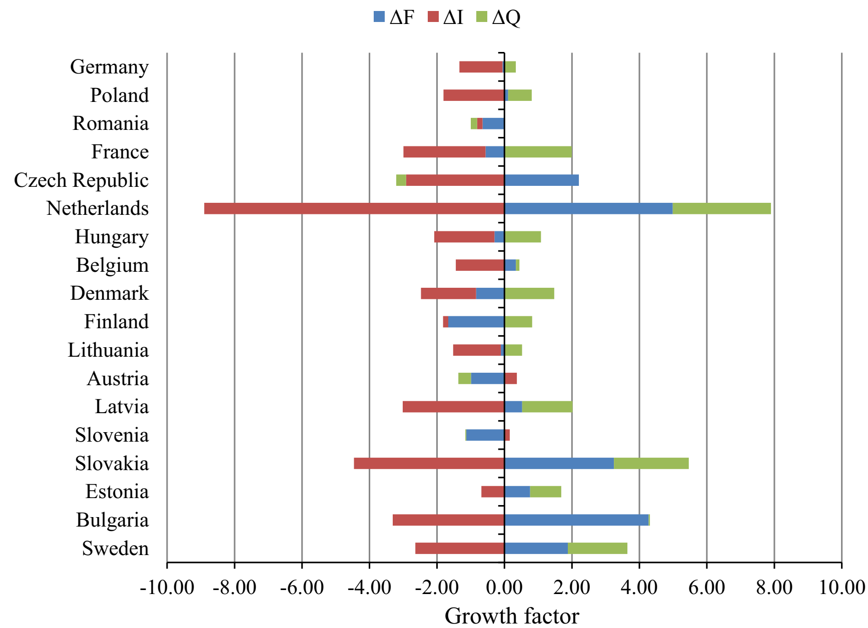

Fig. 5. Decomposition of change in CO_2 emission across the analysed countries, 1995–2009 (relative terms). Notes: ΔF, ΔI, and ΔQ stand for carbon factor, energy intensity, and activity effects, respectively. Growth rates are negated for countries with a decrease in carbon emission.

rather insignificant in Slovenia (a reduction in CO_2 emission of 1 kt). Indeed, a steeper decrease in carbon factor and economic activity yielded a higher decrease in Austria (191 kt) as compared to Slovenia (38 kt).

The last group of countries comprises Slovakia, Estonia, Bulgaria, and Sweden. These countries showed an increase in CO_2 emission during 1995–2009 and shared the same pattern of decomposition. Specifically, the increase in CO_2 emission was mainly driven by increasing carbon factor and economic activity in those nations. Energy intensity effect was negative for all four countries. Estonia is distinctive in that the carbon factor effect (56 kt) was lower than the economic activity effect (68 kt). Therefore, carbon factor remains the most important factor behind an increase in energy-related CO_2 emission from agricultural sectors in this group of countries. Abatement of CO_2 emission in these countries, therefore, might involve relatively higher costs, as changes in carbon factor are closely linked to fuel-mix. Indeed, a systematic approach is needed to implement and streamline effective changes in fuel-mix.

In order to compare the extent of contribution of various factors to CO_2 emission from agricultural sectors across different countries, Fig. 5 presents a relative decomposition[6]. In this comparison, the contributions of all the factors are normalised with respect to the overall change in CO_2 emission. Obviously, energy intensity effect had the same relative importance across most of the analysed countries, with the exception of Romania, Finland, Austria, Slovenia, and Estonia. Therefore, technological advancement aimed at reduction of energy intensity is topical for those particular countries. The relative contribution of carbon factor is much more varying across the countries.

The results of IDA have also been aggregated across countries to present the temporal developments in the driving forces of CO_2 emission from agricultural sectors (Fig. 6). Noticeably, the period before year 2002 shows a more or less constant impact of energy intensity effect. Excluding the period 1995–1996, the energy intensity effect pushed CO_2 emission down by 1014–6993 kt every year. The period 2002–2005 experienced diverse directions of the impact of energy intensity. However, the increases in CO_2 emission due to energy intensity during 2002–2003 and 2004–2005 of 1317 and 3055 kt, respectively, are netted out by a reduction of 8133 kt in 2004 (as well as subsequent developments). The period of 2005–2008 experienced a decreasing absolute impact of energy intensity, and a rebound was observed during 2008–2009.

The direction of the impact of carbon factor changes year to year. However, the period of 1996–2001 generally marks an increase in CO_2 emission due to the dynamics in carbon factor. A significant negative impact upon emission volume is observed only for 1995–1996 and 2001–2002. The period 2002–2006 shows no important contribution of carbon factor to CO_2 emission. During the rest of the research period, only 2007–2008 is associated with a decisive effect of carbon factor, namely an increase in emission by 1596 kt.

Turning to the impact of activity effect, the latter mostly contributed to CO_2 emission during 1995–2002. Afterwards, direction of the effect varied, being positive during 2003–2004 and negative throughout 2004–2008. Indeed, the latter trend can be attributed to a reduction in output during a period of unfavourable climatic conditions. Economic growth, however, gained momentum again in 2007–2009, and the activity effect played an important role during the last period examined, 2008–2009.

To sum up, CO_2 emission from agricultural sectors went down by some 14 thousand kt in the analysed countries during 1995–2009. The major factor behind this change is intensity effect, which rendered a reduction of 29 thousand kt. Carbon factor inflated CO_2 emission by 4 thousand kt. A much higher impact was attributed to activity effect, i.e., 11 thousand kt. Therefore, gains in energy efficiency were the main factor contributing to the reduction in CO_2 emission, whereas changes in fuel-mix exerted an opposite effect of half the magnitude.

4.2. Environmental efficiency and shadow pricing

In previous sub-section we looked at the causes behind the dynamics in CO_2 emission from agricultural sectors. This sub-section focuses on performance gaps as measured by an environ-

[6] Alternatively, one could employ multiplicative IDA to calculate relative contributions of the underlying factors.

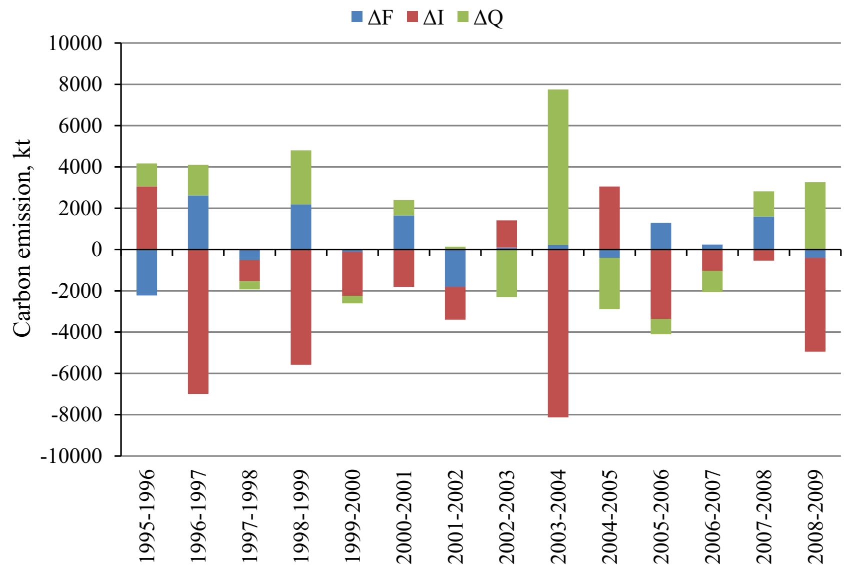

Fig. 6. Decomposition of carbon emission for the whole sample, 1995–2009. Notes: ΔF, ΔI, and ΔQ stand for carbon factor, energy intensity, and activity effects, respectively. The data cover the 18 countries as described in Section 3.3.

mental efficiency model (see Section 3.2). These approaches complement each other, as both of them take economic activity and CO_2 emission into account. However, the environmental efficiency model also accounts for production factors other than energy. For example, it would take into account countries with high energy efficiency and/or low carbon factors that might not necessarily maintain technical and, hence, environmental efficiency.

As the SBM model rests on a simultaneous consideration of both input and output slacks, the resulting efficiency scores cannot be interpreted straightforwardly. However, the higher values of efficiency scores indicate lower slacks of inputs and/or outputs. Indeed, it is possible to decompose the SBM efficiency scores [12]; however, for the sake of brevity, we do not take this approach.

Analysis of the weighted mean environmental efficiency scores (Fig. 7) indicates an upward trend in environmental performance. Note that the agricultural GVA is used as a weighting factor. Two major falls in efficiency are observed for the year 2001 and the period 2005–2007. At the beginning of the research period, the mean efficiency score was 0.47. It peaked in 2004 at 0.61, and, following a decline, stood at 0.59 in 2009.

Another important aspect of the analysis is the convergence in efficiency scores. The results indicate (Fig. 8) that the CV for environmental efficiency scores experienced a downward trend during 1995–2009. This implies the analysed countries achieved a certain degree of convergence in terms of environmental performance. However, this process was subdued after 2001. In any event, the coefficient of variation went down from 0.56 in 1995 to 0.40 in 2009. Note that the bottom values, namely 0.37, were achieved in 2001 and 2005. Therefore, the analysed countries managed to converge in terms of environmental performance, as suggested by efficiency measures, yet this process was subdued in 2003–2009.

Table 2 presents mean efficiency scores for each country. The highest scores are observed for Belgium, Slovenia, Romania, Austria, and France (efficiency scores for these countries fall in the range of 0.78–0.66). Of the best performing countries, Austria and Belgium both exhibited a decrease in efficiency during 1995–2009. As regards Belgium, these changes can (partially) be attributed to poor energy and carbon productivity. For Austria, an increase in energy intensity might have had a negative effect, yet the magnitude of that change was not a decisive one (an increase in CO_2 emission of 70 kt during 1995–2009). Therefore, technical inefficiency might be a more important source of environmental inefficiency in this case. Looking at the least efficient states, one can notice that an increase in efficiency is observed in most cases during 1995–2009. However, the two lowest-ranking countries – Czech Republic and Estonia – do not follow this trend. In the latter two cases, mean efficiency was 0.26, thus indicating a serious performance gap.

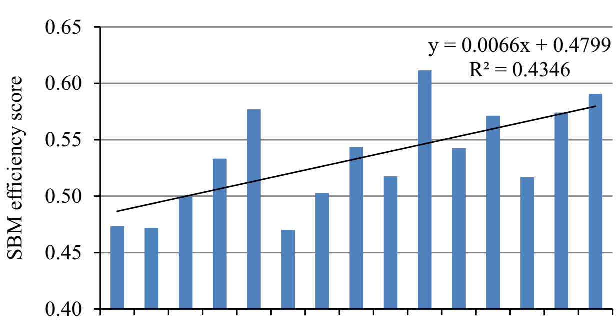

Fig. 7. Weighted mean environmental efficiency, 1995–2009. Note: Agricultural GVA is used for weighting. *SBM* stands for Slack-based Model.

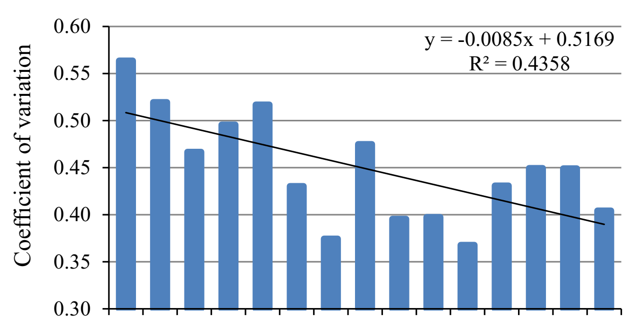

Fig. 8. Variation in environmental efficiency across the analysed countries, 1995–2009. Note: The data cover the 18 countries as described in Section 3.3.

Table 2
Mean environmental efficiency scores across countries, 1995–2009.

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Mean	Rank
Austria	1.00	0.75	0.77	0.85	0.89	0.70	0.60	0.54	0.51	0.59	0.56	0.56	0.61	0.74	0.65	0.69	4
Belgium	0.89	1.00	1.00	1.00	0.93	1.00	0.86	1.00	0.67	0.74	0.52	0.60	0.55	0.50	0.47	0.78	1
Bulgaria	0.40	0.37	0.63	0.62	0.65	0.53	0.57	0.60	0.58	0.79	0.57	0.61	0.40	0.53	0.50	0.56	7
Czech Republic	0.23	0.23	0.21	0.23	0.24	0.25	0.25	0.26	0.29	0.31	0.34	0.29	0.25	0.25	0.26	0.26	18
Germany	0.23	0.25	0.26	0.25	0.29	0.30	0.32	0.30	0.29	0.38	0.34	0.33	0.32	0.30	0.32	0.30	15
Denmark	0.29	0.31	0.31	0.32	0.32	0.35	0.37	0.35	0.37	0.38	0.33	0.30	0.29	0.31	0.46	0.34	13
Estonia	0.26	0.25	0.28	0.33	0.31	0.34	0.27	0.28	0.28	0.25	0.22	0.20	0.21	0.22	0.25	0.26	17
Finland	0.34	0.33	0.39	0.32	0.31	0.33	0.32	0.33	0.31	0.31	0.32	0.32	0.37	0.42	0.41	0.34	12
France	0.60	0.64	0.63	0.66	0.71	0.67	0.61	0.72	0.52	0.74	0.65	0.66	0.63	0.69	0.78	0.66	5
Hungary	0.18	0.19	0.20	0.20	0.21	0.21	0.26	0.23	0.25	0.41	0.42	0.39	0.31	0.50	0.48	0.30	16
Lithuania	0.31	0.36	0.40	0.37	0.34	0.38	0.37	0.38	0.38	0.38	0.37	0.31	0.35	0.37	0.41	0.37	11
Latvia	0.25	0.24	0.29	0.28	0.29	0.35	0.36	0.37	0.34	0.32	0.31	0.27	0.29	0.33	0.34	0.31	14
Netherlands	0.45	0.42	0.49	0.43	0.45	0.45	0.41	0.40	0.43	0.47	0.47	0.48	0.49	0.53	0.63	0.47	10
Poland	0.55	0.54	0.58	0.82	1.00	0.40	0.51	0.52	0.53	0.57	0.55	0.56	0.49	0.48	0.61	0.58	6
Romania	0.53	0.50	0.53	0.51	0.54	0.43	0.73	0.78	1.00	1.00	0.87	1.00	0.72	0.86	0.63	0.71	3
Slovakia	0.37	0.34	0.36	0.34	0.32	0.33	0.38	0.48	0.55	0.52	0.44	0.56	0.82	1.00	1.00	0.52	8
Slovenia	1.00	0.85	0.77	0.60	0.50	0.51	0.50	1.00	0.46	0.77	0.83	0.83	1.00	1.00	1.00	0.77	2
Sweden	0.42	0.41	0.43	0.40	0.41	0.41	0.43	0.44	0.47	0.55	0.50	0.64	0.69	0.65	0.71	0.50	9

Following Eq. (10), shadow prices were derived for energy-related CO_2 emission from agricultural sectors. Fig. 9 presents the weighted mean for the whole sample, with emission volumes used for weighting. Corresponding to an increasing environmental efficiency, the mean shadow price increased during 1995–2009. However, the upward trend for shadow prices is more evident than it was for efficiency (Fig. 7). Decreases are observed for 2001–2003 and 2005–2006. An increase in mean shadow price indicates that reduction in CO_2 emission is in general becoming costlier given the underlying productive technology. Therefore, further reduction in CO_2 emission in agricultural sectors requires reasonable targets and allocation across countries. Still, Fig. 10 implies there has been an increase in variation of shadow prices across the analysed countries. Specifically, a decrease was observed for 1995–2000, yet the trend was reversed afterwards. Alongside several declines, CV for shadow prices increased from its lowest point of 1.34 in 2001 up to 1.90 in 2009. Note that the initial value (in year 1995) was 1.81. In general, an increase in agricultural GVA is related to an increase in CV of carbon shadow prices, as is confirmed by a linear trend for CV against GVA: $CV = 0.024GVA - 1.56$, where GVA is measured in billion PPS of 1995, $R^2 = 0.41$. Therefore, increases in economic activity seem to have had different impacts on shadow carbon prices across European agricultural sectors.

A marginal abatement cost curve was established for the entire sample (Fig. 11). Clearly, the curve features a downward trend, which indicates that abatement costs rise along with emission intensity. Emission intensity and abatement costs are exponentially related. Fig. 11 suggests that the rate of increase in abatement costs increases faster when emission intensity falls below 0.5 t/thousand PPS. An even more steep increase is observed for intensities below 0.25 t/thousand PPS. These figures provide some insights into possible reductions in emission intensity in European agriculture. Specifically, aiming at reducing emissions below 0.25 t/thousand PPS would require significant support measures and might not be reasonable in terms of food security goals.

Country-specific results regarding abatement costs are presented in Table 3. The latter table also presents the data on carbon factors and energy intensities. These two relative indicators can give some insights into the level of shadow prices. However, the ratios of relative indicators and shadow prices between countries

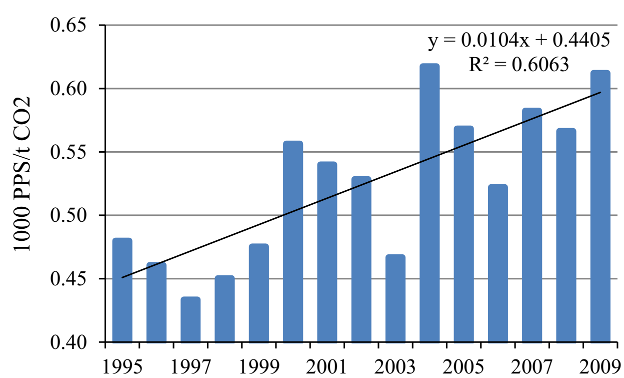

Fig. 9. Weighted mean CO_2 emission shadow price, 1995–2009. Notes: Carbon emission is used as the weight factor. *PPS* stands for Purchasing Power Standards. The data cover the 18 countries as described in Section 3.3.

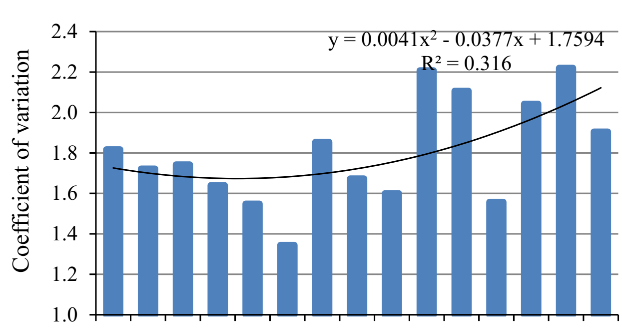

Fig. 10. Variation in shadow prices of CO_2 emission across the analysed countries, 1995–2009. Note: The data cover the 18 countries as described in Section 3.3.

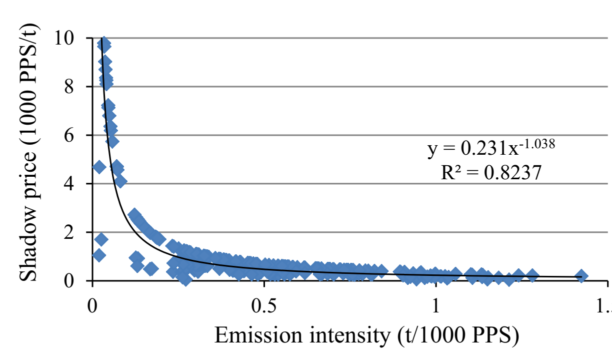

Fig. 11. Marginal abatement cost curve for the analysed countries, 1995–2009. Notes: Carbon emission is used as the weight factor. *PPS* stands for Purchasing Power Standards, *t* stands for tonnes. The data cover the 18 countries as described in Section 3.3.

Table 3
Marginal abatement costs as represented by carbon emission shadow prices across European countries, 1995–2009.

	Abatement costs				Mean carbon factor, t/GJ	Mean energy intensity, kJ/PPS
	Mean (1000 PPS/t)	Rank	Coefficient of variation	Rank		
Austria	0.58	10	0.27	10	40.19	7.46
Belgium	0.15	18	0.38	8	75.61	14.17
Bulgaria	1.55	5	0.49	3	55.55	2.88
Czech Republic	0.59	9	0.18	14	94.81	6.23
Germany	0.78	7	0.22	12	52.12	8.75
Denmark	0.34	15	0.18	16	50.18	15.61
Estonia	1.09	6	0.46	4	41.19	8.07
Finland	0.42	13	0.18	15	55.76	12.04
France	0.42	12	0.08	18	73.35	5.81
Hungary	1.57	4	0.38	7	49.10	4.85
Lithuania	2.11	3	0.21	13	41.89	3.95
Latvia	0.51	11	0.14	17	60.05	11.14
Netherlands	0.24	16	0.23	11	43.63	26.15
Poland	0.23	17	0.32	9	70.25	11.79
Romania	9.96	1	0.60	1	17.10	2.01
Slovakia	8.39	2	0.39	6	11.74	4.10
Slovenia	0.67	8	0.53	2	48.25	5.88
Sweden	0.41	14	0.45	5	69.33	7.68

are not of the same magnitude, as shadow prices rely on efficiency measures and, thus, capture more information regarding trade-offs in the production process.

Given both Fig. 10 and Table 3 confirm the differences existing among countries in terms of carbon shadow prices, it might be concluded that the costs associated with environmental pressures are not internalised in agricultural sectors. Indeed, the agricultural sector has not been included in such frameworks as the Emission Trading Scheme in the EU.

Romania and Slovakia show the highest mean shadow prices of 9.96 and 8.39 thousand PPS/t, respectively. The third highest mean price is observed for Lithuania, namely 2.1 thousand PPS/t. This indicates an important gap between shadow prices for the second- and third-highest positions. Such differences, indeed, are not observed between other positions. The highest ranking countries feature rather low values of carbon factor and energy intensity. Therefore, application of innovative energy technologies should go beyond state-of-the-art there, which would require tremendous investment. However, IDA showed that changes in fuel-mix would contribute to reductions in CO_2 emission in Romania and Slovakia.

The lowest carbon shadow prices are observed in France, Finland, Sweden, Denmark, the Netherlands, Poland, and Belgium. Specifically, the shadow prices range between 420 and 410 PPS/t for France, Finland, and Sweden. The shadow price for Denmark is 340 PPS/t, whereas the Netherlands and Poland share rather similar values of 240 and 230 PPS/t, respectively. Finally, Belgium shows the lowest price of 150 PPS/kt. These countries, therefore, feature the highest potential for reduction in CO_2 emission.

The results of the IDA might be helpful in identifying the prospective development paths for curbing CO_2 emission. Considering data in Table 3 and Fig. 5, one can conclude that France needs improvements in fuel-mix in order to reduce the carbon factor there. Focusing on Finland, Sweden, the Netherlands, and Belgium, energy intensity might be the primary way for a reduction in CO_2 emission. Even though Denmark has seen a decrease in both carbon factor and energy intensity, their values still remain relatively high. Therefore, further implementation of sustainable energy technologies is important in both areas.

5. Conclusions

Agricultural activities are rather important in terms of food security. However, it is also important to balance food security and climate change mitigation strategies. In this paper, we attempted to look into energy-related CO_2 emissions from agricultural sectors of selected EU Member States. The analysis was based on aggregate data from the World Input-Output Database. Methodologically, two main directions were taken for the research. Firstly, Index Decomposition Analysis was facilitated by means of the Shapley index. Secondly, the Slack-Based Model was applied to gauge the environmental efficiency of European agricultural sectors. Therefore, the combination of the two techniques allowed us to gain deeper insights into the trends in CO_2 emission and the policy options to mitigate it.

The results indicate that absolute decoupling between economic activity and energy use/CO_2 emission was achieved for the whole sample during 1995–2009. Energy intensity appeared to be the main factor behind the decreasing energy-related CO_2 emission. The downward trend in energy intensity can be explained by technological innovations and transition in the post-communist countries, where technological innovations were intertwisted with economy-wide shifts in production and distribution. Carbon factor fuelled growth in CO_2 emission, yet the effect was not a decisive one. The substitution of natural gas by other fuels was the main factor inducing the increase in carbon factor.

The analysis of environmental efficiency suggested that the weighted mean efficiency increased in general during the research period. Furthermore, the coefficient of variation decreased, thus implying a convergence among the analysed countries. The highest efficiency scores were observed for Belgium, Slovenia, Romania, Austria, and France, whereas Czech Republic and Estonia were the lowest performing countries.

The Data Envelopment Analysis model allowed us to compute shadow prices for CO_2 emission. The general trend was that of an increase in the shadow price, which indicates that more output should be abandoned in order to facilitate a reduction of the same magnitude in CO_2 emission. Therefore, an increase in carbon productivity over time can be assumed. However, a kind of disparity was noticed among the countries with respect to shadow prices. These findings imply that, even though opportunity costs for reductions in CO_2 emission have increased on average, there are certain countries with relatively low carbon performance. Therefore, there is a need to better coordinate the process of reduction in CO_2 emission among EU nations. The lowest carbon shadow prices are observed in France, Finland, Sweden, Denmark, the Netherlands, Poland, and Belgium. These countries, thus, feature the highest potential for reduction in CO_2 emission.

As there are two main paths to curb CO_2 (or, more generally, GHG) emissions related to energy consumption in agriculture, namely to increase energy efficiency and to increase the use of renewable energy sources, the present study sheds some light on the choice of such policies. It turns out, policies aimed at increasing energy efficiency were the most effective in terms of CO_2 emission reduction in agriculture. On the other hand, the share of renewables in final energy consumption in agriculture did not affect the development of CO_2 emission significantly. Therefore, greater emphasis on energy efficiency policies is necessary in Europe to achieve CO_2 emission reduction targets. Furthermore, costs associated with energy efficiency improvements and the use of renewables should be considered in order to mesh the goals of food security with those of climate change mitigation. The use of improved machinery and farming practices can reduce energy intensity, whereas promotion of renewable energy production would enable to dampen carbon intensity of energy. In case of the EU, the Common Agricultural Policy (as implemented via rural development programmes) could foresee measures aimed at encouraging investments into energy-efficient machinery and buildings. The extension and advisory services could be useful in developing the human capital through systematic education on energy-saving practices of farming. Regional differences should also be taken into account. Precision farming, recycling of agricultural residues, cooperation, and integrated decision making would provide a sound basis for development of energy- and carbon-efficient agriculture.

There are a number of avenues for further research in regards to carbon efficiency and productivity in European agriculture. It is possible to include more factors into the IDA model. This is especially relevant for the agricultural sector. For instance, the effects of re-allocation of agricultural production across different countries can be taken into account. A comparison of different efficiency measures might enable delivery of deeper insights into the environmental performance of European agriculture. Therefore, application of the framework of by-production would enrich the analysis in the latter sense. Results of the study might also be fed into models for a quantitative allocation of emission reduction. The main factors of environmental performance could be analysed by applying regression techniques. Furthermore, marginal abatement cost curves could also be adjusted to contextual variables. Besides carbon efficiency, carbon productivity could also be analysed based on different efficiency measures. It is also important to isolate structural inefficiency. Finally, the changes in shadow prices can be decomposed in terms of different factors.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.08.031.

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