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Research article

Efficiency under different methods for incorporating undesirable outputs in an LCA+DEA framework: A case study of winter wheat production in Poland

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ABSTRACT

Incorporating undesirable outputs in the operational assessments through the integration of Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) has received great attention recently. There are many studies throughout literature that apply various methods to integrate LCA and DEA. In this case study, the six most common approaches were employed to assess the winter wheat cropping system in Poland. These six methods were: a) ignoring undesirable outputs, b) treating undesirables as inputs to the DEA model, c) data transformation, d) impact rate, e) ratio model, and f) slack based measurement DEA with undesirable outputs. The environmental impact of wheat production was assessed by determining its carbon footprint (CF). The mean CF equalled 0.45 kg CO_{2eq} per kg wheat grain (ranging from 0.25 to 0.67). According to the model comparison results, a slack based measurement DEA with undesirable outputs could better reflect the performance of undesirable outputs, and was selected as the most appropriate method to maximize the efficiency of winter wheat production while minimizing undesirable outputs. The advantage of applying the slack based model with undesirable outputs was that the targets presented by this model were based on existing efficient farms, as opposed to theoretical results; thus achieving these targets are feasible. The average efficiency score equalled 0.43, whereby few farms were classified as efficient farms. The results of the proposed integrated model showed a high reduction potential for mineral fertilizers (up to 595 kg ha^{-1} y^{-1}), seed (up to 37 kg ha^{-1} y^{-1}), and fuel (up to 75 L ha^{-1} y^{-1}) in winter wheat farms. These results help farmers to obtain a realistic and reliable usage pattern for inputs in a winter wheat production system, whereby the greatest production can be achieved in conjunction with the lowest possible environmental impact.

1. Introduction

Wheat, as the second most important food crop, can be planted in most regions of the world. In 2017, 771 million metric tons of wheat was produced globally on 218 million hectares of farm-land (FAO, 2017). Winter wheat is the most widely planted crop in Poland, being planted on an area of around two million hectares, offering the highest added value in Poland's economy (Statistics Poland, 2018).

Sustainable production in agriculture provides food security, while limiting the impacts on the environment through the efficient use of resources. Among the environmental impacts, greenhouse gas (GHG) emissions is appraised as the most threatening to the environment and the economy (Stocker et al., 2014). Agriculture, forestry, and other land use (AFOLU) are responsible for about 25% of anthropogenic GHGs (Smith et al., 2014). The agricultural sector is one of the main sources of GHGs, including carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) (De Cara and Jayet, 2000).

Carbon footprint (CF) is the sum of GHG emissions in a production system, expressed in equivalent kg of CO_2. There is little knowledge about CF of agricultural products and the efficiency of production systems in Poland. With respect to the high cultivation area and the economic importance of wheat, identifying the main sources of GHGs in this crop could provide solutions for reducing these emissions. Life cycle assessment (LCA) is an approach to determine the environmental impacts associated with all production stages of a commodity. Many studies have conducted LCA of winter wheat production (Charles et al., 2006; Liang et al., 2009; Wang et al., 2006, 2007).

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Acronyms

AFLS	Agriculture, forestry and other land use
BCC	Banker, Charnes and Cooper
CCR	Charnes, Cooper and Rhodes
CF	Carbon footprint
CH_4	Methane
CO_2	Carbon dioxide
CRS	Constant returns to scale
DBSCAN	Density based spatial clustering of application with noise
DEA	Data envelopment analysis
DMUs	Decision-making units
ETS	Emission trading scheme
EU	European Union
FADN	Farm Accountancy Data Network
FU	Functional units
GHG	Greenhouse gasses
GHG_D	Direct GHG
GHG_{ID}	Indirect GHG
GHG_{Total}	Total GHG
GTP	Global temperature potential
LCA	Life cycle assessment
LCI	Life cycle inventory
LULUCF	Land use, land use change and forestry
N_2O	Nitrous oxide
SBM	Slack based measurement
SF	Supplementary file
TE	Technical efficiency
VRS	Variable returns to scale
Y	Yield

Data envelopment analysis (DEA) is a non-parametric approach to assess the relative efficiencies of the decision-making units (DMUs) in a multi-input and output production system. In general, DEA models are either input oriented (reducing input level while maintaining the outputs unchanged) or output oriented (increasing the outputs level by a given level of inputs). DEA has been used in many studies in agriculture to determine the efficiency of crop and animal production systems (Aravindakshan et al., 2015; Blancard and Martin, 2014; Dong et al., 2015; Jha et al., 2000; Masuda, 2016).

One approach proposed for evaluating a particular production system involves a combination of LCA and DEA (Iribarren et al., 2010; Lozano et al., 2009; Vázquez-Rowe and Iribarren, 2015). This combined approach enables to find efficient producers with focus on both economic and environmental performance. Moreover, the LCA + DEA framework avoids the use of averaged inventory data, an important factor due to the large variability of inputs and environmental impacts amongst farms. There are three different classifications for the LCA + DEA framework which include either three, four or five-step, respectively (Adenuga et al., 2018; Laso et al., 2018; Lozano et al., 2009, 2010; Rebolledo-Leiva et al., 2017; Vázquez-Rowe et al., 2010). In each classification, undesirable outputs can be treated differently, including (but not limited to): a) ignoring undesirable outputs in the DEA model (Alemdar and Oren, 2006; Chebil et al., 2015; Mohseni et al., 2018; Nabavi-Pelesaraei et al., 2017; Syp et al., 2015), b) treating undesirables as inputs to the DEA model (De Koeijer et al., 2002; Kuosmanen and Kortelainen, 2005; Lozano et al., 2009; Picazo-Tadeo et al., 2011; Ullah et al., 2016), c) data transformation (Golany and Roll, 1989; Rebolledo-Leiva et al., 2017), d) impact rate, and e) ratio model. Treating undesirable outputs through the impact rate and ratio model methods hve previously been suggested by You and Yan (2011). In addition to these methods, few studies have applied a new method known as a DEA model with undesirable outputs. Cecchini et al. (2018) applied a slack based measure (SBM)-DEA model with undesirable outputs for analysing the environmental efficiency of dairy cattle farms in Italy. In Ireland, the directional output distance function DEA based model was applied to optimize both the desirable and undesirable outputs on dairy farms (Adenuga et al., 2018). Dong et al. (2018) combined an energy based indicator and the SBM-DEA model with undesirable outputs to evaluate the resource use in crop production during the 1978 and 2014 in a province in China. Vázquez-Rowe et al. (2010) applied a SBM-DEA model with undesirable outputs for assessing fisheries in Spain. In a recent study, Angulo-Meza et al. (2019) applied a multi-objective DEA model to reduce the CF of organic blueberry orchards, while maintaining a high production level.

Regarding the fact that; 1) few studies focusing on crop production systems in Poland combined LCA and DEA, 2) different scenarios and approaches can be applied for the LCA + DEA framework, and 3) to the best of our knowledge, to date, no study has employed and evaluated the SBM-DEA model with undesirable outputs for wheat production, thus, this paper focused on combining LCA and DEA using alternative methods to find an appropriate DEA model to evaluate the environmental efficiency of the winter wheat cropping system in Poland. The results of this study can help policy makers and winter wheat farmers as a support tool to provide reliable usage patterns, whereby the highest production with the lowest environmental impact can be achieved.

This paper consists of three sections. Section 1 presents the literature review and objectives of present study. Section 2 describes the data collection process and the methodology of calculating the CF in the LCA framework and the DEA models. This section eventually describes the integrated LCA-DEA framework. Lastly, Section 3 presents the obtained results and related discussions.

2. Methodology

2.1. Data collection and carbon footprint calculations

Data for the LCA were collected from 250 representative farms throughout the country monitored by the Polish Farm Accountancy Data Network (FADN) system. This database has been created as a deliverable of the LCAgri project[1] through face-to-face surveys with farmers. Information related to the amount of agricultural inputs, wheat yield, and agricultural operations for the 2015/2016 cropping season were derived from that database. To apply standard DEA approaches, it is essential to have identical production systems. Therefore, only 151 winter wheat farms, growing wheat as their main product without raising livestock, were considered for the pre-assessments.

The next step involved the identification of outliers. To identify the outliers, the density-based spatial clustering of application with noise (DBSCAN) method proposed by Ester et al. (1996) was applied. DBSCAN is capable of detecting data outliers in multi-dimensional data space. This algorithm detects the outliers as the points which are far from their nearest neighbouring points. Some studies have employed DBSCAN for detecting outliers within crop datasets (Majumdar et al., 2017), identifying temperature hotspots (Sukmasetya and Sitanggang, 2016), while also for identifying outliers in dairy energy and water datasets (Shine et al., 2018). The fixed radius (*eps*) and minimum number of points required to create a cluster (*minpts*) are two important parameters in DBSCAN. To determine a desired *eps* value, Ester et al. (1996) introduced *k-dist* method. According to *k-dist* method, the *eps* and *minpts* were determined at 0.06 and 5, respectively. Consequently, DBSCAN results identified 15 outlier data and these farms were excluded from the

[1] www.lcagri.iung.pl.

calculations (for more information about the data collection and the outlier detection method please see *Section S1* in Supplementary File (SF)). Therefore, 136 farms were considered for further analysis.

To calculate the CF of the farms, all emissions, including both indirect (related to production and transport of inputs) and direct (related to application of inputs) were calculated as a part of the LCA framework. An attributional LCA was applied to calculate the GHG emissions caused by winter wheat cultivation to assess the environmental efficiency of winter wheat farms. The system boundary was from cradle to farm gate (Fig. 1) and two functional units (FUs) were defined as 1 ha (total GHG) and 1 kg (CF) of winter wheat grain. Representing the results per ha helps to evaluate the intensity of a production system, while the efficiency of a production system is represented by a FU per kg of wheat grain (Ali et al., 2017). In a DEA model, the desirable (wheat grain) and undesirable outputs (total GHG emissions) must be expressed in the same units, thus, 1 ha was applied as the second FU for undesirable outputs.

Total GHG and CF for winter wheat farms were calculated using Eq. (1) and Eq. (2) as follows:

$$GHG_{Total} = GHG_{ID} + GHG_D \tag{1}$$

$$CF = \frac{GHG_{ID} + GHG_D}{Y} \tag{2}$$

where GHG_{Total} denotes the total GHG (kg CO_{2eq} ha^{-1} y^{-1}), *CF* implies the carbon footprint (kg CO_{2eq} (kg wheat)$^{-1}$), GHG_{ID} is indirect emissions (GHGs related to production and maintenance of materials and energies as inputs) (kg CO_{2eq} ha^{-1} y^{-1}), GHG_D is direct emissions (GHGs related to application of materials and energies) (kg CO_{2eq} ha^{-1} y^{-1}) and Y denotes winter wheat grain yield (kg ha^{-1} y^{-1}).

The amount of chemical fertilizer (kg), manure (kg), fuel (L), biocide (kg of active ingredient), machinery (h), and seed (kg) were determined per ha for each farm and were used to estimate the indirect and direct GHG emissions. Indirect emissions were estimated using Ecoinvent database version 3.4 (Wernet et al., 2016). For more details about the GHG calculations see *Sections S2* and *S3* of SF.

Direct GHG emissions for mineral and organic fertilizers were estimated according to IPCC (2006) guidelines and the method developed by Emmenegger et al. (2009) and Nemecek et al. (2016). The SF provides details related to the calculating the GHG emissions due to the application of fertilizers. CH_4 emissions from the application of organic fertilizers in wheat production was not considered in the calculation due to the low level of emissions on farms (Chianese et al., 2009). The methodology of Milà i Canals et al. (2013) was applied to calculate GHG emissions due to land use change. The changes in land use in Poland during the last 20 years were not significant (FAO, 2017). Thus, GHGs due to land use change were assumed to be zero in this study. Due to the lack of information in research regions and the low contribution to total GHG emissions (Frischknecht et al., 2007), GHGs from the production and the transport of capital goods (except agricultural machinery) were also not considered.

To allocate the CF to the wheat grain and straw, economic allocation was applied. This was carried out based on the prices of 145 and 70 € per metric tons for wheat grain and straw, respectively. CO_2, CH_4 and N_2O emissions, as the most important GHGs, were aggregated using their 100-year global temperature potential (GTP) of 1, 30.5 and 265 CO_{2eq}, respectively (IPCC, 2013).

2.2. Data envelopment analysis approach

DEA is a widely used non-parametrical and linear programming technique for evaluating the relative efficiency of DMUs (Emrouznejad and Yang, 2018). Since DEA can handle multiple inputs and outputs, it is an appropriate technique to discover the relationships that remain unclear in other methodologies. The process is carried out by detecting and quantifying the sources of inefficiency for each DMU. For the first time, Charnes et al. (1978) applied linear programming to estimate an empirical production technology frontier. Charnes, Cooper and Rhodes (CCR) extended an optimization model with constant returns to scale (CRS). Later, Banker, Charnes and Cooper (BCC) developed the model with variable returns to scale (VRS) and the CCR model transformed into the BCC model (Banker et al., 1984). These models measure the

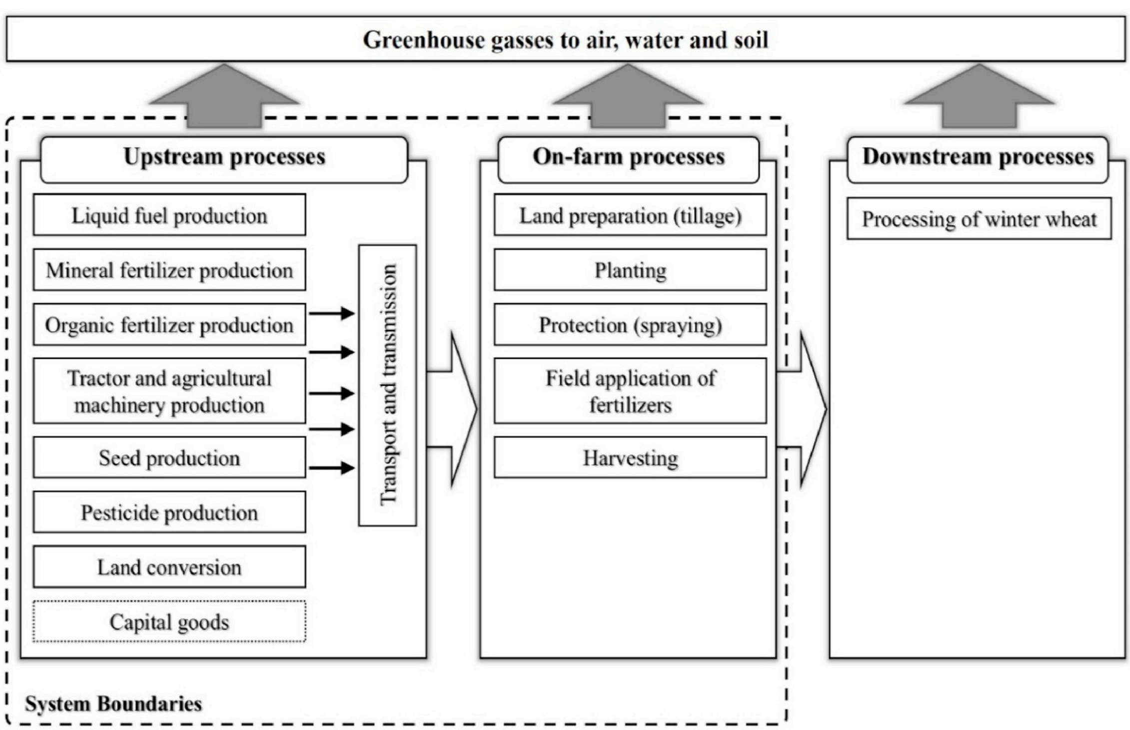

Fig. 1. Winter wheat production system boundary (dashed line). Emissions from production of capital goods (dotted gray lines) were excluded from system boundary.

technical efficiency (TE) of a DMU relative to other DMUs under the CRS (or VRS) conditions. The TE (efficiency score in this study) of winter wheat farms was estimated by using Eq. (S6) (see *Section S4* of SF). Efficiency in a DEA model is measured according to radial and non-radial methods (Cooper et al., 2007). The radial DEA model (Eq. (3) and Eq. (4)) concerns the proportionate change of input or output values without considering the slacks (defined as the difference between the inputs surplus and the outputs deficit).

Based on the potential of a DMU to achieve the maximum output or alternatively, to reach the minimum input quantities by the given output, DEA models are classified as output-oriented and input-oriented, respectively (Farrell, 1957; Lorenzo-Toja et al., 2015). Due to the fact that a farmer has more control over inputs rather than the outputs, the input oriented model was applied in this study. According to the input-oriented CCR model (radial model), Eq. (S6) can be converted to a linear programming problem as Eq. (3) and Eq. (4):

$$Min\theta = \sum_{i=1}^{m} v_m x_{mj} \tag{3}$$

Subjected to the following conditions:

$$\begin{aligned} &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\ &\sum_{r=1}^{s} u_r y_{rj} = 1 \ ; \ u_r \geq 0 \ ; \ v_i \geq 0 \end{aligned} \tag{4}$$

where x denotes the inputs vector, y is the outputs vector, v and u are the inputs' and outputs' weights, i and r show the number of inputs and outputs, respectively. An efficiency score varies between zero and one. Efficiency score equal to one is associated with an efficient DMU which has no reduction potential. An efficiency score lower than one, is related to an inefficient DMU. In contrary to radial models, non-radial models not only deal with the proportionate change of inputs or outputs, but also consider the slacks (Cooper et al., 2007). More details regarding the differences between radial and SBM models can be found in the *Section S5* of SF. The efficiency of non-radial models is measured in the form of a scalar known as the slack based measure of efficiency (SBM). SBM was introduced and developed by Tone (2001). SBM is generally expressed as follows:

$$min_{\lambda,S^-,S^+} \quad \rho = \frac{1-(1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1+(1/s)\sum_{r=1}^{s} s_r^+ / y_{r0}} \tag{5}$$

Subject to: $x_0 = X\lambda + s^-$; $y_0 = Y\lambda - s^+$; $\lambda \geq 0$, $s^- \geq 0$, $s^+ \geq 0$

where x and y are vectors of inputs and outputs; i and r are the indices of inputs and outputs; j denotes the firms; λ is a nonnegative vector; s^- and s^+ are the input excess and output shortfall, respectively.

The above equation can easily be formulated in the similar way of CCR model as follows (Tone, 2001):

$$min_{t,\lambda,s^-,s^+} \quad \tau = t - \frac{1}{m}\sum_{i=1}^{m} ts_i^- \Big/ x_{i0} \tag{6}$$

Subject to: $1 = t + \frac{1}{s}\sum_{r=1}^{s} ts_r^+ / y_{r0}$; $x_0 = X\lambda + s^-$; $y_0 = Y\lambda - s^+$; $\lambda \geq 0$, $s^- \geq 0$, $s^+ \geq 0$, $t > 0$

The above nonlinear problem can be transformed into a linear programing problem as follows (Tone, 2001):

$$\text{Minimize} \quad \tau = t - \frac{1}{m}\sum_{i=1}^{m} S_i^- \Big/ x_{i0} \tag{7}$$

Subject to: $1 = t + \frac{1}{s}\sum_{r=1}^{s} S_r^+ / y_{r0}$; $tx_0 = X\Lambda + S^-$; $ty_0 = Y\Lambda - S^+$

$\Lambda \geq 0, \quad S^- \geq 0, \quad S^+ \geq 0, \quad t > 0$

where: $S^- = ts^-, \quad S^+ = ts^+, and \ \Lambda = t\lambda$

If the optimal solution of linear programming is $\tau^*, t^*, \Lambda^*, S^{-*}, S^{+*}$, then the optimal solution of SBM will be $\rho^* = \tau^*$, $\lambda^* = \Lambda^*/t^*$, $s^{-*} = S^{-*}/t^*$, $s^{+*} = S^{+*}/t^*$. By neglecting the denominator of the objective function of Eq. (5), the input-oriented SBM model is defined.

2.3. Integration of LCA and DEA

One of the most important parts of the sustainability assessment involves evaluating the environmental impact. LCA evaluates the environmental impacts of a production system, while it does not provide any alternative for improvement. DEA provides the proper amount of inputs (i.e. less or more usage of inputs) which can push an inefficient wheat farm towards an efficient production system, while the environmental impacts are ignored. The successful integration of LCA and DEA has been one of the most challenging issues over the past few years. Such integration allows for the verification that reduced input consumption levels may (or would lead to) reduce environmental impacts. Moreover, this approach helps policy makers and farmers to evaluate both the operational and environmental performance of production systems.

As discussed in Section 1, several classifications have been introduced for integrating LCA and DEA including three, four and five-step approaches (Adenuga et al., 2018; Laso et al., 2018; Lorenzo-Toja et al., 2015; Lozano et al., 2009, 2010; Rebolledo-Leiva et al., 2017; Vázquez-Rowe et al., 2010). The most challenging issue, regarding LCA + DEA, and the main focus of this study is how to treat undesirable outputs in DEA models. Thus, the most common approaches for incorporating undesirable outputs in DEA models are discussed and assessed. It should be noted that within each approach, different DEA models (including radial (input, output, graph oriented etc.) and non-radial) can be employed.

2.3.1. Ignoring undesirable outputs

This approach does not include the undesirable outputs into the DEA model. An example of this approach is the five-step LCA + DEA framework stablished by Vázquez-Rowe et al. (2010) and applied by Iribarren et al. (2010) and Lozano et al. (2009). In this approach, the physical amount of inputs and desirable outputs are considered as DEA inputs and outputs, respectively. The life cycle impact assessment (LCIA) is carried out both for current and target (given as DEA results) situations and the potential improvements in the environmental impacts are addressed. Given the fact that desirable and undesirable outputs are produced at the same time during the crop production process, ignoring the undesirable outputs in a DEA model may lead to underestimation of DMUs' efficiency scores. In this study, DEA inputs for this method were mineral fertilizer (kg ha^{-1}), organic fertilizer (kg ha^{-1}), liquid fuel (L ha^{-1}), pesticide (kg$_{\text{active ingredient}}$ ha^{-1}), machinery (h ha^{-1}) and seed (kg ha^{-1}), and the model output was wheat grain yield (kg ha^{-1}).

2.3.2. Treating undesirable outputs as inputs

Introduced by Dyckhoff and Allen (2001) and Scheel (2001), this approach involves incorporating the undesirable outputs into the DEA models as inputs. Treating undesirable outputs as inputs may result in an erroneous interpretation. An unlimited reduction in undesirable outputs is not technically feasible and, moreover, this method may lead to ignoring some ecological slacks (Dyckhoff and Allen, 2001; Yang et al., 2008). A modified version of this approach was applied by Lozano et al. (2010) and Iribarren et al. (2010) (known as the three-step LCA + DEA framework), which treated both undesirable outputs and inputs as inputs of the DEA model and calculated the reduction of inputs consumption and environmental impacts by using a SMB-DEA model. One criticism to this approach is the higher sample size (DMUs) requirement. Since the minimum total number of DMUs in a DEA model should be greater than $I \times O$ or $3 \times (I + O)$, where I and O are the numbers of inputs and outputs, increasing in the number of model inputs and outputs, in this case the aggregated number of inputs and undesirable outputs, creates the need for more data (larger sample size), which represents a limitation (William et al., 2007). In our study and for the current approach, total GHG emissions (kg CO_{2eq} ha^{-1} y^{-1}) from the use of inputs were considered as DEA inputs, and wheat grain yield (kg ha^{-1} y^{-1}) was assumed as DEA output.

2.3.3. Data transformation

Introduced by Golany and Roll (1989) and Scheel (2001), this approach transforms an undesirable output into a desirable output by applying a reverse function. Rebolledo-Leiva et al. (2017) introduced and employed this method in a four-step LCA + DEA framework. An output oriented DEA model was recommended and the desired levels of inputs were calculated based on benchmarking intensities. Given this method, in this study DEA inputs were the physical amount of inputs per ha, and the model outputs were wheat yield (kg ha^{-1} y^{-1}) and the inverse of the total GHG (ha y (kg CO_{2eq})$^{-1}$).

2.3.4. Impact rate

With this approach, which has been introduced by You and Yan (2011), undesirable outputs are incorporated with their negative impact (or ratio) on efficiency score of a DMU. This approach can be formulated as follows:

$$EF_{IR} = [1 - (EF_{CU} - EF_{CD})] \times EF_{CD} \tag{8}$$

where EF_{IR} represents the efficiency score of a DMU using impact rate approach, EF_{CD} denotes the efficiency score for conventional DEA models without considering (ignoring) the undesirable outputs, and EF_{CU} refers to conventional DEA models by considering the undesirable outputs. Inputs in a conventional DEA model, regardless of undesirable outputs, were physical amounts of inputs, while the output was the wheat yield (kg ha^{-1} y^{-1}), similar to the model expressed in Section 2.3.1. Incorporating the undesirable outputs into the conventional DEA model, causes the model output to contain the total GHG (kg CO_{2eq} ha^{-1} y^{-1}) in addition to the wheat yield (kg ha^{-1} y^{-1}).

2.3.5. Ratio model

You and Yan (2011) proposed this model to adjust the efficiency scores of DMUs when considering the undesirable outputs in the DEA models. In the ratio model, desirable and undesirable outputs are defined as O_p^+ ($p = 1, 2, \ldots, n_1$) and O_q^- ($q = 1, 2, \ldots, n_2$), respectively. The undesirable outputs are treated as penalty parameter as follows:

$$\psi_j = \rho_1 O_{1j}^- + \ldots + \rho_{n2} O_{n2j}^- \tag{9}$$

where ψ_j expressed as a penalty parameter for j_{th} DMU, and ρ_q *is* the penalty value for q undesirable outputs ($q = 1, 2, \ldots, n_2$).

According to the ratio model and applying Eq. (9), the desirable outputs (Y_p) are modified as:

$$Y_p^{'} = \frac{1}{\psi} O_p^+ \qquad (p = 1, 2, \ldots, n_1) \tag{10}$$

2.3.6. SBM with undesirable outputs

The SBM model with undesirable outputs was introduced by Cooper et al. (2007) to take undesirable outputs into account in the DEA model. Vázquez-Rowe et al. (2010) applied this method to link environmental and socioeconomic assessments in fisheries. In this method, an efficient DMU is the one with more desirable outputs and less undesirable outputs (relative to less input). Therefore, each DMU has three vectors such as X, Y^g, and Y^b for inputs, good outputs and bad outputs, respectively. The excessive values in inputs, and bad outputs can be illustrated by s^-, s^b, while the shortfall in good outputs can be shown by s^g. The SBM with undesirable outputs can be presented as follows:

$$\text{Minimize } \rho^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s2} \frac{s_r^b}{y_{r0}^b}\right)} \tag{11}$$

$$\text{Subject to: } x_0 = X\lambda + s^- \; ; \; y_0^g = Y^g\lambda - s^g \; ; \; y_0^b = Y^b\lambda + s^b$$

$$s^- \geq 0, \quad s^g \geq 0, \quad s^b \geq 0, \quad \lambda \geq 0$$

By transferring Eq. (11) into a linear programing problem, Eq. (11) is displayed as follows:

$$\text{Minimize } \tau^* = \min t - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}} \tag{12}$$

$$\text{Subject to: } 1 = t + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{S_r^b}{y_{r0}^b}\right)$$

$$x_0 t = X\Lambda + S^- \; ; \; y_0^g t = Y^g\Lambda - S^g \; ; \; y_0^b = Y^b\lambda + S^b$$

$$S^- \geq 0, \quad S^g \geq 0, \quad S^b \geq 0, \quad \Lambda \geq 0, \quad t > 0$$

If the optimal solution of linear programming is $t^*, \Lambda^*, S^{-*}, S^{g*}, S^{b*}$, then the optimal solution of SBM with undesirable outputs will be $\rho^* = \tau^*$, $\lambda^* = \Lambda^*/t^*$, $s^{-*} = S^{-*}/t^*$, $s^{g*} = S^{g*}/t^*$, $S^{b*} = s^{b*}/t^*$.

The six methods, as were discussed in Section 2.3.1 to Section 2.3.6, were evaluated based on the radial and SBM models, and their results were compared. Due to nature of the sixth method (SBM-DEA model with undesirable), only the SBM was calculated for this method. There are several other DEA models that can be used in the LCA + DEA framework such as multiple objective ratio optimization with dominance (MORO-D) (Angulo-Meza et al., 2019; Estellita Lins et al., 2004), directional distance function (DDF) (Adenuga et al., 2018; Beltrán-Esteve et al., 2014, 2017) and weak disposability assumption (WDA) (Dakpo et al., 2016), which were out of the scope of this study.

Operational and environmental aspects of this study can be summarized in different steps. In the first step, the life cycle inventory (LCI) and subsequently total GHG for each DMU were calculated. In the next steps, six methods for incorporating undesirable outputs in the radial and SBM-DEA models were developed for DMUs and the obtained results were compared. Finally, efficiency scores of the winter wheat farms in the research area were assessed according to the most appropriate model. All calculations and analyses were conducted using Microsoft Excel 2016, SimaPro 8.5.2.0, R-software and DEASolver 15.

3. Results and discussions

3.1. Life cycle assessment of winter wheat

The annual average GHG emissions and CF of winter wheat production were 2485 kg CO_{2eq} per ha and 0.45 kg CO_{2eq} per kg wheat grain (see Table S8 in SF). Also, the average indirect and direct GHG emissions were reported as 1615 and 870 kg CO_{2eq} per ha per year, respectively. This result was in agreement with the result of similar studies on wheat production in Europe; such as Syp et al. (2015) in Poland (0.45 kg CO_{2eq} per kg wheat grain), Fantin et al. (2017) and Ali et al. (2017) in Italy (0.44 and 0.30 kg CO_{2eq} per kg wheat grain), Hayer et al. (2008) in Germany (0.53 kg CO_{2eq} per kg wheat grain, respectively), Audsley et al. (2010) in UK (0.51 kg CO_{2eq} per kg wheat grain), and Hayer et al. (2008) in Denmark (0.36 kg CO_{2eq} per kg wheat grain). Wójcik-Gront (2018) reported wheat CF around 0.27 kg CO_{2eq} per kg wheat grain for Poland. The difference between the reported CF in previous study and our study is due to differences in wheat grain yield. The wheat farms studied by Wójcik-Gront (2018) were experimental farms type with the average yield higher than the actual wheat yield in Poland. A considerable difference was found between the results of this study and previous works, such as Williams et al. (2010) and Hayer et al. (2008), in which the emissions were reported as 0.70 and 1.07 kg CO_{2eq} for the production of 1 kg wheat grain in UK and Poland, respectively. This discrepancy may be due to the inventory data and modelling approaches used (Corrado et al., 2018). As there is an inverse relationship between CF and yield rates, factors which influence the yield may indirectly have impact on CF. According to the results of the study conducted by Wójcik-Gront

(2018), water overflow is a yield restricting factor of winter wheat grain yield in Poland. Since most winter wheat production in Poland is rain fed, high precipitation during final wheat growth phase has negative consequences for plant growth conditions. Improved drainage may increase the yield directly and decrease CF indirectly (Lv et al., 2011). N_2O emission due to it's high GTP is an important source of emissions in soils. Soil N_2O emissions depend on the soil moisture and soil mineral nitrogen level (Wójcik-Gront, 2018). In addition to these factors, organic soils have previously showed higher levels of N_2O emissions when compared to mineral soils (Bouwman et al., 2002). Unfortunately, there were no details available detailing the soil quality of the studied farms. This information helps to have more reliable results. Bouwman et al. (2002) reported higher levels of emissions in poorly drained soils compared to well-drained soils, due to denitrification. Owing to the high level of precipitation in Poland, drainage in crop production systems is an important issue and may lead to a lower CF in winter wheat production. According to the results obtained, the production and application of mineral fertilizers and liquid fuel contributed most to the total GHG emission in the research area (see Table S8 in SF). Also, Ali et al. (2017), Wang et al. (2007) and Sefeedpari et al. (2013) found chemical fertilizer and diesel fuel as the largest sources of emissions in a wheat production system. Ali et al. (2017) found that around 52.6% of total emissions were due to their production and field application of urea, and moreover, there was a positive correlation between nitrogen rate and CF. Fig. 2 shows the variability in GHG_{ID}, GHG_D, CF and total GHG. In Fig. 2, GHG_{ID}, GHG_D and total GHG are based on kg CO_{2eq} per ha per year, while CF is based on kg CO_{2eq} per kg wheat grain. The CFs of winter wheat farms in the research area ranged from 0.25 to 0.67 kg CO_{2eq} per kg wheat grain (5th −95th percentile) (Fig. 2). Achten and Van Acker (2016) found a range of 0.30–1.07 for CF of wheat production in Europe. Total GHGs varied between 1207 (5th percentile) and 3686 (95th percentile) kg CO_{2eq} per ha per year. The coefficient of variation (CV) showed the larger variability of total GHG compared to the variability of GHG_D, GHG_{ID} and CF. According to the results obtained, GHG_{ID} contributed to 57% of total GHG emission. Ali et al. (2017) found that more than 51% of total GHG in wheat production comes from indirect emissions.

3.2. Comparison of various DEA models in an LCA + DEA framework

The eco-efficiency taken into account in this study was based on the fact that decreasing inputs use resulted in higher levels of efficiency and

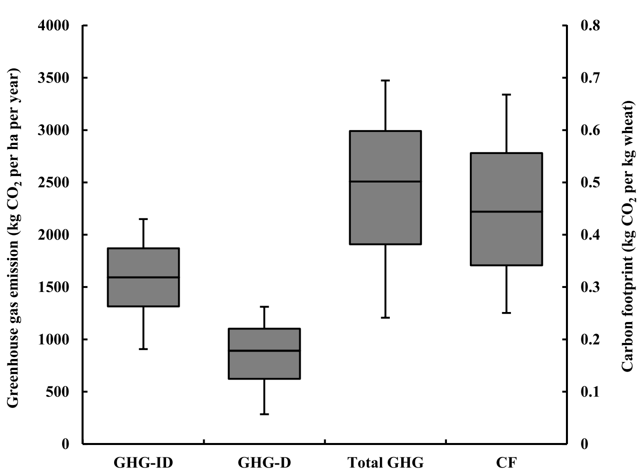

Fig. 2. GHG emissions and CF variability of winter wheat farms. The midpoints of each box plot represent the 50th percentile; lower and upper edges of the boxes show the 25th and 75th percentiles, respectively; and the whiskers denote the 5th and 95th percentiles.

greater environmental performance in winter wheat production in Poland. Multiple methods and DEA models were assessed to select the most appropriate one for the eco-efficiency assessment. Table 1 shows the descriptive statistics of the results obtained from six DEA models in a LCA + DEA framework for the 136 winter wheat farms in the research area. For each method, the results of the radial and SBM models are represented. As shown, the number of efficient farms (farms with efficiency score equal to 1.00) for studied methods varied from 7 (according to method 5) to 18 (according to method 2). For all methods, the average efficiency scores from the radial model were higher than the SBM model. Since SBM considers not only the proportional reduction but also the slacks in the variables, the efficiency scores from the SBM model can be expected to be smaller than the radial models (Tone, 2001). Therefore, by comparing radial and SBM-DEA models, the following goals were pursued: 1) estimating the reduction rate of efficiency scores due to application of SBM model within each method, and 2) comparing methods in terms of their reduction in (changes of) efficiency scores. As shown in Table 1, method 5, in which SBM-DEA is applied, achieved the least changes (with the lowest standard deviation) in efficiency scores. Lower efficiency scores from the SBM models indicate that the DEA models can compare and evaluate the DMUs better (with less changes) than the radial models (You and Yan, 2011). For example, a DMU determined as an efficient DMU in the radial model can be turned out to be inefficient based on the SBM model (for more detail please see *Section S5* in SF where the difference between radial and SBM models were discussed). Therefore, it can be concluded that the SBM model offers a more realistic efficiency score for a DMU. Standard deviations (SDs) of a farms efficiency scores were in almost the same range. The highest SD was calculated for the SBM model in method 4. The minimum efficiency scores ranged from 0.06 (methods 4 and 5) to 0.41 (method 3) (Table 1). The coefficient of variation showed greater variability among farms for the SBM model in methods 4 and 5 (Table 1 and Fig. 3).

Fig. 3 presents the efficiency score variability of winter wheat farms for six DEA methods (including radial and SBM models). The efficiency scores showed large variability among DMUs for the SBM models in comparison with the radial models in all studied methods. As illustrated in Fig. 3, the variability of the calculated efficiency scores of method 1 was fairly equal to methods 2 and 3, while a large variability was calculated among the efficiency scores estimated by methods 4, 5 and 6.

Methods 1, 2 and 3 were not found to be appropriate DEA models in our study when the undesirable aspects of the winter wheat farms are taken into consideration. Due to the different nature of desirable and undesirable outputs, undesirable outputs should be distinguished in the DEA models in which both desirable and undesirable outputs are considered. Literature review shows that the majority of prior research on DEA of wheat production have applied and are continuously applying method 1 (Alemdar and Oren, 2006; Chebil et al., 2015; Moradi et al., 2018; Nabavi-Pelesaraei et al., 2016; Syp et al., 2015). However some of them applied method 2 at the regional level (Kuosmanen and Kortelainen, 2005; Masuda, 2016) and at the farm level (Picazo-Tadeo et al., 2011; Ullah et al., 2016). In addition, some agricultural studies used method 6 (Adenuga et al., 2018; Cecchini et al., 2018; Dong et al., 2018). In studies where method 1 was employed, DEA modelling aimed at optimizing the production system without treating the undesirable outputs and ultimately evaluating the environmental consequences of DEA results. On this basis, however, a reduction in environmental impacts due to the application of method 1 is an apparent conclusion, this model ignores undesirable outputs during the optimization process and does not address the production process completely (Dakpo et al., 2016). The goal of this method, referred to a five-step LCA + DEA approach by Lozano et al. (2009) and Iribarren et al. (2010), is not minimization of undesirable outputs. Instead, this method aims to measure the potential reduction of undesirable outputs in an efficient production situation. Comparing to the three-step LCA + DEA approach (where both undesirable outputs and inputs are treated as inputs), method 1 has an additional advantage of requiring less samples (DMUs) in the DEA

Table 1
Descriptive statistics of the results obtained from six DEA methods (including radial and SBM models) for 136 winter wheat farms.

Items	Method 1		Method 2		Method 3		Method 4		Method 5		Method 6
	Radial	SBM	Radial	SBM	Radial	SBM	Radial	SBM	Radial	SBM	SBM
No. of efficient DMUs	13	13	18	18	16	16	13	13	7	7	13
Average efficiency score	0.70	0.52	0.72	0.56	0.73	0.53	0.59	0.40	0.37	0.31	0.43
S.D of efficiency score	0.17	0.21	0.17	0.22	0.16	0.22	0.22	0.25	0.21	0.20	0.23
Min efficiency score	0.33	0.20	0.34	0.23	0.41	0.20	0.17	0.06	0.13	0.06	0.15
Max efficiency score	1	1	1	1	1	1	1	1	1	1	1
Coefficient of variation	0.24	0.40	0.24	0.39	0.22	0.41	0.38	0.63	0.57	0.66	0.53

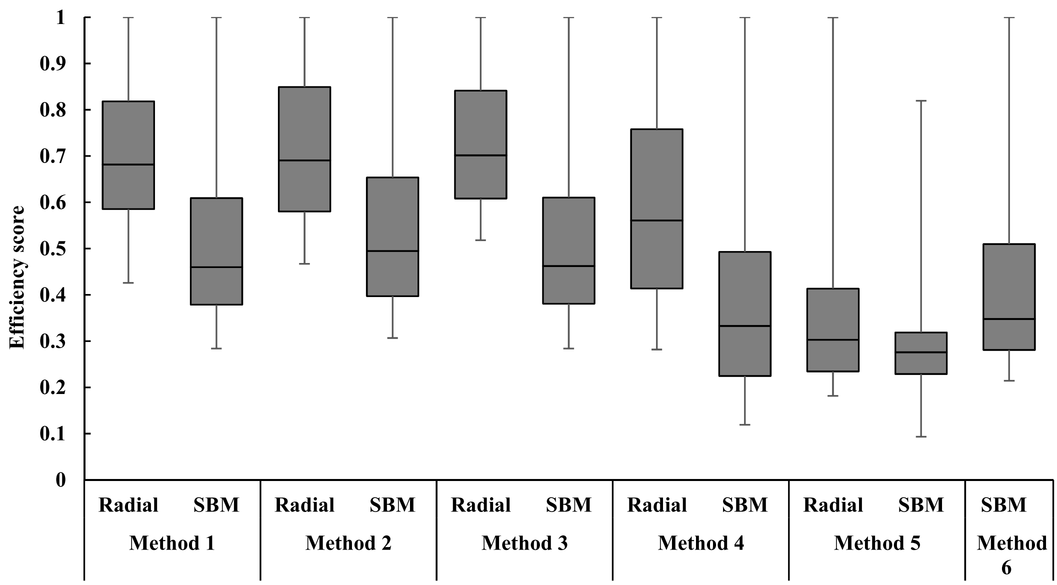

Fig. 3. Efficiency score variability of winter wheat farms for six DEA methods. The midpoints of each box plot represent the 50th percentile; lower and upper edges of the boxes show the 25th and 75th percentiles, respectively; and the whiskers denote the 5th and 95th percentiles.

model. Method 2 (considering undesirable outputs as inputs into DEA) was unable to truly reflect the production process. Dyckhoff and Allen (2001) expressed that by applying method 2 in an input oriented DEA model, some ecological slacks are not detected and, moreover, an infinite reduction of undesirables is not possible (Yang et al., 2008; You and Yan, 2011). Although in method 3 the undesirable output is being treated as an output variable, the scale has been changed and subsequently the intervals have also been changed. Moreover, the value of zero for undesirable output is not defined in this method (You and Yan, 2011). A modified method for treating undesirable outputs as DEA model inputs (three-step LCA + DEA model (Lozano et al., 2010)), which was not studied in this study is treating both undesirable outputs and inputs as DEA model inputs. As Seiford and Zhu (2002) specified, undesirable outputs are not inputs, thus, treating them as additional inputs will not reflect the real situation of the production process. Moreover, it is not physically acceptable due to the fact that it violates the constraints of outputs (Dakpo et al., 2016). As shown in Table 1 and Fig. 3, the larger efficiency scores for DMUs were estimated when the undesirable output was treated in the DEA model (methods 2 and 3) in comparison to method 1. The results of our study for methods 1–3 were in agreement with Hua et al. (2007) and You and Yan (2011), whom mentioned that disregarding the undesirable outputs in DEA models decreases the estimated efficiency scores. Lower average efficiency scores were reported for methods 4 and 5 in comparison with the methods 1–3 (Table 1 and Fig. 3). These differences for methods 4 and 5 can be explained by Eq. (8) and Eq. (10), where the undesirable output is considered as a negative impact or penalty parameter, which decreases the efficiency score of a DMU. Although method 4 reflects the efficiency score of DMUs well, it cannot discuss the possible amount of input reduction for a DMU.

Among the conventional DEA models (methods 1–5), method 5 showed the lowest average efficiency score which also can imply the better performance of this method in evaluating the DMUs. The variability between efficiency scores of DMUs in method 5 was higher than in method 6 and also the higher average efficiency score was reported for method 6. In method 5, the model output is defined as a fraction of desirable and undesirable outputs (Eq. (10)). Due to the fact that in an input-oriented model, the output is considered as a fixed parameter, the undesirable output is treated likewise, and thus, it is not minimized as it happens with the inputs; whereas in method 6, only the desirable outputs are considered as fixed parameters and both inputs and undesirable outputs are aimed to be minimized. To obtain a greater understanding of the obtained results, the current and target values (based on DEA results) of inputs and outputs according to the six methods are presented in *Section S7* (Table S9) in the SF. Similar trends for the potential reduction of inputs and undesirable outputs were observed in the efficiency scores of the six DEA methods. According to Table S9, the lowest target values for inputs and undesirable outputs were reported for method 5. A deeper examination of the target values of method 5 revealed that the estimated target values for mineral fertilizers, liquid fuel, seed and total GHG emission were not in the acceptable (actual) range (level) of inputs use and GHG emissions in winter wheat production. Therefore, this method could not present the input values within the acceptable range (as defined in the DEA model constraint). According to this finding, method 6 reflects the performance of undesirable outputs to a greater extent compared to methods 1–5.

3.3. SBM-DEA model with undesirable output

After comparing multiple DEA methods and selecting method 6 as the most appropriate method, the performance results of winter wheat farms in this research area based on method 6 are presented. The average efficiency score was 0.43 with a standard deviation of 0.23. This value shows that around 57% of resources could be saved by raising the performance of inefficient farms to the efficient levels. According to the results, 123 farms were classified as inefficient farms (efficiency score less than one), while 13 farms were efficient (with efficiency score equal to one). The largest number of efficiency scores were reported between 0.2 and 0.4 (around 57% of all efficiency scores) (See Table S10 in SF). Table S11 shows the target values and reduction level of inputs and undesirable output for each inefficient farm in order to perform at the efficient level according to the method 6. Target values and changes allow the decision makers and farmers to produce winter wheat crop more sustainably. According to the 'change' column in Table S11, fuel contributed most (−69%) to the total change of inputs, followed by machinery (−65%), biocide (−63%) and mineral fertilizer (−57%). The highest reduction potential (in amount) among all inputs was for mineral fertilizer and since the amount of fuel, machinery, and biocide consumption per hectare was small, a small reduction in these inputs would result in a large percentage change. Comparatively, the results of the current and optimum (target) (DEA results) situations tie in well with previous studies, wherein the highest reduction of inputs usage was seen for chemical fertilizers and diesel fuel (Alemdar and Oren, 2006; Syp et al., 2015). The total GHG reduction potential for the inefficient farms varied from 479 to 3353 kg CO_{2eq} per ha per year. Results showed that the reduction potential of total GHG emissions in the research area was around 49%. In the DEA models, inefficient farms selected a composition of efficient farms as the best option or sample, which have the lowest levels of inputs and undesirable outputs and the highest level of desirable outputs. Thus, a farm which appeared more often than others in the reference set is selected as the most efficient farm. Accordingly, farms 3, 19, 26, 36, 52, 75, 80 and 102 were the most efficient farms while appearing more frequently in the reference set. Fig. 4 represents the current situation of yield and GHG emission of the most efficient winter wheat farms in comparison to other farms. As it is seen, the yield of efficient farms are well distributed among all wheat farms. However, GHG emissions of efficient farms were in the first 50th percentile among all farms. For more detailed information about the current situation of all inputs consumption for the most efficient farms in comparison to other farms see Fig. S2 in the SF. The achievement of targets presented by the SBM model with undesirable outputs (see Table S11 in SI) are feasible due to the fact that they are based on the existing efficient farms, as opposed to theoretical results. There are many useful strategies for lowering GHG emissions caused by nitrogen fertilizers such as; avoiding the excessive use of nitrogen, incorporating N fertilizers into the soil (>5 cm deep), precision agriculture, and using legumes in crop rotations. Excessive use of nitrogen fertilizer, not only has no effect on increasing the yield, but also leads to environmental damages (Wójcik-Gront, 2018). One of the most important environmental consequences of excessive use of nitrogen fertilizer is N_2O emissions from soil. Yearly soil monitoring helps to obtain more precise estimates of N_2O emissions from agricultural production systems (Zhou et al., 2017), which was not available in this study. As an option which can be studied on crop production in Poland, Liu et al. (2013) suggested the use of nitrification inhibitors for reducting nitrogen without having a negative impact on wheat grain yield. One of the strategies aimed towards reducing the amount of mineral fertilizer is replacing portions of mineral fertilizer by organic fertilizer. However, the results from the DEA model recommend a lower level of organic fertilizer usage. To explain this confliction and to check the importance of the current usage of manure on wheat production, we omitted the organic fertilizer input from the DEA model and reran the model. The average results did not change, showing that manure application does not have a negative impact on the efficiency score of winter farms. Besides chemical fertilizer, Wójcik-Gront (2018) expressed that fungicides play a crucial role during winter wheat growth in Poland. In a situation with high precipitation and low solar radiation in wheat farms, the possibility of foliar diseases increases, which leads to wheat grain yield loss (Wójcik-Gront, 2018). High precipitation also causes a loss of soil nitrogen and subsequently poor nitrogen availability to wheat plants (Huang et al., 1995).

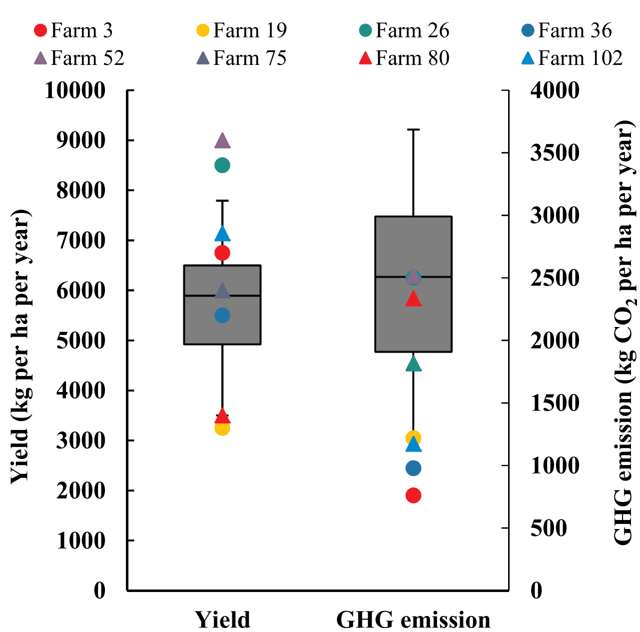

Fig. 4. Current situation of yield and GHG emission for the most efficient farms in comparison to other farms. The midpoints of each box plot represent the 50th percentile; lower and upper edges of the boxes show the 25th and 75th percentiles, respectively; and the whiskers denote the 5th and 95th percentiles.

4. Conclusion

In this paper the efficiency of winter wheat farms in Poland was evaluated by integrating LCA and DEA. To select the most appropriate DEA model, six methods treating the undesirable factors into the DEA models were applied and the results were compared. Based on the results, the following conclusions were drawn:

The annual average CF was 0.45 kg CO_{2eq} per kg of wheat grain whereby the production and application of mineral fertilizers and liquid fuel contributed most to the CF in the research area. According to another classification, the average indirect GHG emissions were higher than direct GHG emissions. Results of different DEA methods showed that the average efficiency scores in all methods for the radial DEA models were higher than for the SBM-DEA models. The variability of efficiency scores for method 1, was fairly equal to methods 2 and 3, while considerable variability was seen between the efficiency scores for methods 4, 5 and 6. According to the obtained results, an SBM-DEA model with undesirable outputs was the model that reflecting the performance of undesirable outputs to a greater extent than other methods presented in this study. This conclusion was based on the fact that a large difference was seen in the SBM-DEA models in comparison to the radial models. Moreover, the SBM-DEA model with undesirable outputs reported the lowest efficiency scores between the studied models, which distinguishes winter wheat farms better. Finally, the selected model presented the greatest potential improvement for inputs consumption and undesirable outputs. Thus, this method was employed for maximizing the wheat production efficiency and minimizing undesirable outputs. Since the targets presented by this model are based on the existing efficient farms, these targets can be feasibly achieved. The average efficiency score for winter wheat farms, according to this method, was reported as 0.43 which shows that around 57% of resources could be saved by raising the performance of inefficient farms to the efficient levels. Results showed that the largest change (in amount) among all inputs was observed for mineral fertilizer, while the largest change in percentage was for fuel, machinery, and biocide consumption per hectare. This study can help winter wheat farmers to obtain real and reliable usage pattern for inputs in winter wheat production system, in which highest production with the lowest environmental impact can be achieved. The results of this study can be applied by policy makers as a support tool to establish reference values for inputs consumption and GHG emissions in winter wheat production. For future works, other methods and techniques such as Multiple Objective Ratio Optimization with Dominance (MORO-D), Directional Distance Function (DDF) and Weak Disposability Assumption (WDA) are recommended to be employed for comparing different approaches.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110138.

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