Journal of Cleaner Production 164 (2017) 686–694

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

# Energy-related GHG emission in agriculture of the European countries: An application of the Generalized Divisia Index

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ARTICLE INFO

*Article history:*
Received 12 May 2017
Received in revised form
2 July 2017
Accepted 2 July 2017
Available online 3 July 2017

*Keywords:*
GHG emissions
Energy consumption
Agriculture sector
Index decomposition analysis
Generalized Divisia Index

ABSTRACT

Sustainable agriculture, food security, and welfare of the farmers require an integrated analysis of the performance of the agricultural sector. In this paper, we follow the energy-environment-economy framework and focus on decomposition of changes in the energy-related greenhouse gas (GHG) emission in agricultural sectors of the selected European Union (EU) countries. The research relies on country-level data from FAO and Eurostat describing economic activity, energy use, and GHG emission in the agricultural sectors of the European countries during 1995–2012. The main drivers (carbon factor of energy consumed in agriculture, energy intensity of agricultural production and growth in agricultural production) and their impacts on the energy-related GHG emissions in agriculture are analysed for selected countries. The Generalized Divisia Index is applied to decompose the changes in the energy-related GHG emissions. France, Latvia, and Belgium appeared as the only countries with increase in GHG emissions during 1995–2012. In the case of France, energy intensity went up along with increase in the scale of agricultural production. In Latvia and Belgium, an increase in carbon factor appeared as the major factor driving an increase in GHG emissions. The appropriate policies need to be employed in these countries seeking to reduce GHG emissions from energy consumption in agriculture. Improvements in energy efficiency appear to be a more feasible mean for ensuring further reductions in GHG emission.

## 1. Introduction

Creation of low-carbon economy can contribute to climate change mitigation. In order to streamline this process, international bodies have made attempts to define the corresponding policy guidelines and support measures (Jänicke, 2012; Liobikienė et al., 2017; Liobikienė et al., 2017; Beltrán-Esteve, Picazo-Tadeo, 2017; Yang et al., 2017). Promotion of renewable energy is rather important in this context (Boyle, 1997; Boroojeni et al., 2016). Besides normative approach towards the issue, one also needs to assess the progress in achieving the goals of low-carbon economy. Therefore, it is important to trace and analyse the trends in GHG emission across countries and sectors. Sheng et al. (2016a, 2016b), and Miao et al. (2016) proposed principles and models for reallocation of GHG emissions.

Economy-wise, Moutinho et al. (2017) and Beltrán-Esteve and Picazo-Tadeo (2017) compared performance of the European Union (EU) Member States by applying data envelopment analysis. Madaleno and Moutinho (2017) and Liobikienė and Butkus (2017) analysed the trends in GHG emission across the EU Member States. A similar vein can be followed at the industry level. For instance, Robaina-Alves et al. (2016) looked into the energy related greenhouse gas (GHG) emission from the Portuguese tourism sector. Suchlike analysis enables one to identify the best practice along with possible means for improvement.

The mitigation of environmental pressures should allow for economic growth (Dirzyte, Rakauskiene, 2016; Fuinhas et al., 2016; Wu et al., 2017). Following the concept of energy-environment-economy (E3), the energy-related environmental pressures should be analysed in the light of dynamics in the economic activity. Such an analysis can be facilitated by means of decomposition analysis, among other techniques. The main idea of the decomposition analysis is to factorize the changes in the aggregate

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http://dx.doi.org/10.1016/j.jclepro.2017.07.010

**Nomenclature**

| | |
|---|---|
| $t$ | time index |
| $Y_i$ | agricultural output for the $i$-th country |
| $E_i$ | energy consumption for the $i$-th country |
| $GHG_i$ | GHG emission for the $i$-th country |
| $F_i$ | the carbon factor effect |
| $\Delta Z_{X_i}$ | the change in $Z$ due to change in $X_i$ |
| $\Delta Z$ | the change in $Z$ |
| $I_i$ | the energy intensity effect |
| $X_i$ | the factor variable of the IDA identity |
| $S_i$ | the structural effect |
| $Y$ | the total agricultural output |
| $Z$ | the aggregate variable of the IDA identity |
| *Subscript* | |
| $i$ | country index |
| *Greek* | |
| $\mathbf{\Phi}(\mathbf{X})$ | equation system for the Generalized Divisia Index |
| $\mathbf{\Phi}_X$ | Jacobian matrix of $\mathbf{\Phi}(\mathbf{X})$ |

variable with respect to the underlying factors. This allows identifying the key contributors to dynamics in the variable of interest.

Index decomposition analysis (IDA) is an appealing tool for decomposition analysis (Ang and Choi, 1997; Xu and Ang, 2013). IDA can be carried out at international level (Ang et al., 2015), national level (Zhang et al., 2017; Shao et al., 2016a; Zhao et al., 2016; Madaleno and Moutinho, 2017), and sectoral level (Shao et al., 2016b). Also, sectoral performance across different countries (Kopidou et al., 2016) and regions (Lu et al., 2015) can be analysed by means of the IDA. Therefore, the approach is rather flexible in terms of the level of aggregation.

Different approaches can be taken for the IDA in terms of the underlying index numbers. Recently, Vaninsky (2013, 2014) proposed the Generalized Divisia Index approach. The latter technique allows for more complex interrelationships among the underlying factors governing the change in the aggregate variable and, therefore, allows for a finer decomposition. Shao et al. (2016b) applied the Generalized Divisia Index approach in the context of the Chinese mining sector.

In the European Union (EU), several strategic documents have been released with focus on resource-efficient and low-carbon economy. Strategy Europe 2020 (European Commission, 2010) and the flagship initiative *A resource-efficient Europe* (European Commission, 2010) can be regarded as examples of documents on environmentally-sensitive policies in the region. To successfully address the issues of sustainable growth, sectoral analysis is also important. As noted by European Environment Agency (2014), agricultural products appear among the most GHG emission-intensive products in the EU. What is more, the Common Agricultural Policy (European Parliament, Council of the European Union, 2013) seeks not only for productivity but also for sustainability in the agricultural sector for the period of 2014–2020. Therefore, Vlontzos et al. (2014) applied data envelopment analysis to estimate the efficiency of agricultural sectors of the EU countries with focus on energy use. Ghali et al. (2016) followed a similar approach at a farm level in French agriculture. Martinho (2016) and Robaina-Alves and Moutinho (2014) applied IDA to analyse energy use and energy-related GHG emissions in the European agriculture, respectively. However, the Generalized Divisia Index has not been applied in this area yet and the structural effects capturing the effects of re-allocation of agricultural production activities across the countries have not been considered yet. Therefore the paper applies new method for the analysis of the main drivers of energy related GHG emissions including the capture of the effects of re-allocation of agricultural production activities across the EU member States.

In this paper we decompose the changes in the energy-related GHG emission with respect to multiple drivers across agricultural sectors of the selected EU countries. Empirically, we contribute to the discussion on the energy-related emissions and their drivers in agriculture. We also focus on transition countries in the EU, which often remain neglected in the analysis. Methodologically, we apply an innovative approach, namely the Generalized Divisia Index which allows identifying the effects of multiple inter-related factors driving the GHG emission. We include the structural element in the IDA identity to account for shifts in the agricultural production across the countries. The research relies on country-level data from FAO and Eurostat describing economic activity, energy use, and GHG emission in the agricultural sectors of the European countries. Indeed, we focus on the 17 European countries featuring rather similar production structure (mainly, Northern, Central, and Eastern Europe). The data cover years 1995–2012. The Generalized Divisia Index is applied to decompose the changes in the energy-related GHG emissions. The paper proceeds as follows: Section 2 presents the preliminaries of the research with focus on the Generalized Divisia Index and data used. Section 3 discusses results of the analysis. Finally, Section 4 concludes.

## 2. Preliminaries

This section presents the approach taken for the IDA as well as the data sources. The Generalized Divisia Index is presented in order to demonstrate its differences from the conventional techniques. The IDA model for energy-related GHG emission from agriculture in European countries is then adapted for the Generalized Divisia Index. Finally, data used are described. Fig. 1 presents the schematic overview of the research.

### 2.1. The Generalized Divisa Index

The IDA identity rests on the ideas out forward by Laspeyres (1871), Paasche (1874) and Divisia (1925). Specifically, it represents the main objective of the factorial decomposition, namely factorization of the aggregate variable into terms associated with the underlying indicators. Let $Z$ be the aggregate variable defined as a product of the underlying indicators (factors) $X_i$, $i = 1, 2, \ldots, n$. Thus, the IDA identity can be given as follows:

$$Z = \prod_{i=1}^{n} X_i. \tag{1}$$

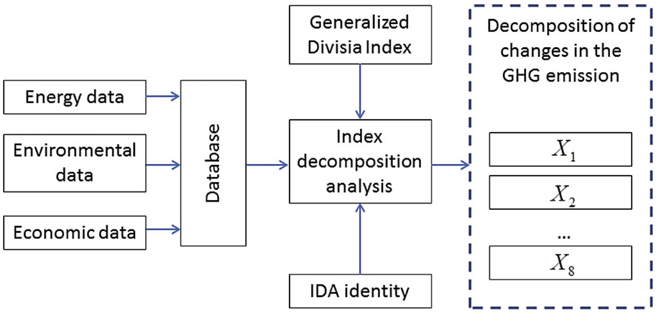

**Fig. 1.** Framework of the research.

The change in the aggregate variable $Z$, denoted as $\Delta Z$, can also be factorized accordingly:

$$\Delta Z = Z_T - Z_0 = \sum_{i=1}^{n} \Delta Z_{X_i}. \tag{2}$$

where $\Delta Z_{X_i}$ is the contribution of change in a certain variable, $X_i$, to the change in the aggregate variable; $T$ and 0 denote the current and base time periods, respectively.

In the spirit of Divisia (1925), assuming continuous change of the underlying indicators (factors), the level of a certain indicator can be given as a function of time, i.e. $X_i = X_i(t)$. Then, the change in $Z$ decomposes as follows:

$$\Delta Z = \sum_{i=1}^{n} \Delta Z_{X_i} = \sum_{i=1}^{n} \int X_1 X_2 \ldots X_{i-1} X_i' X_{i+1} \ldots X_{n-1} X_n dt, \tag{3}$$

where $X_i' = dX_i/dt$. Vaninsky (2014) noted that a more general relationship among the underlying variables (factors) can be assumed, i.e.:

$$Z = f(X_1, X_2, \ldots, X_n). \tag{4}$$

The change in $Z$ then decomposes as follows:

$$\Delta Z = \int_L dZ = \sum_{i=1}^{n} \Delta Z_{X_i} = \sum_{i=1}^{n} \int_L f_i' dX_i, \tag{5}$$

where $L$ defines the trajectory of the change in the underlying variables, $f\prime_i$ is the partial derivative of $f(X_1, X_2, \ldots, X_n)$ with respect to $X_i$. Given $X_i = X_i(t)$, the following relationship holds:

$$\Delta Z_{X_i} = \int_L f_i' dX_i = \int_{t_0}^{t_1} f_i' X_i' dt, \tag{6}$$

where $t_1$ and $t_0$ denote the current and base periods, respectively. Eq. (6) can also be presented by using the vector notation (henceforth, $T$ denotes the transposition operator):

$$\Delta \mathbf{Z} = \int_L \nabla \mathbf{Z}^T d\mathbf{X}, \tag{7}$$

where $\Delta \mathbf{Z} = (\Delta Z_{X_1}, \Delta Z_{X_2}, \ldots, \Delta Z_{X_n})$ is the row decomposition vector, $\nabla \mathbf{Z} = (f_1', f_2', \ldots, f_n')$ is the column gradient vector of function given in Eq. (4), the dot-multiplication of the two vectors is applied for multiplication with the diagonal matrix $d\mathbf{X} = diag(dX_1, dX_2, \ldots, dX_n)$.

Vaninsky (2014) noted that the aforementioned decomposition features certain limitations due to the restricted assumptions about the interrelations among the underlying variables (factors). Therefore, Vaninsky (2014) presented the Generalized Divisia Index decomposition, which takes interrelations of the underlying factors into account and thus offers an improved decomposition of the aggregate variable. More specifically, the Generalized Divisia Index decomposition assumes $Z$ being a function of the factors and includes the system of equations describing the interdependencies among these:

$$\begin{aligned} & Z = f(X_1, X_2, \ldots, X_n), \\ & \Phi_j(X_1, X_2, \ldots, X_n) = 0, j = 1, 2, \ldots, k. \end{aligned} \tag{8}$$

Using the vector notation, the second part of Eq. (9) can be given as

$$\mathbf{\Phi}(\mathbf{X}) = 0 \tag{9}$$

In order to improve the decomposition, the Generalized Divisia Index decomposition model projects the vectors defining the change in each factor onto the surface defined by the system of equations describing the interrelationships among the factors. Therefore, the decomposition vector becomes (Vaninsky, 2014):

$$\Delta \mathbf{Z}(\mathbf{X}|\Phi) = \int_L \nabla \mathbf{Z}^T \left( \mathbf{I} - \mathbf{\Phi}_X \mathbf{\Phi}_X^+ \right) d\mathbf{X} \tag{10}$$

where $\mathbf{I}$ is the identity matrix, $\mathbf{\Phi}_X$ is the Jacobian matrix of $\mathbf{\Phi}(\mathbf{X})$ with its elements defined as $[\mathbf{\Phi}_X]_{ij} = \frac{\partial \Phi_j}{\partial X_i}$, and $\mathbf{\Phi}_X^+ = (\mathbf{\Phi}_X^T \mathbf{\Phi}_X)^{-1} \mathbf{\Phi}_X^T$ is the generalized inverse matrix.

### 2.2. IDA model for GHG emission

In order to decompose the changes in the energy-related GHG emission from agriculture with respect to the underlying factors, the IDA identity needs to be specified for this particular case. Specifically, the general case given by Eq. (1) can be adapted to account for both intensive and extensive factors behind the dynamics in the GHG emission.

We consider agricultural output as the absolute indicator resembling the scale of operation of agricultural sector in the region under analysis. This variable, indeed, appears as the extensive factor of changes in the GHG emission. We further look into the spatial distribution of the agricultural output across different countries and thus develop a structural factor, which depends on the degree of change in the scale of agricultural production (i.e. extensive development) in a certain country in relation to the rate of growth observed in the rest of the countries. Indeed, the structural component was integrated in the IDA identities by Ang and Choi (1997), Ang et al. (2015) and Wang et al. (2017), among others. Finally, the two country-specific indicators associated with purely intensive development are included, namely energy intensity and carbon factor or carbon intensity of energy consumption. Thus the traditional IDA identity used for the analysis of the energy-related GHG emission in the European countries would take the following form:

$$GHG_i = \frac{GHG_i}{E_i} \frac{E_i}{Y_i} \frac{Y_i}{Y} Y = F_i I_i S_i Y, \tag{11}$$

where $GHG_i$ is the energy-related GHG emission from agriculture in the $i$-th country, $E_i$ is the final energy consumption in agriculture in the $i$-th country, $Y_i$ is the agricultural output produced in the $i$-th country, and $Y = \sum Y_i$ is the agricultural output for the whole group of countries. Accordingly, the four factors emerge as determinants of the dynamics in GHG emission: $F_i$ is the carbon factor (or carbon intensity of energy) effect, $I_i$ is the energy intensity effect, $S_i$ is the structural effect, and $Y$ is the effect of the overall economic activity. Note that these four factors are defined in the traditional IDA models. However, the application of the Generalized Divisia Index allows accounting for inter-relationships existing among the absolute and relative indicators in Eq. (11) and, thus, considering more factors driving the GHG emission.

The use of the Generalized Divisia Index allows defining relationships among both absolute and relative indicators and thus expanding the number of terms actually affecting the dynamics in GHG emission. For sake of brevity, we apply the following shorthand notations: the absolute variables are denoted as $Z = GHG_i$, $X_1 = Y_i, X_3 = E_i, X_5 = Y$, whereas the resulting relative variables are denoted as $X_2 = GHG_i/Y_i$, $X_4 = GHG_i/E_i$, $X_6 = GHG_i/Y$, $X_7 = Y_i/Y$, and $X_8 = E_i/Y_i$. Due to application of the Generalized Divisia Index, the IDA identity in Eq. (11) takes a more general form, i.e. $Z = f(X_1, X_2, ..., X_8)$. Following Vaninsky (2014), Eq. (8) for this particular case is defined as:

$$\begin{aligned} &Z = X_1X_2,\\ &X_1X_2 - X_3X_4 = 0,\\ &X_1X_2 - X_5X_6 = 0,\\ &X_1 - X_5X_7 = 0,\\ &X_3 - X_1X_8 = 0. \end{aligned} \tag{12}$$

Therefore, the gradient and Jacobian matrix of $Z(\mathbf{X})$ required for Eq. (10) are defined in the following manner (Vaninsky, 2014):

$$\begin{aligned} &\nabla\mathbf{Z} = (X_2, X_1, 0, 0, 0, 0, 0, 0)^T,\\ &\Phi_X = \begin{pmatrix} X_2 & X_1 & -X_4 & -X_3 & 0 & 0 & 0 & 0\\ X_2 & X_1 & 0 & 0 & -X_6 & -X_5 & 0 & 0\\ 1 & 0 & 0 & 0 & -X_7 & 0 & -X_5 & 0\\ -X_8 & 0 & 1 & 0 & 0 & 0 & 0 & -X_1 \end{pmatrix}^T. \end{aligned} \tag{13}$$

The change in the absolute indicators with time is defined by considering exponential function (Vaninsky, 2014):

$$Q(t) = (Q_1/Q_0)^t, \tag{14}$$

where $t$ is time variable such that $0 \le t \le 1$, $Q$ is the absolute variable of interest (i.e. $Z$ or $X_i$). The derivative of $Q(t)$ with respect to time is then given as (Vaninsky, 2014)

$$\frac{dQ(t)}{dt} = \ln(Q_1/Q_0)Q(t). \tag{15}$$

Finally, the diagonal matrix $d\mathbf{X}$ in Eq. (10) becomes (Vaninsky, 2014)

$$d\mathbf{X} = diag(X_1', X_2', ..., X_n')dt. \tag{16}$$

Thus, the presented approach allows one to decompose the change in the GHG emission with respect to the eight terms: those presented in the traditional IDA identity (Eq. (11)) and some additional ones (both absolute and relatives ones). The decomposition is implemented by using the R programming language and the code provided by Vaninsky (2014).

### 2.3. Data used

The data on agricultural production and environmental impacts come from Eurostat (European Commission, 2017) and FAOSTAT (FAO, 2017) databases. The agricultural output is chosen as the economic activity indicator as energy is also considered in the analysis. The agricultural output is taken from the economic accounts for agriculture provided by Eurostat. The latter indicator is measured in purchasing power standards at the constant prices of 2010. The data on final energy consumption (measured in tonnes oil equivalent) in agriculture and forestry come from Eurostat energy statistics database. The GHG emission in tonnes of $CO_2$ equivalent is obtained from the FAOSTAT database. Energy-related GHG emission from agriculture (excluding fisheries) is considered.

Due to data availability, we chose 17 European countries featuring rather similar production structure. These countries are Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Hungary, Latvia, Lithuania, the Netherlands, Poland, Romania, Slovakia, Slovenia, Sweden. The data cover years 1995–2012. The missing values have been extrapolated by using the most recent data. Germany has been dropped from the analysis due to lack of the data.

## 3. Results

### 3.1. The trends in GHG emission and related variables

In order to present the major trends in agricultural production and the resulting environmental pressures, Fig. 2 depicts the dynamics in the main absolute indicators for the group of the 17 European countries. The 17 European countries (see Section 2.3) saw a slight increase in agricultural production, as measured by the agricultural output indicator. Specifically, the increase of 7% was observed during 1995–2012. However, this estimate is affected by seasonal shocks (e.g. the growth of 12% was observed for 1995–2011).

Final energy consumption went down steadily during 1995–2003, whereas the dynamics in the period of 2003–2012 is less certain. Specifically, the energy consumption declined by some 15% during 1995–2003, whereas the period of 2003–2012 saw a decline in the energy consumption of just 3.8%. All in all, the energy consumption went down by 18% during the period of 1995–2003. Therefore, one can observe an absolute decoupling between the economic activity (as represented by the agricultural output) and energy consumption and decoupling between energy consumption and GHG emissions from energy consumption in agriculture at the aggregate level of the 17 European countries. Such a trend indicates positive developments in regards of sustainable development and climate change mitigation as reduction in energy consumption and GHG emissions allows for subsequent reduction in energy related GHG emission in agriculture sector of EU member States.

The trend of the GHG emission was closely related to that of energy consumption. Indeed, the two trends virtually coincided during 1995–2003, when declines in energy use and GHG emission were observed. Later on, the GHG emission decreased to a higher extent if compared to the energy use in the agricultural sectors of the 17 European countries. The GHG emission decreased by some 4.9% during 2003–2012 (as opposed to the aforementioned rate of growth of −3.8% for energy consumption) and resulted in the decrease of 22% during 1995–2012. Again, the absolute decoupling is evident between the economic activity and GHG emission.

The dynamics and absolute indicators suggest generally positive developments in regards to energy use and the associated environmental pressures as represented by the GHG emission (i.e. absolute decoupling is observed for both indicators against the economic activity). This implies that further expansion in the scale of agricultural production might be feasible without inducing additional environmental pressures. Noteworthy, these changes are result of multiple factors, including tightened regulations on fuel quality, improved farming practices, climate change, re-allocation of agricultural production and changes in production structure.

The dynamics in the relative indicators is given in Fig. 3.

As GHG emission and energy consumption both went down with agricultural output remaining rather stable, both energy and GHG intensities went down. At the aggregate level of the 17 European countries, GHG emission intensity went down from 0.35 kg $CO_2$ eq./PPS to 0.26 kg $CO_2$ eq./PPS during 1995–2012, whereas energy intensity declined shrunk from 0.11 toe/PPS to 0.09 toe/PPS during the same period. As regards the carbon factor, it followed a slightly negative trend indicating that changes in the energy-mix were much less apparent than the relative savings in energy used. Specifically, decreased from 3.13 t $CO_2$ eq./toe down to 2.99 t $CO_2$ eq./toe during 1995–2012.

The country-level trends in the agricultural output, energy use, and GHG emission are presented in Table 1. The steepest increase in agricultural output is observed for Latvia, Lithuania, Belgium, and Estonia. Note that Latvia, Lithuania, and Estonia gained independence from the Soviet Union in early 1990s and subsequently faced

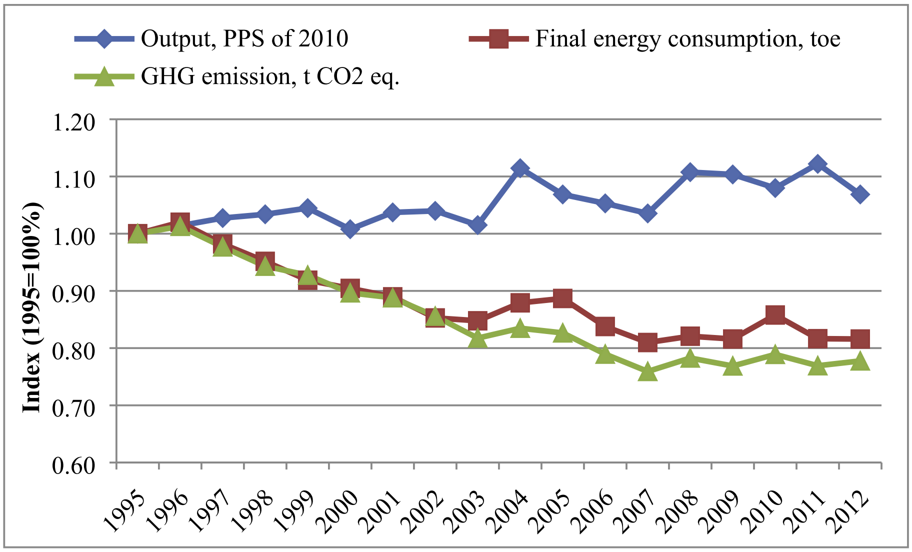

**Fig. 2.** Indices of agricultural output and energy-related indicators for the 17 European countries, 1995–2012.

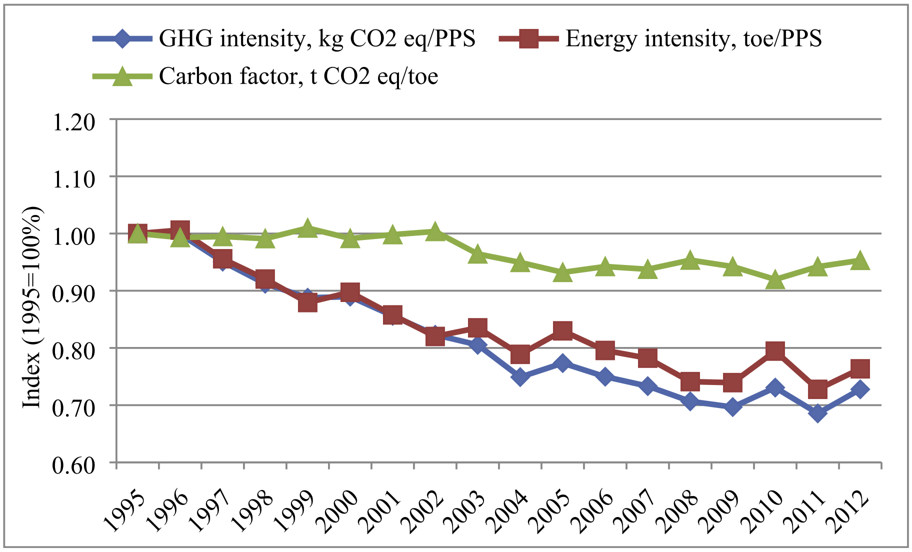

**Fig. 3.** Indices of the relative indicators for the 17 European countries, 1995–2012.

a transition from collective farming towards family and corporate farming. Thus, even growth rates are rather high, agricultural productivity still needs to be improved there if contrasted to the other EU Member States, especially the “old” ones. Most of the countries saw a decrease in both energy use and GHG emission with exceptions of France and Latvia. Even though Austria increased energy consumption in agriculture, the associated GHG emission went down. These patterns of dynamics in the underlying variables require an integrated assessment of drivers behind the GHG emission.

The differences among countries in energy and emission intensity calls for coordinated actions aimed at spill-over of cleaner energy and improvements in energy efficiency. At the EU level, such schemes as the Common Agricultural Policy with Rural Development policy (European Parliament, Council of the European Union, 2013), strategy Europe 2020 (European Commission, 2010), Flagship initiative a resource-efficient Europe (European Commission, 2011) aim to improve resource efficiency in general and reduce environmental impacts of the economic activities (among other objectives). Therefore, it is important to ascertain whether there has been a convergence among the European countries in regards to indicators corresponding to the goals of sustainable and efficient energy use. In order to check the convergence among the countries analysed, the coefficients of variation (CVs) are calculated for the three relative indicators (i.e., GHG intensity of agricultural output, energy intensity, and carbon factor of energy consumed). Table 2 summarizes the results for the period of 1995–2012.

The results indicate that the convergence has decreased in terms of energy intensity, yet the countries analysed have converged in terms of carbon factor and GHG intensity. This implies the countries follow different paths in the sense of energy efficiency, yet energy-mix has been becoming cleaner there.

### 3.2. IDA

The decrease in GHG emission for the 17 European countries

**Table 1**
The logged rates of growth (in per cent) for the key variables defining E3 interaction in the agricultural sectors of the selected EU countries, 1995–2012.

| | Agricultural Output, PPS of 2010 | Final energy consumption, toe | GHG emission, t CO2 eq. |
|---|---|---|---|
| Austria | 12.0 | 4.2 | −14.2 |
| Belgium | 40.4 | −45.7 | 12.6 |
| Bulgaria | −24.0 | −65.9 | −52.3 |
| Czech Republic | −1.2 | −75.4 | −87.6 |
| Denmark | 21.1 | −10.8 | −12.4 |
| Estonia | 30.1 | 27.4 | −3.4 |
| Finland | 6.5 | 0.3 | −14.5 |
| France | 5.1 | 12.1 | 8.4 |
| Hungary | −7.9 | −51.0 | −54.7 |
| Latvia | 42.9 | 12.3 | 136.4 |
| Lithuania | 50.0 | −62.8 | −47.5 |
| Netherlands | 15.3 | −13.5 | −5.6 |
| Poland | 13.3 | −26.6 | −48.1 |
| Romania | −7.5 | −70.1 | −67.5 |
| Slovakia | −4.2 | −74.2 | −83.9 |
| Slovenia | −1.9 | −2.5 | −6.5 |
| Sweden | 13.9 | −57.3 | −81.3 |

**Table 3**
Decomposition of the change in the GHG emission for the 17 European countries during 1995–2012.

| Factors | Absolute contribution, 1000 t CO$_2$ eq. | Relative contribution, per cent | Trend coefficient, 1000 t CO$_2$ eq./year |
|---|---|---|---|
| 1. Output | 1970.2 | 13.7 | −2.1 |
| 2. GHG/Output | −6012.7 | −41.8 | 31.9 |
| 3. Energy | −3501.1 | −24.3 | 25.0 |
| 4. GHG/Energy | −756.1 | −5.3 | 3.9 |
| 5. Total Output | 1331.3 | 9.3 | −16.4 |
| 6. GHG/Total Output | −5924.5 | −41.2 | 46.9 |
| 7. Output/Total Output | −251.0 | −1.7 | −1.0 |
| 8. Energy/Output | −1239.2 | −8.6 | 4.2 |
| **Change in the total GHG emission** | **−14383.2** | | **92.4** |

Notes: Total Output refers to the agricultural output for the whole group of countries, whereas Output refers to the agricultural output for a certain country; relative contributions have been negated.

(Fig. 2) corresponds to 14.4 million t CO$_2$ eq. Application of the Generalized Divisia Index allows to decompose this quantity in terms of the underlying factors. As it was mentioned in Section 2.2, the changes in the GHG emission are decomposed with respect to the eight factors. Table 3 presents the aggregate results for the period of 1995–2012. Indeed, the chain-linked analysis was carried out for each two years and then the resulting values added up for the whole period of 1995–2012.

Much of the change in the total GHG emission can be attributed to the two indicators representing emission intensity. Indeed, the indicator of GHG emission intensity (at the country level; denoted as $X_2$) captures country-specific developments in regards to cleaner production, whereas the ratio of country-specific GHG emission to the aggregate output of the 17 countries ($X_4$) reflects the deviation of changes in environmental pressures in a certain country from the changes in economic activity at the aggregate level. The latter two indicators have virtually equal importance in reducing the total GHG emission during 1995–2012: the reducing country-specific GHG intensities rendered a decrease in the aggregate GHG emission of 6 million t CO$_2$ eq., whereas the disparities in dynamics of country-specific GHG emission and aggregate economic activity yielded a decrease of some 5.9 million t CO$_2$ eq. In relative terms, these two factors account for more than 80% of the total change in the aggregate GHG emission over 1995–2012.

The energy-related factors also appeared as important drivers of decrease in GHG emission. Specifically, decrease in energy consumption ($X_3$) pushed the GHG emission down by 3.5 million t CO$_2$ eq., whereas the decrease in energy intensity ($X_8$) caused a decline in the GHG emission of 1.2 million t CO$_2$ eq. Indeed, the trends present in Fig. 3 imply decreasing energy use was the main contributor towards decline in GHG emission. However, the Generalized Divisia Index allows for multiple interdependencies among the underlying factors and these impacts become rather complicated. However, the effect of the carbon factor ($X_4$) is much lower than the effects of energy use and GHG intensity (a decrease in GHG emission of 0.76 million t CO$_2$ eq. or 5.3%). This finding confirms the dominance of energy efficiency in reducing the GHG emission if opposed to carbon factor.

As regards the scale effect, it can be quantified by considering the two factors, viz. change in the country-specific output levels ($X_1$) and the aggregate output for the whole group of countries ($X_5$). Both of these effects are positive and imply an increase in the GHG emission of 1.97 million t CO$_2$ eq. and 1.3 million t CO$_2$ eq. respectively. The structural component showed the lowest influence representing a decrease in the total GHG emission of 0.25 million t CO$_2$ eq. note that the structural effect is also partially represented by the ratio of country-specific emission to the total output ($X_6$), which results in a decreased contribution of the pure structural effect. The observed pattern imply that structural changes have reduced the GHG emission, i.e. the production has been concentrated in countries featuring less GHG-intensive agriculture (note that we focus on energy-related GHG emission in this case).

The last column of Table 3 presents the trend coefficients for each factor as well as for change in the total GHG emission. The results indicate that in spite of the negative change in the GHG emission during 1995–2012, the trend coefficient indicates an upward trend for the indicator of change. This implies that, in case the current trends prevail, the reduction in energy-related GHG emission is likely to slow-down or even be reversed for the 17 European countries in the longer perspective. However, the cumulative decrease in the GHG emission for 1995–2012 of over 14 million t CO$_2$ eq. is much higher if contrasted to the trend coefficient of just 92 thousand t CO$_2$ eq. In general, the main factors causing a decline in the total GHG emission followed a slightly upward trend (GHG intensity, energy consumption, and the ratio of country-specific GHG emission to the total output). The scale effects contributed to growth in the total GHG emission, yet their trend was negative and indicated that expansion of scale is likely to have a lower impact on the growth in GHG emission in the future.

We further look at the dynamics of the change in the GHG

**Table 2**
Coefficients of variation for the relative indicators and their trends, 1995–2012.

| Indicator | 1995 | 2000 | 2005 | 2010 | 2012 | Rate of change | Trend |
|---|---|---|---|---|---|---|---|
| Energy intensity, kg oe/PPS | 0.61 | 0.62 | 0.62 | 0.64 | 0.67 | 0.07 | 0.0021 |
| Carbon factor, t CO2 eq/toe | 0.41 | 0.36 | 0.26 | 0.26 | 0.26 | −0.15 | −0.0065 |
| GHG intensity, kg CO$_2$ eq./PPS | 0.62 | 0.61 | 0.60 | 0.58 | 0.61 | −0.01 | −0.0009 |

Note: the last column presents the coefficients of the linear trend.

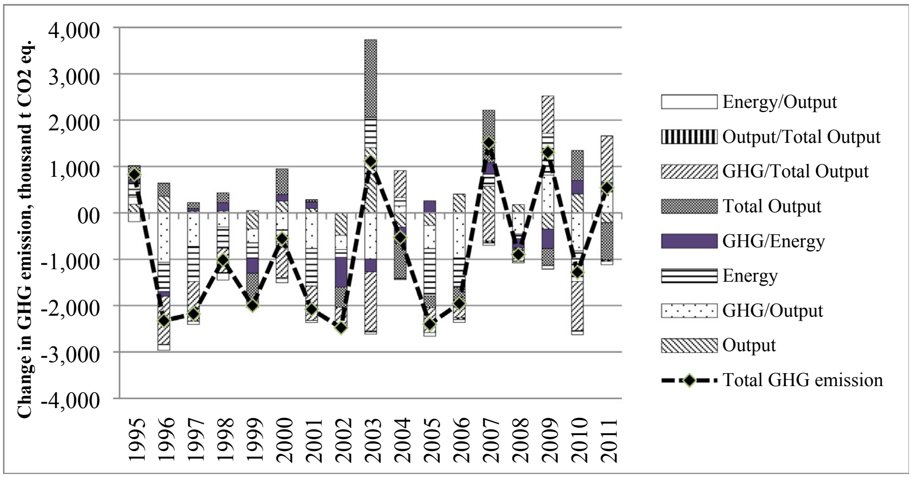

**Fig. 4.** The chain-linked decomposition of the change in the total GHG emission for the group of 17 European countries, 1995–2012 (base years are given in the figure).

emission throughout 1995–2012 and its decomposition for each two consecutive years (Fig. 4). The results are given at the aggregate level of the 17 European countries. Such an analysis enables to check the persistence of particular drives of changes in the GHG emission throughout the time.

The period of 1995–2006 marked just two cases of an increase in the total GHG emission. However, the subsequent period of 2006–2012 showed three such cases. Therefore, the dynamics in the energy-related GHG emission from agricultural sector has become less certain (this is also confirmed by Fig. 2).

The dynamics in the components of the change in GHG emission reveal certain patterns in driving GHG emissions during specific periods.

During 1995–2003, the periods of decrease in the GHG emission can be grouped into those where energy efficiency gains play the most important role and those specific with decreasing carbon factor (i.e. switch to cleaner energy mix). The decrease in the total GHG emission due to energy efficiency gains was observed during 1995–1999 and 2000–2002. The major factors affecting the decrease in GHG emission were energy use and GHG intensity at both country and semi-aggregate level. Another type of decrease in the GHG emission was observed during 1999–2000 and 2001–2002. These periods are related to both decreased economic activity, as suggested by the negative effects of the total output factor, and decrease in the carbon factor. Obviously, certain energy sources are more elastic with respect to economic activity.

Following year 2003, the two patterns of the effects of the underlying factors associated with an increasing GHG emission appeared. For instance, increases in the GHG emission observed during 2003–2004 and 2007–2008 were mainly driven by increasing agricultural output and energy use. The periods of 2009–2010 and 2011–2012 exhibited increases in the GHG emission due to increasing GHG intensity, which is obviously related to changes in the fuel mix. The period of 2005–2007 saw a decline in the GHG emission due to decreased economic activity and energy use. The period of 2010–2011 marked a decline in the GHG emission which was mainly due to energy efficiency gains as represented by the negative effects of energy use and GHG emission per output.

We further look into the factors driving the change in GHG emissions at the country level. This will provide insights into possibly different paths for improvements in certain countries. First, we aggregate the absolute data for each country over the research period. Then, we normalize the contributions of each factor by the total change in the GHG emission for each country (the results are negated for countries with a decrease in the GHG emission over 1995–2012). Table 4 presents the country-specific decomposition of the changes in GHG emissions.

**Table 4**
Relative contributions of different factors to the change in GHG emissions, 1995–2012.

| Country | Energy | Energy/Output | GHG/Energy | GHG/Output | GHG/Total Output | Output | Output/Total Output | Total Output |
|---|---|---|---|---|---|---|---|---|
| Austria | 10.6 | −4.2 | −43.2 | −60.9 | −49.5 | 31.2 | −1.3 | 17.3 |
| Belgium | −119.9 | −43.6 | 181.2 | −57.4 | 16.5 | 107.8 | −4.9 | 20.3 |
| Bulgaria | −40.7 | −14.7 | 12.2 | −9.3 | −37.7 | −12.0 | −2.3 | 4.5 |
| Czech Republic | −28.4 | −7.5 | −1.1 | −30.6 | −34.3 | 0.0 | −0.2 | 2.1 |
| Denmark | −27.4 | −4.5 | −5.9 | −88.5 | −50.4 | 59.1 | −2.8 | 20.4 |
| Estonia | 350.4 | −253.4 | −206.4 | −212.2 | −64.6 | 261.8 | −46.2 | 70.6 |
| Finland | −0.6 | −8.6 | −29.0 | −41.1 | −49.1 | 16.1 | −6.3 | 18.5 |
| France | 49.7 | −3.3 | −15.2 | 15.2 | 8.0 | 21.5 | −2.8 | 26.8 |
| Hungary | −29.5 | −6.2 | −2.6 | −26.7 | −38.6 | 1.3 | −2.7 | 5.0 |
| Latvia | 8.5 | −2.7 | 26.0 | 14.5 | 32.3 | 21.8 | −2.8 | 2.5 |
| Lithuania | −35.4 | −6.7 | 3.8 | −59.7 | −36.0 | 33.7 | −4.1 | 4.4 |
| Netherlands | −64.0 | −28.0 | 47.8 | −113.8 | −68.5 | 90.4 | −6.8 | 42.8 |
| Poland | −16.7 | −2.4 | −15.8 | −38.2 | −37.8 | 6.6 | −0.6 | 5.0 |
| Romania | −28.2 | −14.0 | −1.0 | −22.3 | −34.1 | −1.2 | −1.2 | 1.9 |
| Slovakia | −29.8 | −3.7 | −2.1 | −31.0 | −35.5 | −0.1 | −0.6 | 2.9 |
| Slovenia | −6.1 | −43.3 | −19.1 | −1.2 | −70.4 | 13.3 | −12.9 | 39.8 |
| Sweden | −20.7 | −6.2 | −9.7 | −37.7 | −37.5 | 7.2 | −0.5 | 5.1 |

Note: results have been negated for countries exhibiting a decrease in GHG emission.

Among countries with decreasing GHG emission, Romania, Czech Republic, Slovakia, Sweden, Hungary, Bulgaria, Lithuania and Denmark showed the pattern of the factors of the change in GHG emissions where GHG emission was mainly reduced due to decrease in the energy use (i.e. energy intensity effect). Note that such countries as Denmark and Lithuania also featured rather strong scale effect. Such countries as Poland, Finland, Austria, and Slovenia managed to decrease carbon factors as represented by the effect of the ratio of GHG emission to energy use. The Netherlands achieved reduction in the GHG emission in spite of increasing carbon factor.

France, Latvia, and Belgium appeared as the only countries with increase in GHG emissions during 1995–2012. Indeed, these three countries showed somewhat different patterns in the factors driving the change in the GHG emissions. In the case of France, energy intensity went up along with increase in the scale of agricultural production as measured by the agricultural output. Indeed, the energy effect played the most important role. Therefore, the measures of energy efficiency are especially important in order to curb energy-related GHG emission in French agriculture. Looking at Latvia, an increase in carbon factor appeared as the major factor driving an increase in GHG emission there. This implies Latvian agricultural sector should pay more attention on “greening” of the energy-mix. Belgium exhibited a pattern similar to the Latvian one. Therefore, energy-mix should also be adjusted to effectively reduce GHG emission.

## 4. Conclusions

The dynamics and absolute indicators suggest generally positive developments in regards to energy use and the associated environmental pressures as represented by the GHG emission (i.e. absolute decoupling is observed for both indicators against the economic activity). These changes are result of multiple factors, including tightened regulations on fuel quality, improved farming practices, climate change, re-allocation of agricultural production and changes in production structure.

The differences among countries in energy and emission intensity calls for coordinated actions aimed at spill-over of cleaner energy and improvements in energy efficiency. In order to check the convergence among the EU Member States, the coefficients of variation (CVs) are calculated for the three relative indicators (i.e., GHG intensity of agricultural output, energy intensity, and carbon factor of energy consumed). The results indicated that the convergence has decreased in terms of energy intensity, yet the countries analysed have converged in terms of carbon factor and GHG intensity. This implies the countries follow different paths in the sense of energy efficiency, yet energy-mix has been becoming cleaner in terms of carbon factor.

Though the comparison of trends in GHG emissions and their driving forces in agricultural sector indicated generally positive trends at the country-group level, the country-level analysis allowed to identify countries requiring more attention in regards to energy-related GHG emission mitigation in agriculture. On individual country level, France, Latvia, and Belgium appeared as the only countries with increase in GHG emissions during 1995–2012. Indeed, these three countries showed somewhat different patterns in the factors driving the change in the GHG emissions. In the case of France, energy intensity went up along with increase in the scale of agricultural production as measured by the agricultural output. Indeed, the energy effect played the most important role. Therefore, the measures of energy efficiency are especially important in order to curb energy-related GHG emission in French agriculture. Looking at Latvia, an increase in carbon factor appeared as the major factor driving an increase in GHG emission there. This implies Latvian agricultural sector should pay more attention on “greening” of the energy-mix. Belgium exhibited a pattern similar to the Latvian one. Therefore, energy-mix should also be adjusted to effectively reduce GHG emission.

Among countries with decreasing GHG emission, Romania, Czech Republic, Slovakia, Sweden, Hungary, Bulgaria, Lithuania and Denmark showed the pattern of the factors of the change in GHG emissions where GHG emission was mainly reduced due to decrease in the energy use (i.e. energy intensity effect). Denmark and Lithuania also featured rather strong scale effect. Poland, Finland, Austria, and Slovenia managed to decrease carbon factors as represented by the effect of the ratio of GHG emission to energy use. The Netherlands achieved reduction in the GHG emission in spite of increasing carbon intensity of energy consumption. For these countries, the gains in energy efficiency are rather important factor behind mitigation of the GHG emission.

The EU agricultural policy (Common Agricultural Policy) is likely to stimulate agricultural production in the future. The structural changes might also appear. Anyway, the carried out analysis indicates that the scale and structural effects are less important than energy-mix and energy intensity effects.

Further research is important in identifying the targets for reductions in GHG emission and energy use in agriculture. Production decomposition approach can be applied in this regards by combining production theory and IDA. Emission allocation models can be applied to identify the possible re-allocation of emissions under certain economic assumptions. Finally, agricultural sector can be compared to the other economic activities.

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