Measuring agricultural sustainability of European countries with a focus on transportation

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Abstract: Agriculture is one of the most important sectors for the development of countries. Furthermore, it can affect and be affected by climate change, especially since agricultural products are increasingly being transported to meet the demands of an increasing and urbanized population. Consequently, the measurement of agricultural sustainability should include transportation elements. The purpose of the current paper is to calculate the agricultural sustainability of European countries using two-stage Data Envelopment Analysis (DEA). Different variations of the model are used to gain better insights into the overall agricultural performance. The results illustrate that Malta, Italy, the Netherlands and Denmark perform well compared to other European countries in both two-stage DEA variations that were used and the differences that are observed in the variations are attributed to the different number of constraints. Finally, a computational experiment is performed to investigate the phenomenon of rank reversal and a new index is proposed.

Keywords: agricultural sustainability; data envelopment analysis; transportation; two-stage DEA; rank reversal;

Reference to this paper should be made as follows: Author. (xxxx) 'Title', *Int.*

1 Introduction

Agriculture is one of the most important sectors in the economy and it can have effects (negative or positive) in environmental conservation and economic development (Pang et al., 2016). Furthermore, agriculture plays an important role in social support since it provides nutrition to an increased global population.

However, current nutrition choices and consequently current production practices are considered unsustainable and one of the main drivers of climate change (Poore & Nemecek, 2018; Pradhan et al., 2020). Moreover, an increased urbanization and globalization of supply chains means that food demands are met only after transportation over long distances (Kissinger, 2012; Weber & Matthews, 2008).

Nonetheless, the increased transportation of goods (and people) is considered one of the main sources for Greenhouse Gas emissions (Fuglestvedt et al., 2008), which contribute further to climate change. For example, the dairy sector emitted 4% of the total greenhouse gas emissions (Aggestam & Buick, 2017).

As a result, efficient and cost-effective transportation can be a driver for sustainability (Gao et al., 2019); in the opposite case, climate change will hinder sustainable agriculture, which due to globalization will cause disruptions with cascading, global effects. An inefficient transportation has a severe impact on the small (and medium) agricultural enterprises (Han et al., 2020).

Since the primary objective of farmers is to increase their profits, an increased transportation cost might lead them to employ unsustainable production practices that cause further damage to the environment (Hoang & Alauddin, 2012). Hence, farmers are trapped in a vicious cycle where in order to survive they must be detriment to the environment which further hinders any effort for sustainability that results in more dire consequences for farmers.

In conclusion, sustainable agriculture is a key goal for all. Therefore measuring the performance of the agricultural sector of countries can provide essential information to policy makers in order for them to design appropriate policies that could lead to sustainable development (Picazo-Tadeo et al., 2011).

One way to measure the sustainability of the agricultural sector is with the use of Data Envelopment Analysis (DEA). DEA is a non-parametric, mathematical programming technique that is used to measure the technical efficiency of Decision-Making Units (DMUs). Technical efficiency is an engineering term and can be defined as:

$$technical\ efficiency = \frac{\sum w_{output} * y}{\sum w_{input} * x}, where\ x = input\ level\ and\ y = output\ level \quad (1)$$

In DEA each DMU uses inputs to produce outputs and one of the advantages of DEA is that there is no need to have a relation between inputs and outputs (Thanassoulis, 2001). Furthermore, the weights are not assigned by the analyst or the policy maker, but are calculated by the linear program for each DMU separately. The method was established in the seminal papers of Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984).

As a result, DEA has been used to measure performance in various echelons of the agricultural sector. Dhungana et al. (2004) used DEA to 76 Nepalese rice farms to reveal significant variations in the levels of inefficiency that were attributed to the manner that the inputs were used; Rebolledo-Leiva et al. (2017) combined carbon footprint assessment with DEA to measure the eco-efficiency of organic blueberry orchards, while Atici and Podinovski (2015) analyzed the efficiency of wheat production in various farms in Turkey.

The efficiency measurement was not limited to the farm level. Toma et al (2015) applied DEA to measure the sustainability of agriculture in regions of Romania, while Li et al. (2018) calculated the relative efficiency of 30 regions in China for several years. Furthermore, Arnade (1994) measured the efficiency of agricultural sectors in 77 countries; Hoang and Rao (2010) evaluated the agricultural efficiency of 29 OECD countries. Moreover, DEA has been used to measure agricultural efficiency in Europe (Bojnec et al., 2014; Kočišová, 2015; P. Toma et al., 2017).

However, several gaps were identified in the literature. Firstly, Toma et al. (2017) identified that in general there is a lack of studies to evaluate agricultural efficiency at national level. Secondly, to the best of our knowledge, transportation of agricultural goods has not been considered in the studies associated with agricultural efficiency. Finally, the classic, one-stage DEA models is the preferred method for the majority of the studied papers. However, evaluating agricultural efficiency is a complex effort and one-stage DEA models can be considered “black boxes” since no knowledge is required about how inputs are transformed into outputs (Färe & Grosskopf, 2009). Thus, two-stage DEA models might be more suitable, since they can provide a decomposing of the overall efficiency into two different elements and reveal more insights to the policy maker.

The objective of the current paper is to provide a calculation of the sustainability of agriculture of European countries taking also into account the transportation of goods by employing a two-stage Data Envelopment Analysis (DEA) model. The rest of the paper is organized as follows: Section 2 is focused on the description of the mathematical model and the data that was used for the current paper. In section 3 the results are presented and discussed, while conclusions and future research directions are presented in the last section.

2 Methodology

In the classic Data Envelopment Analysis, a DMU consumes inputs and produces outputs and there is no need to have knowledge of or define a function (or a relationship) between inputs and outputs. While this is considered an advantage for the methodology, in certain settings, it is necessary to include more details regarding the inner workings within a DMU in order to assess its efficiency. Two-stage DEA models have been developed for this purpose and are considered a special category of network DEA models (Seiford & Zhu, 1999). Figure 1 below illustrates the typical structure of a two-stage DEA model.

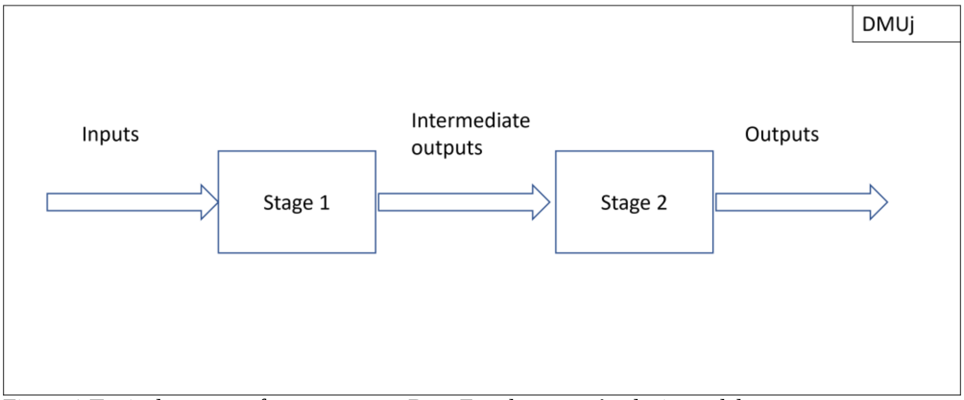

Figure 1 Typical structure for a two-stage Data Envelopment Analysis model

Each stage is considered to be a separate decision centre and the overall goal is the simultaneous improvement of the efficiency of each stage and the efficiency of the DMU as a whole. The mathematical formulation of the model is: For a two-stage DEA model, assume there are n DMUs. For each DMU_j (j=1..N) in the first stage uses m inputs (x_{ij}, i=1…m, j=1…N) to produce D intermediate outputs (z_{dj}, d= 1…D, j=1…N), which are used as inputs in the second stage to produce s outputs (y_{rj}, r=1…s, j=1…N).

Liang et al. (2006, 2008), Kao and Hwang (2008), Chen et al. (2009) and Cook et al. (2010) provided integrated models that attempted to simultaneously optimize the efficiencies of the two stages. The model that the authors proposed is:

$$\max E_0 = \sum_{r=1}^{s} \gamma_r y_{r0} \tag{2}$$

Subject to Constraints

$$\sum_{d=1}^{D} \mu_d z_{dj} - \sum_{i=1}^{m} \omega_i x_{ij} \leq 0, j = 1, \dots, N \tag{3}$$

$$\sum_{r=1}^{s} \gamma_r y_{rj} - \sum_{d=1}^{D} \mu_d z_{dj} \leq 0, j = 1, \dots, N \tag{4}$$

$$\sum_{i=1}^{m} \omega_i x_{i0} = 1 \tag{5}$$

$$\omega_i \geq 0, i = 1, \dots, m \tag{6}$$

$$\mu_d \geq 0, d = 1, \dots, D \tag{7}$$

$$\gamma_r \geq 0, r = 1, \dots, s \tag{8}$$

The notations ω_i, μ_d, γ_r are used to represent the weights of the inputs, intermediate outputs and outputs respectively. The above model provides a number between 0 (inefficient) and 1 (efficient) for each DMU and the optimal values of ω_i, μ_d, γ_r are used to calculate the efficiencies of each individual stage according to the formulas:

$$E_0^1 = \frac{\sum_{d=1}^{D} \mu_d^* z_{d0}}{\sum_{i=1}^{m} \omega_i^* x_{i0}} \tag{9}$$

$$E_0^2 = \frac{\sum_{r=1}^{s} \gamma_r^* y_{r0}}{\sum_{d=1}^{D} \mu_d^* z_{d0}} \tag{10}$$

However, the model calculates different optimal values for the ω_i, μ_d, γ_r for each DMU, with the purpose of allowing each DMU to choose the values that maximize its own efficiency and removing any bias from the analyst. However, such flexibility in choosing the weights that will determine the efficiency of each DMU means that there might be important inputs and/or outputs that are ignored in the final calculation and further, the different weights do not allow the ranking of the DMUs since their efficiencies are calculated under different bases (Pedraja-Chaparro et al., 1997).

To overcome this limitation, Tsaples (2021) proposed a different variation on the two-stage model:

$$\min n_0 + n_0' \tag{11}$$

Subject to Constraints

$$\sum_{i=1}^{m} \omega_i x_{ij} - \sum_{d=1}^{D} \mu_d z_{dj} \geq 0, j = 1, \dots, N \tag{12}$$

$$\sum_{i=1}^{m} \omega_i x_{i0} - \sum_{d=1}^{D} \mu_d z_{d0} - d_0 + n_0 = 0 \tag{13}$$

$$\sum_{d=1}^{D} \mu_d z_{dj} - \sum_{r=1}^{s} \gamma_r y_{rj} \geq 0, j = 1, \dots, N \tag{14}$$

$$\sum_{d=1}^{D} \mu_d z_{d0} - \sum_{r=1}^{s} \gamma_r y_{r0} - d_0' + n_0' = 0 \tag{15}$$

$$\sum_{d=1}^{D} \mu_d z_{d0} = 1 \tag{16}$$

$$\omega_i \geq 0, i = 1, \dots, m \tag{17}$$

$$\mu_d \geq 0, d = 1, \dots, D \tag{18}$$

$$\gamma_r \geq 0, r = 1, \dots, s \tag{19}$$

$$d_0, n_0, d_0', n_0' \geq 0 \tag{20}$$

For the objective of the current paper, both models will be used to calculate the agricultural efficiency of European countries. As inputs, the following measures were used:

- Utilized Agricultural Area
- Total labor force in agriculture
- Transport infrastructure investment and maintenance spending

As intermediates, the following measures were used:

- Output of agricultural industry – Production value at basic price
- Greenhouse gas emissions from agriculture
- Total transported goods

Finally, as outputs the following measures were used:

- Agricultural income
- Gross value added at basic prices

The data were obtained by Eurostat[1] and OECD[2] for the year 2018. The choice of the year depended on the data availability and 2018 was the most recent, common year for which there was availability for the chosen countries. The choice of the type of inputs, intermediate outputs and outputs was based on the literature and the specific research objective of the current paper, meaning the inclusion of transportation related measures/variables.

3 Results

3.1 Results on Agricultural Sustainability

As it was mentioned above, the agricultural sustainability of European countries is calculated using both models of Chen et al. (2009) and Tsaples (2021). The results are illustrated on Table 1 below.

Table 1 Results of the agricultural sustainability of European countries according to the models by Chen et al. (2009) and Tsaples (2021)

	Chen et al (2009)			Tsaples (2021)		
Country	**Overall agricultural sustainability**	**Efficiency of stage 1**	**Efficiency of stage 2**	**Overall agricultural sustainability**	**Efficiency of stage 1**	**Efficiency of stage 2**
Belgium	0,37	0,82	0,44	0.289	0.34	0.23
Bulgaria	0,15	0,21	0,73	0.28	0.27	0.30
Czech	0,28	0,37	0,75	0.38	0.69	0.08
Denmark	0,87	0,87	1	0.35	0.12	0.57
Germany	0,58	1	0,58	0.28	0.48	0.07
Estonia	0,15	0,48	0,32	0.12	0.20	0.05
Ireland	0,24	0,37	0,64	0.28	0.23	0.33
Greece	0,18	0,20	0,87	0.22	0.11	0.34
Spain	0,48	0,50	0,95	0.34	0.28	0.40
France	0,77	1	0,77	0.18	0.31	0.04
Croatia	0,20	0,24	0,83	0.19	0.09	0.29
Italy	1	1	1	0.36	0.23	0.50
Cyprus	0,40	0,47	0,84	0.25	0.29	0.21
Latvia	0,17	0,32	0,54	0.26	0.37	0.15
Lithuania	0,33	1	0,33	0.47	0.79	0.15
Luxembourg	1	1	1	0.23	0.26	0.19

[1] https://ec.europa.eu/eurostat/data/database (accessed in April 2021)

[2] https://stats.oecd.org/ (accessed in April 2021)

Hungary	0,78	1	0,78	0.32	0.285	0.3743
Malta	1	1	1	0.39	0.69	0.09
Netherlands	0,66	1	0,66	0.55	0.68	0.42
Austria	0,30	0,40	0,74	0.18	0.18	0.18
Poland	0,14	0,23	0,60	0.18	0.12	0.25
Portugal	0,55	0,82	0,67	0.25	0.13	0.37
Romania	0,45	0,58	0,78	0.31	0.12	0.50
Slovenia	0,28	0,28	1	0.38	0.40	0.37
Slovakia	0,27	0,43	0,63	0.31	0.47	0.15
Finland	0,20	0,48	0,42	0.26	0.42	0.10
Sweden	0,28	0,68	0,42	0.39	0.72	0.06

The first column of the table contains the countries that form the DMU set. The next three columns have the overall agricultural sustainability, the efficiency of the first stage and the efficiency of the second stage as they were calculated with the model by Chen et al. (2009). The countries/DMUs can be separated into three general groups: the first group has the countries that have an overall agricultural efficiency of 1 and these are Italy, Luxembourg and Malta. The inclusion of countries like Italy (considered as agriculturally developed) with that of Malta, highlights that agricultural output should not be the only measure of development. Malta, a small country, utilizes a small percentage of its available land for agriculture and has a very small agricultural sector in general. However, the available resources are used in an efficient way and although the country relies on imports for such products, the small population and the relatively effective spending on the infrastructure along with the reduced greenhouse emissions, means that Malta is as agriculturally efficient as Italy.

The second group contains the countries that have an overall agricultural sustainability below 1 and over 0.5. These countries are: Denmark, Germany, France, Hungary, Netherlands and Portugal. These countries are considered among the most developed in the European Union and it appears that the agricultural sector follows (or affects) the overall development of the country.

Finally, the third group contains the rest of the countries that have an overall agricultural performance below 0.5. The majority of these countries are either ones that are considered new in the union (like Poland) or have been affected heavily by the economic crisis of the previous decade (Greece).

The last three columns of Table 1 illustrate the same results but calculated with the two-stage DEA variation proposed by Tsaples (2021). The first fact to observe is that all the values of the overall agricultural sustainability are smaller than in the first case, but the values themselves have a smaller variation. Similar to the results as calculated with the DEA variation of Chen et al. (2009), three groups can be recognized. The first entails the Netherlands and Lithuania that have the largest values of overall agricultural sustainability. The second group consists of Czech Republic, Denmark, Spain, Italy, Hungary, Malta, Slovenia and Sweden and the final group with the rest of the countries.

To get a better understanding of the countries' performance, their rank is displayed on Table 2 and the countries are sorted based on the ranking that was generated with the method of Tsaples (2021). The results illustrate that differences are observed on the two DEA variations; there are countries that fall in their ranking but not by a lot like Malta and there are others where the two rankings are significantly different.

The differences can be attributed to the larger number of inequalities that are introduced in the variation by Tsaples (2021). Furthermore, the specific variation attempts to minimize the deviation from the minimum value of performance for all countries which causes the performances to not present large deviations from one another, thus causing differences in the rankings.

Table 2 Ranking of the countries for the overall agricultural sustainability according to the two variations

	Chen et al (2009)	Tsaples (2021)
Netherlands	7	1
Lithuania	14	2
Sweden	16	3
Malta	1	4
Czech	18	5
Slovenia	17	6
Italy	1	7
Denmark	4	8
Spain	10	9
Hungary	5	10
Slovakia	19	11
Romania	11	12
Bulgaria	26	13
Belgium	13	14
Ireland	20	15
Germany	8	16
Finland	22	17
Latvia	24	18
Cyprus	12	19
Portugal	9	20
Luxembourg	1	21
Greece	23	22
Croatia	21	23
Poland	27	24

Austria	15	25
France	6	26
Estonia	25	27

To gain better insights from the results, the data from Table 1 was used as an input in a K-Means algorithm with 4 clusters. The results are illustrated on Figure 2 below.

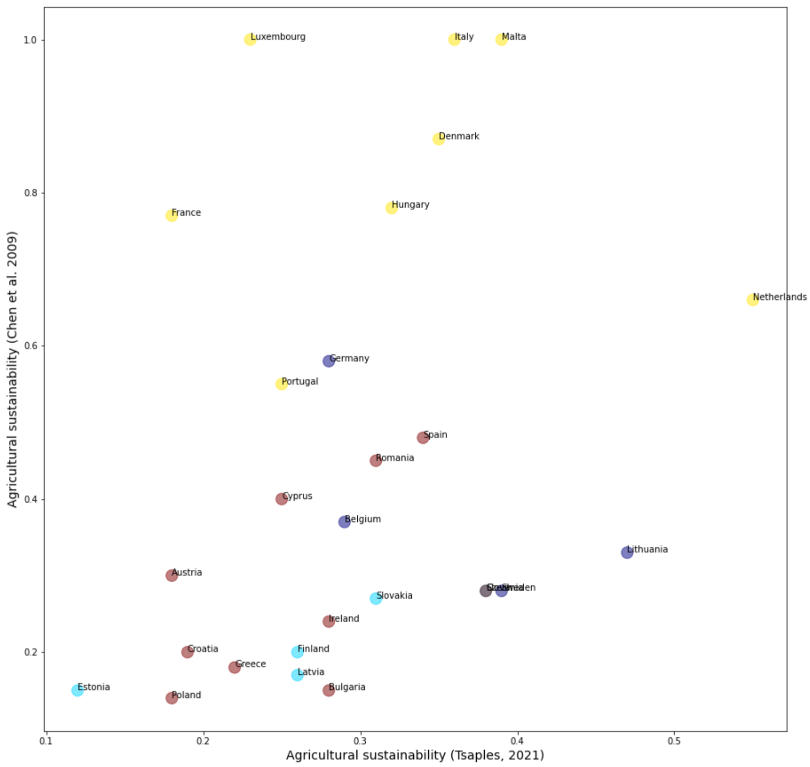

Figure 2 The clusters of countries based on K-Means algorithm

The x-axis has the agricultural sustainability of the countries as calculated with the variation of Tsaples (2021), while the y-axis those values as calculated with the variation of Chen et al. (2009). In the upper part of the graph, with agricultural sustainability values above 0.6 are the countries of Portugal, Netherlands, Denmark, Italy, Malta, Luxemburg and France.

The second cluster entails the countries of Germany, Sweden, Lithuania and Belgium. The third cluster entails the countries of the Czech Republic, Estonia, Latvia, Slovakia and Finland. Finally, the last cluster contains the remaining countries. Consequently, the clustering algorithms provides an opportunity to firstly, better visualize the results for agricultural sustainability and secondly showcase the countries that share similar characteristics.

3.2 Computational Experiment on rank reversal

To test the robustness of the method, a computation experiment has been designed with the purpose of investigating the phenomenon of rank reversal when DMUs are added or deleted from the original set.

The rank reversal phenomenon is known in the Multi-Criteria Decision Analysis (MCDA) field (Y.-M. Wang & Luo, 2009). It occurs when the introduction of a new alternative or the removal of an existing one from the original set of alternatives changes the ranked list (Papathanasiou, 2021). One of the reasons for its appearance is the inter-dependence among the alternatives or the DMUs (Saaty & Sagir, 2009). Consequently, introducing or removing alternatives/DMUs from the original set results in ranking inconsistencies (Sayed et al., 2018; Tofallis, 2014).

Many researchers have studies the rank reversal phenomenon of MCDA, for example in AHP (Belton & Gear, 1983; Dyer, 1990; Shin & Lee, 2013; Troutt, 1988) and in TOPSIS (Garcia-Cascales and Lamata 2012).

The rank reversal phenomenon was also studied in DEA. Wang and Luo (2009) studied the phenomenon of rank reversal in cross-efficiency evaluation of DEA with numerical examples; Sayed et al. (2015) designed an experiment in which they applied DEA in a list of DMUs and followed by separating the original to several sub-groups. The results showed inconsistency in the final ranking when comparing rankings of the full list with those evaluated from different sub-groups. Furthermore, Soltanifar and Shahgobadi (2014) demonstrated rank reversal in several variations of DEA by adding DMUs to an original set. To the best of our knowledge the number of studies for the rank reversal phenomenon in DEA is limited, thus another contribution of the current paper is the design and conduction of a computational experiment to investigate how the proposed, two-stage DEA variation behaves when DMUs are added or removed.

The studying of the literature illustrated that the tests that are performed to check for rank reversal in MCDA methods are grouped into three categories:

(1) Adding copies of non optimal alternatives to the decision problem (Belton & Gear, 1983)

(2) Adding new alternatives or removing existing ones (Dyer, 1990; Kong et al., 2016; Troutt, 1988)

(3) Replacing a non-optimal alternative with a worse one (X. Wang & Triantaphyllou, 2008)

For the current paper, the second category of tests is used. The rationale behind removing or adding DMUs is dictated by the original set of DMUs. The European Union is going through a transition period where countries either opt to move out of the union (for example UK) or there are plans for the introduction of new countries (for example Balkan countries) in the near future. As a result, it would be interesting to investigate how the addition or removal of DMUs would affect the calculations for the environmental performance.

The original set of DMUs is decreased by removing randomly 10 and then 2 DMUs. Following that the original set is increased by adding 2 and 10 DMUs. The values for the inputs and outputs of the added DMUs are random numbers between the maximum and the minimum value of the particular input, intermediate output or output.

The agricultural performance of the new sets of DMUs is calculated using the methods of Chen et al. (2009) and Tsaples (2021). From these calculations, new rankings occur for the new sets of DMUs.

To investigate how the new rankings fare compared to the originals a new index is used. To the best of our knowledge, no such attempt to formalize the sensitivity of a Multi-Criteria Decision Aid method has been attempted in the literature. In the works that investigate the rank reversal phenomenon, the researchers typically count the number of reversals. However, this new, proposed index contains two values: one that represents how many DMUs are common in the compared rankings and one that represents how similar are the rankings of the DMUs. Thus, it can be considered that it provides a more comprehensive picture of the rank reversal phenomenon on the MCDA method. The index is calculated as follows:

Assume there are two sets/rankings, S (containing N elements/DMUs) and T (containing M elements/DMUs). If N=M then the two sets are used as is, otherwise if for example N<M then the N' last elements are removed from S until N''=M (with N=N'+N'').

The subsequent equal sets are compared in the following manner:

Step 1: The common elements (those DMUs that appear in both sets) are found. Assume *C=number of common DMUs between the two sets/rankings*.

Step 2: The non-common elements (those DMUs that appear in only one set) are found. Assume *D=number of non-common DMUs between the two sets/rankings*.

Step 3: The *Elements Similarity Index* is calculated:

$$\textit{Elements Similarity Index} = (C-D)/(C+D) \tag{21}$$

The index takes values between -1 and 1. If for example, two sets have all their DMUs in common (for example 5), then *C=5, D=0 and Elements Similarity Index = 1*. On the contrary, if the two sets have no common elements then *C=0, D=5 and Elements Similarity Index = -1*.

Step 4: The common rankings among DMUs are found (those rankings that appear in both sets). Assume *X= number of common rankings among DMUs between the two sets.* For example, assume that in set S, the following rankings occur:

- DMU_1 ranks in the same place as DMU_2
- DMU_1 ranks better than DMU_3
- DMU_2 ranks better than DMU_3

Furthermore, assume that in set T, the following rankings occur:

- DMU_1 ranks better than DMU_2
- DMU_1 ranks better than DMU_3
- DMU_3 ranks better than DMU_2

As a result, the common rankings (those rankings that appear in both sets are:

- DMU_1 ranks better than DMU_3, thus *X =1*.

Step 5: The non-common rankings among DMUs are found (those rankings that appear in one of the two sets). Assume *Y= number of non-common rankings among*

DMUs between the two sets. Following the example from Step 4, the non-common rankings are:

- DMU_1 ranks in the same place as DMU_2
- DMU_2 ranks better than DMU_3
- DMU_1 ranks better than DMU_2
- DMU_3 ranks better than DMU_2, thus $Y = 4$

Step 6: The *Rankings Similarity Index* is calculated:

$$\text{Rankings Similarity Index} = (X-Y)/(X+Y) \tag{22}$$

Similar to the Elements Similarity, the Rankings similarity index takes values between -1 and 1, with -1 being total un-similarity in rankings between the two sets and 1 total similarity.

Step 7: The *Similarity Index* is:

$$\text{Similarity Index} = \langle \text{Elements Similarity Index, Rankings Similarity Index} \rangle \tag{23}$$

The advantage of such a measure is that it provides an overall assessment of the rank reversal phenomenon, as it takes into account both the DMUs that might appear in two rankings and how stable are the rankings that are produced in the original set. In the context of the current paper, the Similarity Index for the two DEA variations is depicted on Table 3 and Figure 3 below.

Table 3 Similarity Index for the two DEA variations under different scenarios

	Chen et al. (2009)	**Tsaples (2021)**
Original set/Original-10 DMUs	<-0.43, 0.63>	<-0.38, 0.5>
Original set/Original-2 DMUs	<0.57, 074>	<0.57, 0.67>
Original set/Original+2 DMUs	<0.6, 0.79>	<0.64, 0.56>
Original set/Original + 10DMUs	<0, 0.77>	<0.1, 0.7>

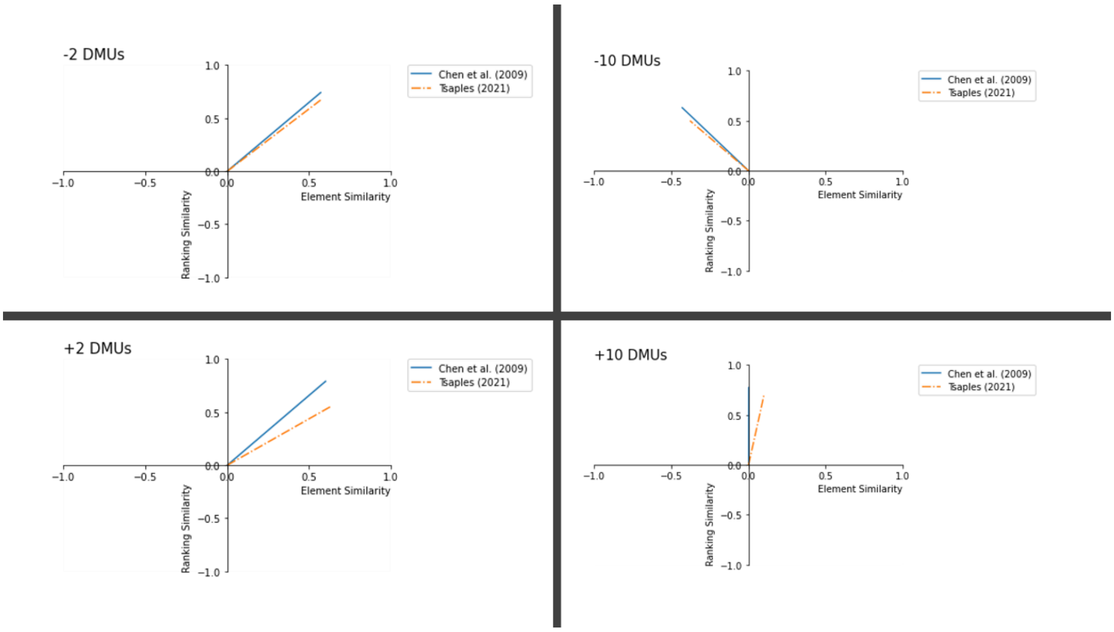

Figure 3 Graphical representation of the Similarity Index for the two DEA variations under different scenarios

As it can be observed, the two variations share almost similar results. The variation by Tsaples (2021) is less sensitive in the Elements Similarity Index as DMUs are added or removed from the original set. However, it shows a larger sensitivity with regards to rankings compared to the variation by Chen et al. (2009). Moreover, it appears that as more DMUs are added in the original set, the variation by Chen et al. (2009) replaces half the DMUs from the original set with the new ones, while in Tsaples (2021) the majority of the DMUs is the same.

4 Conclusions

The objective of the current paper was to calculate the agricultural sustainability of European countries while also considering transportation of goods. Transportation is essential to transportation since it connects the producers with the final consumers. At the same time, it can have a negative effect on the environment with the greenhouse gas emissions and finally, an inefficient transportation can be detrimental to the economic prosperity of the environment. As a result, its inclusion in the measurement of the agricultural performance is considered essential.

Data Envelopment Analysis is a mathematical programming technique that is used to evaluate the efficiency of Decision Making Units without any knowledge on how inputs are transformed into outputs. Consequently, it is suitable to measure a complex notion such as the agricultural sustainability. However, this advantage can be also considered a limitation since the method can be seen as a “black box”. To mitigate this limitation, two-stage DEA models can be used.

Hence, the contributions of the paper are: (1) to the best of our knowledge transportation of agricultural goods has not been considered in previous studies, (2) the employment of two-stage DEA models for the evaluation of agricultural sustainability of countries and the comparison among the different models contributes to the relevant literature to the relevant and (3) a new index is proposed to study the rank reversal phenomenon under different scenarios.

The results illustrate that the variation by Tsaples (2021) changes the agricultural sustainability of DMUs (and their rankings) compared to the variation by Chen et al. (2009) because it employs more sets of constraints in the calculations. Furthermore, the performance results present lower value dispersion, since all DMUs attempt to minimize the negative deviations that could force the value of performance towards its minimum value. Finally, the variation is less Element sensitive and more Rankings sensitive when DMUs are added or removed from the original set.

Measuring the agricultural sustainability of countries is a complex problem, thus any mathematical model that attempts to solve it, will undoubtedly be a simplification of reality. However, this does not render such models useless; on the contrary abstract and mathematical representations of reality can have practical implications on policy design and implementation as long as all the involved stakeholders are aware of the limitations and focus on the useful insights (Delias et al., 2018). In the context of the current paper, the use of more than one variation of Data Envelopment Analysis increases the robustness of and the trust in the results. Countries that perform (or rank) at the upper echelon in both methods are more likely to actual move closer towards agricultural sustainability, while countries that have widely different rankings in each method can indicate that their agricultural sector might be more sensitive to external factors, hence any policy towards its improvement should be well thought-off and robust. Furthermore, the illustration of the results in clusters can be a valuable communication tool that offers assistance to policy makers when they need to justify their potential choices. Finally, such an approach could assist policy makers when new countries might need to be included in the initial group (for example in the case of EU expansion). In such a case, the new country could more easily adapt to EU regulations if they know which best practices (countries) share similar characteristics with them.

Future research directions could target more dimensions of agricultural sustainability by calculating separately indicators about the economic, environmental and social elements of the agricultural sector. Moreover, different combinations of inputs, intermediates and outputs could reveal insights and provide alternate interpretations that if integrated into a single indicator could assist policy makers to design better policies. Finally, the development of a Decision Support System could make the analysis more accessible to the relevant stakeholders like policy makers, farmers etc. thus bringing scientific rigour into their decision-making process.

Acknowledgements

This paper was supported by the Research Committee of the University of Macedonia under the Research Project “Measuring sustainability with a focus on agricultural transportation”.

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