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Green productivity and undesirable outputs in agriculture: a systematic review of DEA approach and policy recommendations

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ABSTRACT
Measuring efficiency in the presence of undesirable outputs could be difficult depending on how to treat these outputs; thus, undesirable outputs modelling has been an exciting subject of several studies in the Data envelopment analysis (DEA) literature in the last two decades. The present study aims to illustrate a thorough overlook of studies in which DEA has applied for measuring efficiency with undesirable outputs. Fifty-eight articles were published from 2000 to 2020 have been systematically reviewed through PRISMA protocol. The results indicated that "Journal of Cleaner Production" ranked first with six published articles, and Chinese scholars have the most contributions to this field, with twenty-third articles. Also, almost a quarter of the published articles' scope was related to agricultural pollution, and thirteen articles were published in 2016, the highest number of published articles annually. Taken together, the theoretical and empirical implications of research in the field of Green Productivity are discussed, and some policies were recommended.

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Data envelopment analysis (DEA); undesirable outputs; green agricultural productivity; agricultural efficiency; environmental policies

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- Systematic literature review on green agricultural productivity;
- Fifty-eight studies dating from 2000 to 2020 were scrutinised;
- How to treat undesirable outputs affects productivity measurement;
- Data Envelopment Analysis found as the primary approach applied;
- Four DEA models named CCR, BCC, SBM, and RAM are widely used in the agri-sector.
- Policy recommendations for promoting green agriculture developed.

1. Introduction

The agriculture sector plays a crucial role in debates on green, circular, and bioeconomy mainstreamed global sustainability concepts (Tsangas et al., 2020). It is

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characterised by several feedstocks appropriate to be improved in terms of material and energy; thus, new opportunities are provided by the circular economy for investors (D'Adamo et al., 2019). The circular economy has two primary goals: improving waste management (or reutilizing), reducing energy consumption (or boosting green energy) (Kapsalis et al., 2019). It is believed that by transforming the agri-sector into circular, apart from the technological sector, circular economy goals could be more achievable; since the agri-sector is one of the most sectors in which a high percentage of biomass has been produced (Jimenez-Lopez et al., 2020). On top of that, renewable biological resources (biomass) and circularity are the critical aspects of the bioeconomy (D'Adamo et al., 2020a); thus, materials recycling, fossil fuel use reduction, and waste management lead the bioeconomy to obtain biofuel, bioenergy, etc., which are vital for achieving sustainable development goals (SDGs) (Duque-Acevedo et al., 2020, Morone & D'Amato, 2019). SDGs could provide a framework of measurable goals and targets and goals, linked directly or indirectly with circular economy principles, to harmonise sustainable development and world economies (Loizia et al., 2021, D'Adamo et al., 2020b).

Economic development and industrialisation rely on high resource input, while the capacities of the environment and resources are neglected, which caused undesirable outputs and ecological crises (Wang et al., 2019). Undesirable outputs comprise wastewater, CO_2 emission, air pollution, etc., which are dangerous for the environment (Tohidi et al., 2014). Undesirable outputs are produced unwillingly in the agricultural sector; thus, policy-makers need to utilise scientific approaches to cope with the undesirable outputs' of production and reduce them (Halkos & Petrou, 2019b, Tohidi et al., 2014). Both undesirable and desirable outputs produce jointly; however, undesirable outputs affect efficiency scores' evaluation of decision-making units (DMUs). Over the last decade, for instance, energy consumption and CO_2 emissions have risen considerably in China, emitting almost 8200 million tons of CO_2 in 2012, produced by industries and agricultural sectors (Sun et al., 2016). Also, waste, an environmental issue having strong relationships whit economic and social dimensions, has increased dramatically over the years (Doula et al., 2019, Doula et al., 2021, Papadopoulos et al., 2021). Zorpas (2020) mentioned various reasons for producing waste in which undesirable outputs, such as CO_2 emissions, were ranked as the most influential reason; also, D'Adamo et al. (2021) mentioned that biomethane could be used as fuel which is an excellent potential for EU leading them towards a green economy; therefore, assessing the environmental productivity in the presence of the undesirable outputs is vital (Dakpo et al., 2014).

There are three popular methods for measuring productivity within a broad context, including index measurement, linear programming, and econometric models (Singh et al., 2000). Index measurement comprises the employing of five ratios for measuring productivity: "single-factor productivity," "multiple factor productivity," "total productivity," "managerial control ratio," and "productivity costing." The most prevalent ratio is the total productivity, in which the productivity is measured as a ratio of various inputs. Linear programming, in which Data envelopment analysis (DEA) is the most prevalent, creates a production frontier and assesses the inputs' contribution to the productivity considering the past performance data (Baležentis et al., 2016). DEA models and econometric models are applicable when large data series are available. In econometric models, statistical models are applied to the data series to estimate productivity. The leaner programming and econometrics models are usually integrated to deal with productivity measurement issues (Singh et al., 2000). The DEA models' main advantages over the other methods are: DEA models could maximise multiple outputs simultaneously, while total productivity index could only maximise one output. DEA is a non-parametric mathematical model; thus, a specific functional form is not required making DEA more flexible and applicable compared to others (Liu et al., 2017). DEA could trace less-productive inputs by employing separate and specific optimisation routines for each input, making DEA more robust than the others.

DEA is a mathematical method proposed by Charnes et al. (1978), and it utilises linear programming methods to turn inputs into outputs to evaluate the performance. Also, any DMUs can freely select any mixture of inputs and outputs to increase their relative efficiency (Kang et al., 2018). By dividing the total weighed output by the total weighted input, the efficiency score or relative efficiency is calculated. The relative efficiency is a non-negative value and calculated concerning linear interactions between the inputs and outputs of the DMUs (Mardani et al., 2018, Zare et al., 2019). Simply put, the relative efficiency shows the level of efficiency of a DMU in a determined level of output concerning the quantity of input, which consumes compared to similar DMUs (Zhou et al., 2019). Shen et al. (2017) mentioned that many researchers used DEA to assess agricultural performance, environmental efficiency, and productivity with undesirable outputs. For instance, Fei and Lin (2017b) utilised Meta-Frontier DEA to tackle the agricultural problems related to carbon dioxide emissions. Li et al. (2013) used constant returns-to-scale (CRS) and variable returns-to-scale (VRS)-DEA to allocate resources to reduce CO_2 emission effectively. Yaqubi et al. (2016) used Directional Distance Functions (DDF)-DEA to assess environmental practices' efficiency and shadow values.

There are three basic DEA models, including radial, additive, and slack-based measure (SBM) models. The radial model was proposed by Charnes et al. (1978) is considered the original DEA model, also called the CCR (Charnes, Cooper, and Rhodes) model (Yang & Wei, 2019). In this model, The DMU's efficiency score is measured based on the proportional or radial distance to the efficiency frontier. The radial models are divided into two models: CCR and BCC (Banker, Chames, and Cooper) models. In the BCC model, the production technology shows variable returns to scale (Paradi et al., 2018). Furthermore, the additive model is used if there are multiple inputs and multiple outputs; therefore, the additive model determines all potential of inefficiency through the summation of the total inputs and desirable outputs slacks. The value of variable data could be zeros or negative in the additive model, unlike the radial DEA model (Cooper et al., 2006). Moreover, the SBM model is considered an extension of the additive model developed by Tone (2001). In this model, like the additive model, a mix of multiple inputs and outputs could be considered; however, it could be a unit invariant and generate a standard efficiency score, unlike the additive model.

Measuring productivity is considered a crucial research avenue in economics since it explains how inputs transform into outputs through factors of changes (Baležentis et al., 2021); however, measuring productivity in the presence of undesirable outputs could be difficult depending on how to treat these outputs. The various treatment methods with undesirable outputs in DEA have recently received more attention (Boussemart et al., 2020). Halkos and Petrou (2019b) did attend to present four possible way to cope with undesirable outputs in DEA, including (1) disregarding negative outputs from the production process, (2) regarding negative outputs as inputs, (3) regarding negative outputs as positive outputs, and (4) applying required modifications to take negative outputs into account. They also mentioned a new model named Zero-Sum Gains-DEA (ZSG-DEA) models utilised by Gomes and Lins (2008) to deal with undesirable outputs. Therefore, it is necessary to a clear and comprehensive review of the various treatment methods with undesirable outputs in DEA models be provided due to the effect of the treatment method on productivity; also, capabilities of various DEA models could be highlighted through a comprehensive review motivating scholars to apply them for measuring productivity with undesirable outputs and compare them with the previous research. On top of that, current research gaps in measuring productivity and methodological concerns are highlighted through a systematic literature review providing a clear pathway for future research.

According to the present research results, agricultural pollution is the most attractive topic for scholars, including Falavigna et al. (2013), Kuhn et al. (2018), Yaqubi et al. (2016), Berre et al. (2013), Skevas et al. (2014), Reinhard et al. (2000), Wu et al. (2013), Vlontzos and Pardalos (2017), Buckley and Carney (2013), Coelli et al. (2007), Zare-Haghighi et al. (2014), Dong et al. (2018), Sun et al. (2016), working on productivity measurement with undesirable outputs. In agriculture, water, soil, and Greenhouse Gas (GHG) are three significant pollution sources (Chen et al., 2017). Furthermore, economic activities, such as heat and electricity production, agriculture, and industry, lead nations to achieve socio-economic development (Yu et al., 2020); however, these activities usually produce harmful and toxic material emissions, such as Nitrogen Oxides (NOx), CO_2 emissions, wastewater, Sulfur Dioxide (SO_2), and heavy metals (Wang et al., 2020, Halkos & Petrou, 2019a). Sepehri et al. (2020) also mentioned that Sustainable development goals, economic growth, and human health are affected by agricultural pollution; while, agriculture sectors contribute to the eutrophication phenomenon, greenhouse effect, waterbodies pollution, climate change, stratospheric ozone depletion, global phosphorous, and air pollution (Adegbeye et al., 2020).

State of the art in applying DEA models for measuring agricultural productivity with undesirable outputs through systematic literature review and recommending applicable policies, based on obtained results, to boost green, circular, and bioeconomy could be considered the present study's novelties. Simply put, providing a broad overview of DEA models' application in agriculture productivity with undesirable outputs is the ultimate aim of the present study; therefore, the ultimate aim can be divided into four research issues: (1) which area of agricultural productivity with undesirable outputs has utilised DEA more? (2) which nationality has conducted further research in this area? (3) in which year did scholars publish the most articles? (4) which journals have further published articles in this field? The present study will focus on the significance of DEA in agricultural productivity with undesirable outputs. The main contributions of this article are as follows: (1) improving the understanding of the current scientific knowledge on green productivity and undesirable outputs (2) highlighting why and how DEA models are widely used to measure productivity with undesirable outputs in the agri-sector (3) providing an overview of research limitations and gaps that hinder measuring productivity with undesirable outputs (4) investigating the current status of DEA application for measuring productivity with undesirable outputs concerning the years of publication, authors' nationality, articles' scope, and publication frequency (5) recommending policies and research avenues to provide a pathway for future empirical and theoretical research.

The article's structure is arranged as follows: Section 2 expresses four DEA models being popular in agricultural productivity with undesirable outputs. Section 3 presents the methodology of the present research and how the articles were classified is presented. Section 4 presents the results, including distribution of articles by publication time, author's nationality, and journals. The results were discussed in Section 5. Section 6 presents conclusions, limitations, policies, and future research recommendations.

2. DEA models for dealing with undesirable outputs

In 1978, Charnes et al. presented the first DEA model, namely CCR, to calculate the technical efficiency of DMUs in the form of a non-parametric model, while there are many inputs and outputs (Charnes et al., 1978). Researchers used CCR-DEA, BCC-DEA, SBM-DEA, and Range-Adjusted Measure (RAM)-DEA to calculate agricultural productivity with undesirable outputs. The four mentioned models, which are the most popular agriculture performance model with undesirable outputs, are presented.

2.1. CCR-DEA model

The overall efficiency for a DMU is calculated through the CCR-DEA model if both scale efficiency and pure technical efficiency are combined into a single value. On top of that, the CCR-DEA model never measures absolute efficiency as it is always measured relatively. Also, CCR-DEA is suitable for a situation in which all DMUs are operating at an optimal scale. Assume a manufacturing system with n DMUs, which has three elements, including inputs (X), desirable outputs (G), and undesirable outputs (B). The three matrices X, G, B, and the production possibility set (P) are defined through equation one and λ is the intensity vector (Li et al., 2013).

$$
\begin{array}{l}
\mathrm{P} = \left\{(\mathrm{X}, \mathrm{G}, \mathrm{B}) | \mathrm{x} \geq \mathrm{X}\lambda, \mathrm{G} \leq \mathrm{G}\lambda, \mathrm{B} \geq \mathrm{B}\lambda, \lambda \geq 0\right\}, \\
\mathrm{X} = (\mathrm{X}_1, \ldots, \mathrm{X}_n) \in \mathrm{R}^{m \times n}, \\
\mathrm{G} = (\mathrm{G}_1, \ldots, \mathrm{G}_n) \in \mathrm{R}^{S_1 \times n}, \\
\mathrm{B} = (\mathrm{B}_1, \ldots, \mathrm{B}_n) \in \mathrm{R}^{S_2 \times n} \\
\mathrm{S.t.} \\
\qquad \mathrm{x} \geq \mathrm{X}\lambda \\
\qquad \mathrm{G} \leq \mathrm{G}\lambda \\
\qquad \mathrm{B} \geq \mathrm{B}\lambda \\
X>0, \; G>0, \; B>0
\end{array} \tag{1}
$$

The output-oriented DEA model coping with undesirable outputs for assessing DMU (x_0, g_0, b_0) is presented below, and σ^* is the inefficiency score of DMUs calculated by equation two (Li et al., 2013). It should be noted that efficiency score can be calculated by $\theta = \frac{1}{1+\sigma}$.

$$\begin{array}{l} \sigma^* = max\sigma_0 \\ \text{S.t.} \\ x_0 \geq X\lambda \\ (1+\sigma_0)g_0 \leq G\lambda \\ (1-\sigma_0)b_0 \geq B\lambda \\ \lambda \geq 0 \end{array} \tag{2}$$

2.2. Bcc-DEA model

Variable return to scale frontiers is assumed in the BCC model, while the CCR model assumes a constant return to scale frontiers. Also, overall technical efficiency is measured by the CCR model, while the BCC model measures the pure technical efficiency. Also, as mentioned, the CCR model is not appropriate if DMUs are not operating at an optimal scale; in contrast, the BCC model was developed to deal with situations in which technical efficiencies variables are measured while confounded to scale efficiencies. Assume a manufacturing system with n DMUs is considered, while it has three elements, including inputs (X), desirable outputs (G), and undesirable outputs (B). The three matrices X, G, B, and the production possibility set (P) are defined through equation three and λ is the intensity vector (Li et al., 2013).

$$\begin{array}{l} \mathrm{P} = \left\{(\mathrm{X}, \mathrm{G}, \mathrm{B}) | \mathrm{x} \geq \mathrm{X}\lambda, \mathrm{G} \leq \mathrm{G}\lambda, \mathrm{B} \geq \mathrm{B}\lambda, \lambda \geq 0\right\}, \\ \mathrm{X} = (\mathrm{X}_1, \ldots, \mathrm{X}_n) \in \mathrm{R}^{m \times n}, \\ \mathrm{G} = (\mathrm{G}_1, \ldots, \mathrm{G}_n) \in \mathrm{R}^{S_1 \times n}, \\ \mathrm{B} = (\mathrm{B}_1, \ldots, \mathrm{B}_n) \in \mathrm{R}^{S_2 \times n} \\ \text{S.t.} \\ \qquad \mathrm{x} \geq \mathrm{X}\lambda \\ \qquad \mathrm{G} \leq \mathrm{G}\lambda \\ \qquad \mathrm{B} \geq \mathrm{B}\lambda \\ X>0, \ G>0, \ B>0 \end{array} \tag{3}$$

The output-oriented DEA model coping with negatives outputs for assessing DMU (x_0, g_0, b_0) is presented below, and σ^* is the inefficiency score of DMUs calculated by equation four (Li et al., 2013). It should be noted that efficiency score can be calculated by $\theta = \frac{1}{1+\sigma}$.

$$\begin{array}{l} \sigma^* = max\sigma_0 \\ \text{S.t.} \\ x_0 \geq X\lambda \\ (1+\sigma_0)g_0 \leq G\lambda \\ (1-\sigma_0)b_0 \geq B\lambda \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda \geq 0 \end{array} \tag{4}$$

2.3. Slack-Based DEA model

Inputs (outputs) may not behave proportionally in reality, while radial DEA models, such as CCR and BCC, deal with proportional changes in inputs(outputs). Also, radial models neglect slacks in measuring efficiency, while non-radial slacks affect managerial efficiency. In contrast, the slack-based DEA model works directly with slacks and puts aside the proportional changes assumption; however, two primary conditions, including unit invariant and monotone, should be met. Let $X = (x_1, \ldots, x_I) \in R_+^I$ be an inputs' vector, $G = (g_1, \ldots, g_J) \in R_+^J$ be a desirable outputs' vector, and $B = (b_1, \ldots, b_L) \in R_+^L$ be an undesirable outputs' vector. Also, λ^k is an intensity vector, and $k = (k_1, \ldots, K)$ is the index of DMUs. Therefore, the SBM-DEA model accounting for any outputs is presented through equation five (Li et al., 2016).

$$\begin{aligned}
&\rho_t = \min_{s_i^x, s_j^G, s_l^B} \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^x}{x_i^t}}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \frac{s_j^G}{x_j^t} + \sum_{j=1}^{J} \frac{s_l^B}{x_l^t}\right)} \\
&\text{S.t.} \\
&\sum_{k=1}^{K} \lambda_k X_i^k + S_i^t = X_i^t, \quad i = 1, 2, \ldots, I; \\
&\sum_{k=1}^{K} \lambda_k G_j^k - S_j^t = G_j^t, j = 1, 2, \ldots, I; \\
&\sum_{k=1}^{K} \lambda_k B_l^k + S_l^t = B_l^t, l = 1, 2, \ldots, L; \\
&\lambda_k \geq 0, \quad k = 1, 2, \ldots, K \\
&s_i^x, s_j^G, s_l^B \geq 0
\end{aligned} \tag{5}$$

where $0 \leq \rho_t \leq 1$ with $\rho_t = 1$ shows total efficiency, while $t = 1, 2, \ldots, K$. it is presented that the t-th observation presented by input-output (x_i^t, g_i^t, b_i^t) is showed in the production frontier at the point $\left(x_i^t - s_i^{X^*}, g_j^t + s_j^{g^*}, b_l^t - s_l^{b^*}\right)$, where $s_i^{x^*}$, $s_j^{g^*}$, *and* $s_l^{b^*}$ are the optimal value of s_i^x, s_j^g, *and* s_l^b, respectively (Li et al., 2016).

2.4. RAM-DEA model

In the non-radial RAM-DEA, desirable and undesirable outputs could easily be incorporated into a unified model compared to the radial DEA models. Also, RAM-DEA is a linear non-radial model making it more applicable than the non-linear conventional DEA models. RAM-DEA model is specially proposed and applied by Sueyoshi and Goto (2012) and Sueyoshi and Goto (2011) to measure productivity in the presence of undesirable outputs. Let $G_j = (g_{1j}, \ldots, g_{nj})^T$ be a vector of desirable outputs, and $B_j = \left(b_{1j}, \ldots, b_{nj}\right)^T$ be a vector of undesirable outputs, while for $j = 1, \ldots, n$, $G > 0$, and $B > 0$; therefore, in the following, the non-radial RAM-DEA proposed by Sueyoshi and Goto (2011) is presented through equation six.

$$
\begin{aligned}
&\text{Max } Z = \sum_{r=1}^{s} R_t^g d_t^g + \sum_{f=1}^{h} R_t^b d_t^b \\
&\text{S.t.} \\
&\sum_{j=1}^{n} g_{rj}\lambda_j^g - d_r^g = g_{rk}, \forall\ r = 1, \ldots, s; \\
&\sum_{j=1}^{n} b_{fj}\lambda_j^b - d_r^b = b_{fk}, \forall\ f = 1, \ldots, h; \\
&\sum_{j=1}^{n} \lambda_j^g = 1; \\
&\sum_{j=1}^{n} \lambda_j^b = 1; \\
&\lambda_j^g \geq 0,\ \ \lambda_j^b \geq 0,\ \ d_r^g \geq 0,\ \ d_r^b \geq 0
\end{aligned}
\tag{6}
$$

where λ_j^g and λ_j^b are, respectively, intensity variables for desirable and undesirable outputs. Also, d_r^g is a surplus variable for r-th desirable output, d_r^b is a slack variable for f-th undesirable output, and R_r^g and R_f^b indicate the DEA model ranges for desirable and undesirable outputs, respectively, presented through equation seven, while s and h show the number of desirable and undesirable outputs.

$$
\begin{aligned}
R_r^g &= \frac{1}{(m+s+h)\left[\max_j(g_{rj}) - \min_j(g_{rj})\right]} \\
R_r^b &= \frac{1}{(m+s+h)\left[\max_j(b_{fj}) - \min_j(gb_{fj})\right]}
\end{aligned}
\tag{7}
$$

where m represents the number of inputs utilised for yielding desirable and undesirable outputs; therefore, the unified efficiency score of the k-th DMU is calculated through equation eight, while d_t^{g*}, *and* d_t^{b*} are the optimal value of d_t^g, *and* d_t^b, respectively.

$$
\theta = 1 - \sum_{r=1}^{s} R_t^g d_t^{g*} + \sum_{f=1}^{h} R_t^b d_t^{b*} \tag{8}
$$

3. Research methodology

The present article used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to conduct a systematic literature review (SLR). SLR maps and evaluates the current knowledge and gaps in research fields, developing the knowledge base further. SLR follows scientific, replicable, and transparent stages differing from conventional narrative reviews (Murschetz et al., 2020). All publications related to the specific issue could be collected concerning the pre-defined criteria to answer research questions. SLR avoids bias occurring throughout searching, identification, appraisal, synthesis, analysis, and summary of studies using the systematic and explicit procedure (Mengist et al., 2020). Therefore, SLR could provide reliable findings and conclusions due to its capabilities to deal with bias, helping scholars and decision-makers to act accordingly (Saraji & Sharifabadi, 2017). Moreover, apart from PRISMA, there are several methodologies to conduct SLR, such as Search, Appraisal, Synthesis, and Analysis (SALSA). However, PRISMA has some advantages over other methods, such as (1) it has a detailed, precise, and well-described checklist helping scholars in improving systematic review reporting and meta-analyses (2) it is an updated protocol due to its various versions were released time to time, which the newest one was released in 2020; therefore, the present study employed PRISMA protocol to conduct a systematic literature review.

Scrutinizing the current literature is the first step of SLR. In this stage, some substantial scientific databases named Google Scholar, Web of Science (WOS), and Scopus are nominated to find the published articles related to the topic. The search is conducted for grey literature; we search for critical journals and scan the references' lists. The second step, named the eligibility criteria stage, focuses on the study's different characteristics, including the population of interest, study design, time duration, publication year, publication status, and language. Next, the PRISMA focuses on the information sources. This stage explains all related information of resources, such as electronic databases, authors' information, trial registers, and coverage date.

3.1. Searching method

According to the first step of PRISMA, some viable databases, e.g., WOS, Google Scholar, and Scopus, have been selected to comprehensively review the implementation of DEA in agricultural productivity with undesirable outputs. To find the related publications, we search in the selected databases with various keywords such as "DEA and energy efficiency in agricultural with undesirable outputs," "DEA and performance assessment in agricultural with undesirable outputs," "DEA and agricultural pollution with undesirable outputs," "DEA and sustainable agriculture with undesirable outputs," "DEA and agricultural economics with undesirable outputs," "DEA and agricultural industry," "DEA and crop production in agricultural with undesirable outputs," "DEA and resource efficiency," "DEA and agricultural production with undesirable outputs," etc. also, we attempt to involve the recently published articles, and therefore, our selection years are between 2000 and 2020. In the first attempt, based on the above keywords, in total, we identify 276 publication records. In the next stage, we screen the publications based on abstracts and titles to eliminate different items. After eliminating different items in this step, in total, 58 articles remained for the following stages. The PRISMA diagram is shown in Figure 1.

3.2. Publications' eligibility

In this step, the full text of the remaining articles has been reviewed one after another. We choose the articles that used an extension of DEA to compute agricultural productivity and efficiency with undesirable outputs. At this stage, we omit some documents such as essays, Ph.D. and master theses, book chapters, books, other

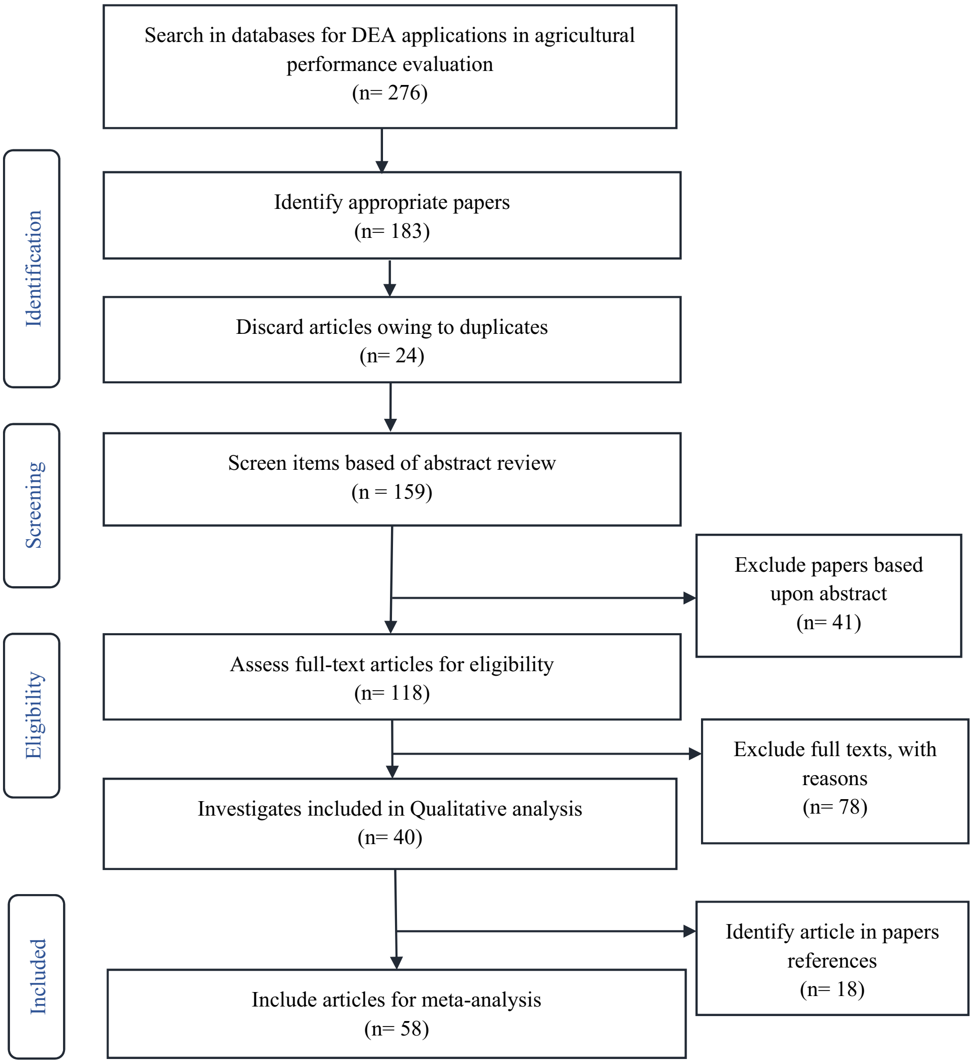

Figure 1. PRISMA flowchart for holistic systematic review.
Source: created by authors.

published resources in other languages except English, and editor's notes. Finally, after the mentioned stages, we choose 58 articles related to the DEA applications in agricultural productivity with undesirable outputs from 36 international scholarly journals between 2000 and 2020.

3.3. Data extraction and summarizing

In this step, firstly, required information has been extracted from the remaining articles. Finally, the remaining articles were classified into different groups (see Table 1) according to the article's primary purpose. Furthermore, all fifty-eight publications are reviewed and summarised based on various views; and are grouped into five

Table 1. Classification articles by their scope.

Categories Based on Scope	Number of Articles	Percentage (%)
Agricultural Pollution	13	22.41%
Sustainable Agriculture	12	20.69%
Agricultural Economics	12	20.69%
Environmental Performance	12	20.69%
Resource Efficiency	9	15.52%
Total	**58**	**100%**

Source: created by authors.

classifications), including agricultural pollution, sustainable agriculture, agricultural economics, environmental performance, and resource efficiency.

4. Results

4.1. Classification articles based on agricultural pollution

A wide variety of agricultural pollution, including air pollution, water pollution, wastewater, CO_2 emissions, etc. considered as significant challenges in countries (Chen et al., 2017). Agricultural activities increase pollutants affecting air quality, environmental performance, water quality, and other areas (Abbasi et al., 2014). Several studies have been conducted to measure productivity in which DEA was used to calculate efficiency of agricultural DMU, while agricultural pollutions were considered undesirable outputs. For instance, Falavigna et al. (2013) used Directional Output Distance Function (DODF)-DEA and Malmquist index to estimate the production possibility for each DMU, while they considered emission quantities of NHO_3 as undesirable outputs, and Kuhn et al. (2018) used SBM-DEA to carry out the difference between waste management in commercials and backyard hog farms, while CO_2 emission as an undesirable output. Table 2 indicates details extracting from the articles were related to agricultural pollution.

4.2. Classification articles based on sustainable agriculture

Sustainability has become attractive among practitioners, scholars, and strategists due to the growing environmental and social concerns (Boussemart et al., 2020). Sustainable agriculture relies on meeting human food, fibre, and biofuel expectations, and it improves the quality of the environment and resource base; the agronomists' living standards, farmworkers, and society to ensure the economic viability of the agricultural sector (Gołaś et al., 2020). Also, sustainable agriculture looks for increasing profitable farm income and promoting environmental stewardship. Therefore, evaluating sustainable agriculture potentials has become attractive for scholars as various methods have been developed for this purpose (Ren et al., 2021). For example, Shen et al. (2018) integrated the by-production model and DEA to calculate the shadow price of CO_2 emission in china's agricultural sectors, since due to the high population of china, having sustainable agriculture is vital, and Vlontzos et al. (2017) developed a synthetic Eco-(in) efficiency index using DDF-DEA model to evaluate the sustainability of the EU agricultural sector over 13 years from 1999 to 2012 on a

Table 2. Classification articles by agricultural pollution.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Falavigna et al. (2013)	DODF-DEA, Malmquist index	Agricultural Industry	To estimate the production possibility for each DMU	To evaluate the effect of regional policies in Italian's agriculture	To find a correlation between the level of production sustainability and funds' flows	Italian environmental performances vary among regions and when emissions are considered so that the productivity estimates differ
Kuhn et al. (2018)	SBM-DEA	pork production	To calculate the technical and environmental efficiency	To find the difference between waste management in commercials and backyard hog farms.	To cope with the Pig waste, which is a severe problem for both surface and groundwater resources	Results showed that limited waste disposal choice causes low environmental efficiency and high pollution costs in mid-size hog farms
Yaqubi et al. (2016)	DDF-DEA	Paddy Cultivation	To estimate DDFs	Proposing a hybrid model to assess the environmental inefficiency and shadow value	Need to assess the marginal abatement expenditure of the primary agricultural pollutants.	The Nitrogen surplus and greenhouse gasses have lower marginal abatement cost compared to pesticides and herbicides
Berre et al. (2013)	LCA, DDF-DEA	milk production	to calculate the inefficiency of a DMU with radial or non-radial distance	to assess shadow prices of outputs based on contradictory aims between the society and the farmers	To investigate the relationship between the nitrogen surpluses and the amount of GHG with economic growth	Results indicated that if societies balance farmers' opportunity costs, farmers can decrease pollution significantly.
Skevas et al. (2014)	DDF-DEA	Dutch Arable farming	Calculating the performance of arable farms	Modelling the available effects on farmers' production environment based on an endogenous point of view.	Need to deal with disadvantages of pesticides which is an undesirable output	Results indicated that crop producers should reduce using of pesticides
Reinhard et al. (2000)	Stochastic Frontier Analysis (SFA)-DEA	Dutch dairy farms	To compare with another method of efficiency calculation	to measure holistic environmental efficiency measures for farms dairy located in the Netherlands	to compare efficiency results calculated by two methods	The results indicated many differences between the two mentioned methods.
Wu et al. (2013)	DEA-Game	15 European Union members	To combine with bargaining game to calculate and	To propose a model to investigate the	To reduce and control emissions from agriculture	

(*continued*)

Table 2. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
			improve the total efficiency	reduction and reallocation of emission permits	to improve the climatic change.	Results showed that the mechanism could be fair in different areas.
Vlontzos and Pardalos (2017)	DEA Window, ANN	EU farms	to estimate and calculate the efficiency of the environment in the EU countries' primary sectors	To study the long-term performance of EU countries primary sectors in Green House Gas emissions	Need to imply new efficiency assessment due to increasing of market force influence	Results indicated that there are meaningful differences among EU countries in terms of environmental efficiencies
Buckley and Carney (2013)	DEA, Regression Analysis	Dairy and tillage farms	To find that what utilising rates, chemical fertilisers might have been greater than optimum levels	To investigate the chance of reducing chemical fertilizers applications.	Need to study the nutrients transformed into water	Results indicated that there is an inefficiency in the application of chemical fertilizers
Coelli et al. (2007)	CRS-DEA	Pig fishing farms	To estimate the environmental efficiency measure, which is based on the materials balance equation	To propose a novel environmental efficiency based on materials balance condition	Previous models in terms of efficiency measurement might be inconsistent with the basic condition	Results indicated that a significant percentage of nutrient pollution on farms could be diminished in a cost-reducing
Zare-Haghighi et al. (2014)	Non-Radial DEA	Industries	To determine the type of congestion and to estimate its sources and amounts	To develop a non-radial efficiency measure to study the environmental performance of Chinese regions	Need to a novel scheme to measure congestion concerning both desirable and undesirable outputs	Results indicated that seven industries try to reduce pollutions
Dong et al. (2018)	SBM-DEA	Crop production	To evaluate the CO_2 efficiency of crop productions system at the provincial and prefecture-levels	To propose a framework to find the efficiency of inputs and outputs and (GHG) emissions reduction	Need to improve efficiency in agriculture production	Results indicated that there are differences between crop production efficiency among provinces
Sun et al. (2016)	Centralized DEA	China's Regions	to find the optimal path to control CO_2 emissions at the sector level	To propose a novel DEA model concerning various technologies for industrial optimisation	to develop a DEA model based on improved Kuosmanen environmental	Results indicated that the model could determine the optimal way of controlling CO_2 emission efficiently

Source: created by authors.

country level. Table 3 indicates all details extracting from the articles were related to Sustainable agriculture.

4.3. Classification articles based on agricultural economics

Agricultural economics looks for applying economic theories to optimise the production and distribution of agricultural production. Also, Agricultural economics is a branch of economics dealing with land usage, and it emphasises maximising agricultural production and maintaining a good soil ecosystem (Martin, 2019). For instance, the low-carbon economy, a part of agricultural economics, aims to reduce greenhouse gas emissions and save energy consumption to have sustainable agriculture (Streimikiene, 2021). Agricultural economics includes many areas and approaches, including DEA models; therefore, many studies have been carried out to compute energy efficiency and CO_2 emission efficiency concerning low carbon economics policies. For instance, Fei and Lin (2017b) used meta-frontier DEA to find an acceptable policy for agricultural energy saving and to carry out the sources of CO_2 emissions reduction, and Rebolledo-Leiva et al. (2017) integrated Life-cycle assessment (LCA) and VRS-DEA to maximise production and to decrease Carbon Footprint (CF) concerning the economics and ecological perspectives. Table 4 indicates details extracting from the articles were related to agricultural economics.

4.4. Classification articles based on environmental performance

Singh et al. (2020) mentioned that environmental performance is the organization's behaviour concerning the natural environment regarding how it goes about consuming resources to scan pollution emissions strictly. It is considered an introduction of biodegradable ingredients in products, reducing waste and pollution, reducing materials being harmful to the environment, enhancing energy efficiency, etc. (Singh et al., 2019). Due to the importance of environmental performance, several studies used different models, such as DEA, to measure environmental performance. For example, Gutiérrez et al. (2017) used a hybrid multi-stages DEA and regression analysis to calculate rain-fed cereals' efficiency based on actual management circumstances and environmental variables. Le et al. (2019) used the SBM-DEA model to determine the differences in productivity and agriculture efficiency among Asian countries. Table 5 indicates all details extracting from the articles were related to environmental performance.

4.5. Classification articles based on resource efficiency

It is challenging to develop indicators reflecting resource use and its impacts on the environment, economy, and security due to several natural resources characterised by different attributes. However, resource use is distinguished into four categories: usage of material, water, land, energy, and climate change. Modern agriculture faces significant challenges, including extreme water supply and fertiliser impacts (Zamparas et al., 2019a), deforestation (Tsiantikoudis et al., 2019), GHG emissions

Table 3. Classification articles by sustainable agriculture.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Shen et al. (2018)	By Production Model- DEA	Agricultural sectors	to determine the gap in the gross agricultural output across different provinces	To apply a new model to calculate the shadow price of CO_2 emission in china's regions	To integrate the approaches of inefficiency decomposition with by-production model	Results indicated that the mixing effect causes inefficiency that needs an improvement in the reallocation of inputs.
Sheng et al. (2016)	Zero-Sum-Gains (ZSG) DEA	Forests	to estimate the national reducing emissions from deforestation and degradation-plus (REDD+) reference levels	To calculate and classify the REDD + reference levels of 89 countries	REDD + implementation needs to study.	Results indicated that the proposed method could estimate the REDD + reference levels efficiently
Angulo-Meza et al. (2019)	Multiobjective DEA model (MORO-D)	organic blueberry orchards	to evaluate the eco-efficiency of units	Proposing a new multi-step model to assess the eco-efficiency of organic blueberry orchards.	Need to calculate environmental effects	Results indicated that the proposed model has some advantages compared to previous models
DE Koeijer et al. (2002)	CRS-DEA	Dutch sugar beet growers	To estimate the sustainable efficiency of farms	Proposing a model to quantify sustainability based on the efficiency theory commonly used in economics.	Need To investigate a vast group of sustainability factors based on production system at farm level	Results indicated that there was a positive relationship between technical efficiency and sustainable efficiency
Babazadeh et al. (2015)	Non-radial DEA	Jatropha curcas L. (JCL)	To calculate the efficiency of each location	To study the efficiency of some areas to cultivate bioenergy crop	Need to study JCL cultivation since it has applicable oily content	Results indicated that the proposed method is practical in terms of location optimization
Sidhoum (2018)	DDF-DEA	arable crop farms	To measure social outputs' shadow prices based on the directional distance function	To propose a framework concerning the state-contingent outputs to measure shadow prices of social outputs	There is not enough study in the field of the quantification of social sustainability and its relationship with the agricultural production efficiency	Results indicated that shadow prices of social outputs, a great value of the farm, are positive

(*continued*)

Table 3. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Vlontzos et al. (2017)	DDF-DEA, Regression	Agricultural Sector	To composite with DDF to estimate the efficiency concerning both desirable and undesirable outputs	To study the sustainability of the EU agricultural sector concerning the Kuznets curve	To investigate the relationship between agricultural sustainability and economic development	Results indicated that the efficiency of the GHG emissions reduction and output development could be improved
Hoang and Alauddin (2012)	CRS-DEA	agricultural production	to measure and decompose the efficiency level in agriculture production	to propose an analytical framework to evaluate the performance differences in economic, environmental, and ecological perspectives	Need to study the relationship between pollution, ecosystem resources, and services.	Results indicated that there is some scope that makes agricultural production eco-friendlier and more sustainable
You and Zhang (2016)	DEA-Tobit Analysis	Agricultural Production	To combine with Tobit model to estimate efficiency and to analyze the factors affecting efficiency	To investigate the eco-efficiency of intensive agriculture in Chinese provinces	To increase the outputs of intensive agriculture without any damage to the environment	The results indicated that six provinces are fully efficient, and some factors like income per capita have affected the efficiency
Pang et al. (2016)	SBM-DEA	Agricultural regions	To combine with Theil index to measure eco-efficiency and the imbalance of regional development	To evaluate the agricultural eco-efficiency using the Theil index approach and DEA	Need to design a new policy to improve eco-efficiency in china	Results indicated that eco-efficiency is different in a different area of china
Hoang and Rao (2010)	CRS-DEA	agricultural production	to calculate efficiency scores based on CRS production technology	To utilise cumulative exergy content to create new efficiency sustainable measures	to propose practical approaches to measure two aspects of sustainable agriculture	Results indicated that sustainable efficiency is likely to be different across countries
Jradi et al. (2018)	Radial-DEA	French vineyards	To propose a unified measure performance evaluation	To study the operational performance of wine estates when the composite factors of carbon footprints are existed	Need to propose a new method to evaluate efficiency under new constraints	Results approved the carbon footprint effect in vineyards

Source: created by authors.

Table 4. Classification articles by agricultural economics.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Fei and Lin (2017b)	Meta-frontier DEA	agricultural sector	To calculate the Malmquist energy productivity index	Dealing with the agricultural problems on energy-related CO_2 emissions issues.	To suggest proper policy for agricultural energy saving and to find the sources of CO_2 emissions reduction	Lower CO_2 emission efficiency was indicated in western China compared with eastern and central China
Rebolledo-Leiva et al. (2017)	LCA, VRS-DEA	Agriculture production	To evaluate the environmental and operational performance of multiple units	Proposing a hybrid four-step approach to assess the carbon footprint (CF)	To maximise production and to decrease CF concerning the economic and ecological perspectives	Results indicated that the proposed method could determine eco-efficiency and reduce CF practically
Tao et al. (2016)	Non-separable input/output SBM- DEA	Agricultural Regions	To measure China's provincial green economic efficiencies	To catch the constant trend of green economic efficiencies in specific periods instead of exploring the dynamic efficiency changes.	To deal with CO_2 emission problem in 2030 in china	Results indicated that the interregional differences are more significant in the field of green economic efficiencies.
Li et al. (2016)	Shapley/Sun index, SBM-DEA	EU Countries	to calculate environmental efficiency and shadow prices of CO_2 emission in European agriculture	Proposing an integrated method to the analysis of CO_2 emission based on advanced decomposition and efficiency analysis models	To deal with greenhouse gas (GHG) emissions in Europe	Results indicated that falling energy intensity is the critical factor to decline in CO_2 emission
Andre et al. (2010)	Modified VRS-DEA, Goal programming	Farmer decision making	To calculate efficiency and preference weights	To show a relationship between DEA and a non-interactive elicitation method	To deal with MCDM problems by translating them into DEA terminology	Results indicated that the weights provided by the proposed method are entirely accurate.
Zhang et al. (2011)	DDF-DEA, Malmquist index	Agricultural regions	To estimate TFP growth	To assess China's progress in total factor productivity (TFP)	To investigate the effect of regulation on productivity	Results indicated that more environmental regulations could improve ML productivity growth in China

(*continued*)

Table 4. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Khoshroo et al. (2018)	Non-radial DEA	Turnip production	to assess the efficiencies of the turnip farms, and measure the optimal use of resources	To propose a new method to study the efficiency of turnip farms	To deal with unwelcome emission produced in Iranian turnip farms	Results indicated that the proposed model could work efficiently
Baležentis and Makutėnienė (2016)	DDF-DEA	Pulp, article, and agricultural sectors	To calculate EPI based on the Hicks-Moorsteen indices	to study the environmental performance index (EPI) for economic sectors in Lithuania	Need to investigate the environmental performance of the Lithuanian economy	Results indicated that article and agricultural sectors are the best performing group in the economy sector
Vlontzos et al. (2014)	Non-Radial DEA	EU countries	To provide different estimations of environmental and energy efficiency scores	To assess the efficiency of environment and energy in the primary sectors in the EU	Need to become low carbon and resource-efficient economy in the EU	Results indicated that the efficiency of the environment and energy had been changed due to changes in agricultural policies
Fei and Lin (2017a)	Non-Radial DEA	agricultural sector	Looking for a unified efficiency score to estimate the coordination between inputs and outputs	To find integrated efficiency of inputs-outputs in the Chinese agriculture sector	Need to enhance environmental and energy efficiency to deal with CO_2 and energy challenges	Results indicated that many Chinese's provinces did not perform in the integrated efficiency of inputs-outputs efficiently
Asmild and Hougaard (2006)	VRS-DEA	Pig Farms	To estimate and to analyze the improvement of the efficiency of pig farms	To study the relationship of economics and environmental improvement in pig farms	To study the effect of Danish pig Production surplus on the environment	The empirical results indicated that there are potentials for considerable improvement on the environmental variables.
Pongpanich and Peng (2016)	Super-SBM DEA	Agricultural cooperatives	To combine with SBM DEA to measure and compare the operation efficiency and inefficiency	To propose a novel approach to analyze the operational efficiency in agricultural cooperatives	To study the agricultural corporative in every province in Thailand	the empirical results indicated that there are some problems and benchmarks related to members and farmers

Source: created by authors.

Table 5. Classification articles by environmental performance.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Hoang and Coelli (2011)	DDF-DEA	Agriculture production	To calculate efficiency scores and productivity change in crop and livestock production	To utilise nutrient-orientated environmental efficiency (EE) measures to build a nutrient total factor productivity index (NTFP)	To propose a novel framework to provide practical and trustable information in the field of environmental management	Results indicated that the government ought to yield current outputs less than aggregate atrophying power
Gutiérrez et al. (2017)	Two-Stage DEA, Regression	rain-fed cereals	To combine with fractional regression to calculate rain-fed cereals efficiency	To calculate the efficiency of rain-fed cereals based on actual management conditions, environmental variables, and integrating technical	To propose an integrative approach to deal with the many challenges faced by global agriculture.	Results indicated that organic production is more efficient than conventional production
Cecchini et al. (2018)	SBM-DEA, LCA	dairy cattle farms	To integrate with LCA to estimate the efficiency of dairy cattle farms	To study CO_2 emission alleviation based on joint production of milk and GHG emissions using efficiency performance measures	Need To increase farmer economic gain without any conflict with reducing GHG	Results approve a positive correlation between CO_2 -eq efficiency scores and marginal abatement
Lin and Fei (2015)	CRS-DEA, Malmquist index	Agricultural Sectors	To estimate the static emission performance of CO_2 emission	To assess the energy-related CO_2 emissions performance in China's agricultural	There are few studies conducted in terms of analyzing carbon emissions performance and its regional differences	Results indicated that the average annual growth and the aggregated growth of the Malmquist index is 6 and 48 percent, respectively
Ferjani (2011)	DDF-DEA	Dairy Farms	To estimate the Malmquist productivity index using comparing distance functions in two different years	To investigate the effect of environmental policy on-farm performance	To test the Porter hypothesis in Swiss dairy farms	The results indicated that the findings did not reject porter views
Le et al. (2019)	SBM-DEA	Agricultural Sectors	To evaluate the technical and	To investigate the change in productivity and	To find leading countries in terms of TFP growth	Results indicated that there are differences in

(*continued*)

Table 5. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
			environmental efficiencies of agriculture	efficiency in agriculture among Asian countries	and environmental efficiency	environmental performance and productivity growth in the agricultural sector among countries
Makutėnienė and Baležentis (2015)	DDF-DEA	Agricultural Sectors	To estimate the efficiency concerning Frontier models	To evaluate the efficiency of a resource, environmental, and economical in the EU agriculture	Need to study productivity and efficiency of agricultural sectors as elements of competitiveness	Results indicated that some countries like Slovenia are the most technically efficient, while others are weak
Baležentis and Makutėnienė (2016)	By-Production, DEA, MCDM	Agricultural Sectors	To compare with the MCDM approach in terms of evaluating countries performance	To propose an MCDM framework to study performance gaps of energy-related CO_2 emission	Need to propose an approach to investigate the effect of the production process on the environment	Results indicated that some countries, including Lithuania, should improve their carbon factors
Nikolla et al. (2013)	CRS-DEA	Farms	To analyzes the efficiency of company units	To study and amalgamate the efficiency of Albanian Farms	To study the efficiency of the production of greenhouse tomato culture	Results indicated that one of the farms is 100% efficient concerning this amount of inputs
Long et al. (2018)	SBM-DEA	Fertiliser Intensity	To calculate the environmental efficiency based on a meta-frontier directional SBM super efficiency method	To compare environmental efficiency in Chinese's provinces	to study the effect of fertiliser on environmental efficiency using intensity	Results indicated that using organic fertiliser can reduce CO_2 emission
Yang et al. (2008)	Shephard output distance function, DEA	swine production	To assess technical efficiency concerning Shephard distance function	To investigate the relationship the environmental regulations and Taiwanese farrow-to-finish swine production	To develop a model which includes undesirable outputs	Results indicated that smaller farms are less technically efficient than larger farms
Zhang (2008)	VRS-DEA	corn production	To calculate the environmental and technical	to study the relationship between demand for green production and eco-efficiency improvement	Need to the policy to improve the environmental performance in agricultural production	Results indicated that improving environmental performance in China is possible

Source: created by authors.

(Kyriakopoulos & Chalikias, 2013, Kyriakopoulos et al., 2010), soil erosion, eutrophication (Zamparas et al., 2019b), and water pollution ((Zamparas et al., 2020). Also, resource use efficiency means allocating and using various scarce resources to reach benefits. Due to the importance of agricultural economics, resource, consumption, and allocation efficiency are the main research stream in this branch of the economy; therefore, Resource consumption and allocative efficiency can be examined through the different approaches, including the DEA model. For instance, Yang and Li (2017) utilised SBM-DEA to evaluate the Total Factor Efficiency of Water resource (TFEW) and the Total Factor Efficiency of Energy (TFEE), and Deng et al. (2016) employed SBM-DEA to calculate the usage efficiency of water in china areas. Table 6 indicates all details extracting from the articles were related to resource efficiency.

4.6. Distribution of articles by journal

Table 7 provides information about the frequency of articles by journals' names. The articles linked to the agricultural performance assessment with undesirable outputs and the DEA models have been chosen through 36 a vast verity of journals from the WOS database, Scopus, Google Scholar. On the surface, "Journal of Cleaner Production" was ranked first with six articles, followed by "Sustainability," "Renewable and Sustainable Energy Reviews," "European Journal of Operational Research," "Agricultural Economics," and "Ecological Indicators" with three articles. The results indicated "Journal of Cleaner Production" made the most contribution in implementing DEA models in agricultural performance assessment with undesirable outputs.

4.7. Distribution of articles by authors' nationality

Table 8 indicates that authors from seventeen countries utilised DEA models in agricultural performance assessment with undesirable outputs, while the Chinese had the most contributions with39.66%. The figure for Australia accounting for the second country is 8.62%. Interestingly, the figure for Iran and Lithuania are the same, with 6.90%. On top of that, the results indicated that Chinese scholars utilised By-production technology and directional distance function (Shen et al., 2017, Fei & Lin, 2017a), the SBM DEA (Kuhn et al., 2018, Deng et al., 2016, Tao et al., 2016, Bian et al., 2014, Dong et al., 2018, Long et al., 2018, Song et al., 2014, Pang et al., 2016, Yang & Li, 2017), the Zero-Sum-Gains DEA (Sheng et al., 2016), meta-frontier DEA (Fei & Lin, 2017b, Fei & Lin, 2016), Malmquist index DEA (Wang et al., 2015, Zhang et al., 2011, Lin & Fei, 2015), DEA-Game (Wu et al., 2013), BCC-DEA (Li et al., 2013), DEA-Tobit (You & Zhang, 2016), centralised DEA (Sun et al., 2016). Australian scholars utilised the directional distance function (Hoang & Coelli, 2011, Azad & Ancev, 2014), CCR-DEA (Coelli et al., 2007, Hoang & Alauddin, 2012), BCC-DEA (Pagotto & Halog, 2016). Iranian scholars utilised the directional distance function (Yaqubi et al., 2016), non-radial DEA (Babazadeh et al., 2015, Zare-Haghighi et al., 2014), BCC-DEA (Khoshroo et al., 2018).

Table 6. Classification articles by resource efficiency.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Deng et al. (2016)	SBM-DEA	Water Efficiency	To estimate the water consumption efficiency	To investigate the water use efficiency in china provinces	To deal with the undesirable water consumption efficiency and water pollution challenges	Water efficiency is higher in developing provinces
Wang et al. (2015)	Malmquist index, CRS-DEA, Tobit Model	Water efficiency	to calculate the efficiency of agricultural water consumption in the Heihe River Basin	To investigate the changing paths of agricultural water consumption concerning the input-output data over nine years	Need to calculate the agricultural water-use efficiency is a vital factor reflecting the effective water allocation and productivity	Results indicated that the average efficiency of agricultural water consumption is far lower than one in different countries over nine years
Fei and Lin (2016)	Meta-frontier DEA, Malmquist index	Agricultural sector	To calculate the Malmquist energy productivity index	Measuring agricultural energy efficiency and exploring the energy productivity alter in China's agriculture	Need to study energy efficiency in the agricultural sector since it is vital for sustainable agricultural development.	The results showed that the agricultural energy efficiency is completely low, and it is different from place to place
Azad and Ancev (2014)	Luenberger Productivity Indicator, DEA	Water efficiency	To calculate efficiency score for the irrigated enterprises	To calculate trade-offs between the economic gain of water consumption in farming	to construct policy instruments to improve water resource management	Results indicated that a significant difference in the environmental performance of irrigation companies in each area was observed
Li et al. (2013)	CRS and VRS DEA	China's Regions	To calculate relative efficiency under CRS and VRS assumptions	To propose a model to allocate resource and reduce emission effectively	To deal with the environmental pollution in china	Results indicated that the proposed model worked effectively.
Bian et al. (2014)	Three Stages-DEA	Water efficiency	To evaluate water, use efficiency based on CSR assumption	To analyses water consumption performance and to investigate waste management systems in China.	Need to investigate the water shortage crisis and tackle it	Results find some practical action to improve efficiency in china

(*continued*)

Table 6. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Pagotto and Halog (2016)	ZSG-DEA	Food Industry	to calculate the eco-efficiency performance of selected DMUs based on I-O-approach	to assess the eco-efficiency of various subsectors in the agri-food network in Australian	To study the environmental burdens being available in the food industry	Results indicated that in the life process of food production, some inefficiencies exist.
Song et al. (2014)	SBM-DEA	Water Efficiency	To calculate efficiency of undesirable outputs and estimate desirable and undesirable outputs separately	To extend the SBM model based on network analysis	Need to propose an SBM model to tackle the scenario characterised by constant desirable outputs	The results indicated that the efficiency calculated by the proposed model is smaller than the outputs of the traditional model
Yang and Li (2017)	SBM-DEA	Water Efficiency	to assess TFEW and TFEE	To study the efficiency of water and energy resources in China	Need to investigate wastewater and water pollution produced in the process of manufacture and economic development	Results indicated that by investing in water resource, the Chinese economy could improve

Source: created by authors.

Table 7. Distribution of articles based upon journals.

Journal's Name	NO.	%	Journal's Name	NO.	%	Journal's Name	NO.	%
Journal of Cleaner Production	6	10.34	Applied Energy	2	3.45	Agricultural Systems	1	1.72
Sustainability	3	5.17	Omega	1	1.72	Technological Forecasting & Social Change	1	1.72
Renewable and Sustainable Energy Reviews	3	5.17	Resources, Conservation and Recycling	1	1.72	Journal of Environmental Economics and Management	1	1.72
European Journal of Operational Research	3	5.17	Industrial Crops and Products	1	1.72	Physics and Chemistry of the Earth	1	1.72
Agricultural Economics	3	5.17	European Journal of Agronomy	1	1.72	Environmental Monitoring and Assessment	1	1.72
Ecological Indicators	3	5.17	Applied Economics Letters	1	1.72	Energies	1	1.72
Management Theory and Studies for Rural Business and Infrastructure Development	2	3.45	Environmental Science & Policy	1	1.72	Environmental and Resource Economics	1	1.72
Science of the Total Environment	2	3.45	Journal of Productivity Analysis	1	1.72	PloS One	1	1.72
Ecological Economics	2	3.45	Agricultural Economics Review	1	1.72	Natural Hazards	1	1.72
Mathematical and Computer Modelling	2	3.45	Journal of Applied Mathematics	1	1.72	Journal of Industrial Ecology	1	1.72
Journal of Environmental Management	2	3.45	Discrete Dynamics in Nature and Society	1	1.72	Computers and Electronics in Agriculture	1	1.72
China Economic Review	2	3.45	Journal of Food, Agriculture & Environment	1	1.72	International Journal of Scientific and Research Publications	1	1.72
						Total	**36**	**100**

Source: created by authors.

Table 8. Distribution of articles based upon the nationality of authors.

Country	NO.	%
China	23	39.66
Australia	5	8.62
Iran	4	6.90
Lithuania	4	6.90
Spain	3	5.17
Greece	3	5.17
Italy	2	3.45
The Netherlands	2	3.45
France	2	3.45
Ireland	2	3.45
Taiwan	2	3.45
Albania	1	1.72
Belgium	1	1.72
Switzerland	1	1.72
USA	1	1.72
UK	1	1.72
Chile	1	1.72
Total	58	100

Source: created by authors.

4.8. Distribution of articles by publication time

Figure 2 illustrates the frequency of the publication time. The number of articles written in applying the DEA model in agricultural performance assessment with undesirable outputs rose dramatically over the past two decades. The first article was published in 2000, while in 2019, the number of articles is 58, while more of them was published in 2016, with 13 articles. It is anticipated the number of articles in this field will be increased in the future.

5. Discussion

Results indicated that DEA models showed great promise to be an excellent assessment tool for further productivity measurement in the agricultural sector, especially when it is complicated to determine the production function represented the inputs and outputs relationships. The DEA models' superiority in dealing with multiple inputs and multiple outputs makes them an exciting research field for scholars interested in productivity measurement with undesirable outputs in agricultural sectors. Not only could DEA models be an alternative for index measurement or econometric models for productivity measurement, but also DEA models could be integrated with various methods, such as game theory (Wu et al., 2013), artificial neural network (ANN) (Vlontzos & Pardalos, 2017), regression (Buckley & Carney, 2013), Tobit analysis (You & Zhang, 2016), LCA (Rebolledo-Leiva et al., 2017), goal programming (Andre et al., 2010) to deal with productivity measurement with undesirable outputs.

Furthermore, the results indicated that there are different types of DEA models such as Meta-frontier DEA, Malmquist index (Fei & Lin, 2016), VRS-DEA (Zhang, 2008), DDF-DEA (Makutėnienė & Baležentis, 2015), SBM-DEA (Le et al., 2019), CRS-DEA (Lin & Fei, 2015), SBM-DEA, Super-SBM DEA (Pongpanich & Peng, 2016), Multiobjective DEA model (MORO-D) (Angulo-Meza et al., 2019) which are helpful and applicable to measure the agricultural productivity with undesirable outputs. DEA

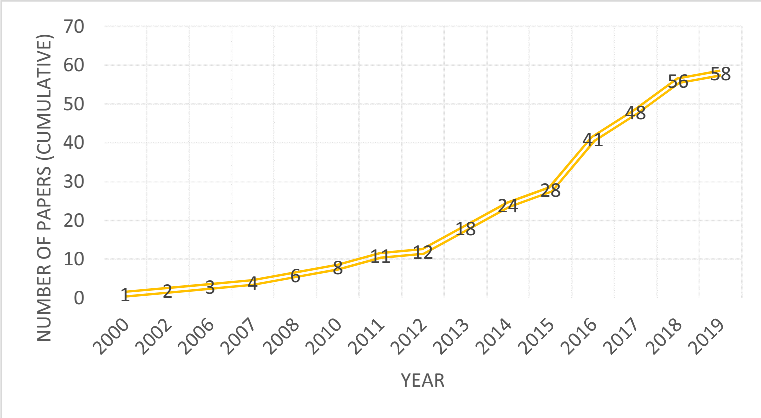

Figure 2. Distribution of articles based upon publication time (cumulative).
Source: created by authors.

models can accommodate multiple inputs and outputs to calculate the relative efficiency of DMUs in agri-sectors, while it is not necessary to set the weights for DMUs since DEA models use a ratio of "weighted outputs sum" to "weighted inputs' sum;" therefore, DEA models could be applied for measuring agricultural productivity due to its superiority in dealing with undesirable outputs, which is consistent with previous studies, such as Baležentis et al. (2016), Zhou et al. (2019), Wang et al. (2019), Halkos and Petrou (2019a), Yang and Wei (2019), Kang et al. (2018), Liu et al. (2017).

6. Conclusion and policy recommendations

The present article's primary purpose is to provide a holistic overview of the DEA's implementation in assessing agricultural productivity with undesirable outputs. In this regard, a systematic review using PRISMA protocol has been conducted to find and review the published articles in agricultural production with undesirable outputs over 2000 to 2020. Primary databases, including Google Scholar, Scopus, and WOS, were searched. This study classified the found articles concerning application areas, including agricultural pollution, sustainable agriculture, agricultural economics, environmental performance, and resource efficiency. Agriculture pollution was ranked first. Also, the selected articles are categorised based on different indicators such as the name of journals, author(s) names, methods, area of implementation, study and DEA purposes, articles' contribution and gaps, outcomes and results, year of publication, and authors' nationalities. In this regard, there were 36 journals had contributed to this article which. The "Journal of Cleaner Production" was ranked the first journal with six publications, followed by "Sustainability," "Renewable and Sustainable Energy Reviews," "European Journal of Operational Research," "Agricultural Economics and Ecological Indicators" journals with three published articles. In terms of country nationality, China was ranked first with 39.66%, followed by Australia, Iran, and Lithuania with 8.62%. And 6.90% respectively.

It could be concluded that DEA models could correctly measure agricultural productivity in the presence of undesirable outputs dut the following advantages: (1)

DMUs could operate under various condition, and DEA avoid this assumption; (2) multiple inputs and multiple outputs could be analyzed simultaneously, and there is no necessity to assign weight by the users in DEA models due to Pareto efficiency used by DEA; (3) the overall efficiency could easily be interpreted, and the most productive units and successful factors could be identified simply due to superiority of DEA in dealing with productivity measurement issues. Also, it is noticeable that the SBM-DEA model was widely used more than other methods, according to table eight. SBM-DEA is appropriate for a situation in which Inputs (outputs) may not behave proportionally. Furthermore, the slack-based DEA model works directly with slacks and puts aside the proportional changes assumption, while radial models neglect slacks in measuring efficiency.

6.1. Policy recommendations

Countries should balance the opportunity cost for the farmers, which is the core principle of agriculture economics. The opportunity cost of farming enables farmers to grow crops, sell, and make money. Society could increase the production profit by decreasing the inefficiency through an undesirable output reduction so that compensation could pay to farmers, considering an opportunity cost for the farmers. Thus, it is unnecessary to produce more without paying a pollution emissions fee, which reduces pollution, a giant leap for sustainable development.

Undesirable outputs, especially in the agri-sector, must be treated carefully. For instance, it is possible to turn nitrogen surpluses, considered an undesirable output, into a desirable input by stocking them into the soil to apply in the future production process. Therefore, setting a price to biomass as pollution or natural fertiliser requires more expertise as either a desirable input or undesirable output. Also, the same could be applied to GHG, such as livestock methane emission as biogas. Biogas is a green form of energy having great potential to use as an alternative to conventional fuel. It can be produced from various sources, such as agricultural waste, manure, and waste dumps.

Assessment of green agriculture productivity using DEA models allows policymakers to promote sustainable agriculture through highlighting various treatment methods with undesirable outputs; then, DEA models could analyze the effect of various subsidy policies concerning the treatment methods with undesirable outputs. Afterward, the empirical results based on DEA models can assess the appropriateness of incorporating subsidy policies and agriculture productivity evaluations.

6.2. Limitations and future research

Like other review articles, this review had some limitations that can be used as recommendations for future works. One of the article's limitations is about the sources of collected articles; this study only selected and collected the published articles from journals of popular databases; therefore, the present article did not consider the published articles from doctoral dissertations and textbooks. Therefore, future studies would consider the published articles of these sources. Another contribution of the article is about the selected journals; in this regard, this study only considered the published articles in English languages, and other published articles in other languages are excluded in this article. Therefore, future works can include the published articles in other languages in the future articles. Another limitation of this review article is related to the classification of the published articles; this study classified the published articles in agriculture into five different application areas; in this regard, it recommends the further works classify the articles in other application areas. Due to this review article's objective, only the implementation of DEA models in agriculture production performance is considered in this article; therefore, future studies can review DEA's application in other application areas, industries, organisations, sectors, and firms. Also of this limitation, the current review article only emphasised the implementation of DEA models in the assessment of agriculture production performance; in this regard, the future works can review the application of other methods like fuzzy sets, decision making, optimizations models, neural networks and econometrics approaches and methods in agriculture production performance assessment.

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