land

MDPI

Article

# Efficiency of Vegetables Produced in Glasshouses: The Impact of Data Envelopment Analysis (DEA) in Land Management Decision Making

**Thomas Bournaris [1,*], George Vlontzos [2] and Christina Moulogianni [1]**

[1] Department of Agricultural Economics, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; kristin@agro.auth.gr

[2] Department of Agriculture, Crop Production and Rural Development, University of Thessaly, 38446 Volos, Greece; gvlontzos@agr.uth.gr

* Correspondence: tbournar@agro.auth.gr; Tel.: +30-231-099-8423

Received: 24 November 2018; Accepted: 10 January 2019; Published: 13 January 2019

check for updates

**Abstract:** Glasshouse farming is one of the most intensive types of production of agricultural products. Via this process, consumers have the ability to consume mainly off-season vegetables and farmers are able to reduce operational risks, due to their ability to control micro-climate conditions. This type of farming is quite competitive worldwide, this being the main reason for formulating and implementing assessment models measuring operational performance. The methodology used in this study is Data Envelopment Analysis (DEA), which has wide acceptance in agriculture, among other sectors of the economy. The production protocols of four different vegetables—cucumber, eggplant, pepper, and tomato—were evaluated. Acreage ($m^2$), crop protection costs (€), fertilizers (€), labor (Hr/year), energy (€), and other costs (€) were used as inputs. The turnover of every production unit (€) was used as the output. Ninety-eight agricultural holdings participated in this survey. The dataset was obtained by face-to-face interviews. The main findings verify the existence of significant relative deficiencies (including a mean efficiency score of 0.87) as regards inputs usage, as well as considerably different efficiency scores among the different cultivations. The most efficient of these was the eggplant production protocol and the least efficient was that used for the tomato. The implementation of DEA verified its utility, providing incentives for continuing to use this methodology for improving land management decision making.

**Keywords:** input optimization; efficiency; intensive farming; glasshouse; DEA

## 1. Introduction

Glasshouses are traditionally used in agriculture for vegetable and flower production because of the significantly reduced risk for both farmers and traders, due to the ability provided to control microclimate conditions. This is quite important for cultivations quite sensitive to weather conditions, like vegetables and flowers. Additionally, continuous and growing demand for such products in places where it is not possible to grow vegetables, mainly due to adverse weather conditions, in accordance with the demand for offseason products, provides the necessary incentives for this type of cultivation to develop. Examining the case from an economic and operational perspective, glasshouse farming is mainly a capital-intensive production process, and in some cases, where low technology is applied, labor intensive. It has been proven that the lower the technology level used, the less capital is invested, increasing in this way the dependence on labor for a successful outcome [1]. Modern glasshouses are not following this trend and on the contrary are adopting high technology standards, driving these holdings to capital-intensive production units [2]. Glasshouse cultivation, when it is applied in low technology premises, contributes to soil degradation and excessive water use [3]. Another characteristic of this sector is its market orientation, which is in contrast with other cultivations (e.g., arable crops and animal feeding) as their development was based on subsidies. Glasshouse farming has proven its feasibility in economic terms, and in many cases its ability to achieve high profitability. Additionally, this close interrelationship with market forces has been an integral part of its organizational culture, in accordance with increased flexibility and adjustment to consumer preferences and demands [4]. Such an intensive production process requires high management standards for succeeding high input utilization scores, increasing in this way their competitive advantage. Moreover, there is a need to identify which crop is better tailored to the structural characteristics of each holding, providing considerable assistance to the decision-making process. Most land management decisions for vegetables are usually taken without examining or evaluating the efficiency results for every production process. Based on this status quo, it is essential research finding and case studies relevant to agriculture (and more specifically to land management issues) be analyzed and taken into consideration in order to specify appropriate methodological approaches for similar cases.

Data Envelopment Analysis (DEA) is a widely accepted methodological approach for assessing productive efficiency or quantifying relative deficiencies. It has been implemented in agriculture in various versions, estimating farmer efficiency and the determinants of yield [5,6] as well as evaluating operational, environmental, and energy aspects of production [7]. The first statement about resolving the issue of productive efficiency was introduced by Farrell [8]. Later, Charnes et al. [9] introduced DEA as a reliable methodological approach for quantifying possible deficiencies for production units using a number of inputs and producing a number of outputs. The extensive acceptance and recognition of this methodology is due to its non-parametric approach, as well as its providing assistance with successful resource allocation, categorizing efficient operating practices, and formulating efficient strategies, as well as monitoring efficiency changes for specific time periods [10]. The most significant uses of the DEA model are its use in peer groups, the setting and dissemination of efficient operational practices, the identification of specific goals, the development of efficient strategies, the capacity to observe efficiency changes over time, and resource allocation [11]. There are, though, considerable limitations regarding DEA implementation. The most important of these are the lack of statistical properties of the sample and the impact of sample size on the results obtained [12–15]. The efficacy of the DEA model has been demonstrated by its use in assessing the effectiveness of very important production sectors of economy, even now [16]. One of the most important practical applications of DEA is its use in banking. Banks use DEA largely as a useful implement for evaluation, monitoring, and developing performance [17,18]. The same methodological approach has been applied for efficiency evaluation of school units with considerable results [19,20]. Another sector in which DEA is increasingly used is logistics [21], while the implementation of the model in the energy sector is also important, as with the use of the model the effectiveness of energy plants has been proven [22]. While DEA has been used in multiple economic-based studies it has been recently used as an agricultural tool. Many studies have used DEA in the agricultural sector, using a plethora of different inputs and outputs for both crop and animal assessments [23]. Due to the fact that water scarcity is a vital issue for agricultural production, DEA has been implemented to evaluate the efficiency of irrigated agricultural holdings [24,25]. The same approach has provided significant results with regards to clarifying the three aspects of efficiency, i.e., the technical, the economic, and the environmental [26]. Additionally, it has been used to classify agricultural holdings producing olive oil in regions with significant production deficiencies [27].

Quite important findings have been obtained by combining DEA with Life Cycle Assessment (LCA). LCA is a methodological tool for evaluating the environmental impact of a production process or a product. Such application can be found in both crop and animal production cases, including fisheries [28], dairy farming [29], arable crops [30], and grape production [31]. In a similar manner, there are cases where undesirable outputs, like greenhouse gas (GHG) emissions, have been assessed by using DEA to improve energy efficiency [32,33]. Quite interesting, however, is a different methodological approach proposed by Cassidy et al. for redefining agricultural yields [34].

Significant increases in human populations, especially in Asia, suggest new ways of facing food security worldwide. DEA gives insight into areas with high potential for maximizing their efficiency in producing food, by improving the effectiveness of input usage [35]. Efficiency of land cultivation can be investigated on a yearly basis, ensuring higher yields [36]. Large areas with multiple variations (plain, hill, and mountain areas) can be categorized and monitored with the use of this model, providing homogenous production clusters [37].

The production process can be assessed using DEA, revealing weak points across the entire farm-to-fork value chain. It can be utilized as a selection tool for choosing the most efficient supplier according to certain criteria (e.g., eco-friendliness) [38]. A survey by Zhou et al. has concluded that there are only a few surveys that combine DEA with socioeconomic characteristics, proving that food production should have a holistic approach [39]. In the same literature review it is underlined that there is a gap in examining the efficiency of industrial value chains.

The same methodological approach has facilitated representative research findings from both the crop and animal production sectors, assessing the eco-efficiency of the production process. Useful findings have been obtained for both citrus and olive cultivations in the Mediterranean region, where water resources are scarce, with the model identifying excessive usage of water for irrigation purposes [40,41]. Impressive results have also been obtained from assessing the operational and environmental efficiency of grape production. In this case, DEA implementation led to the need for 30% reduction of input usage on average. When this reduction was applied it led, during the next cultivating period, to a 28% profitability gain [31]. The same approach has been followed in the milking sector. The assessment of both the operational and environmental performance of milking cows has led to significant reductions in operational costs, as well as to the improvement of their environmental footprint [42].

Intensive agricultural production is heavily dependent on energy consumption. The most characteristic cases of this are glasshouse production systems. Several cases have been assessed focusing on the efficiency of their energy management protocols. One application of DEA on a tomato production process succeeded in achieving a stable harvest by reducing energy consumption by 25.15% [43]. Quite interesting is the efficiency comparison between holdings producing cucumbers and tomatoes. For the former, technical efficiency calculations verified that 27% of the sample was efficient. For the latter, the average efficiency score for tomato cultivation was 0.94, signifying the considerable difference of competitiveness between the two cultivations [44]. The same trend has been verified for glasshouse rose production, where 43.59% energy savings has been seen to be able to be achieved without jeopardizing existing yields [45]. Keeping in mind the above findings, it is interesting to identify efficiency levels of input use in glasshouse production in regions where similar research findings have not yet been published. For this reason, we undertook field research in order to identify possible over-usage of inputs in glasshouse vegetable production and to quantify them. Such findings assess on a realistic basis the direct negative impacts of these practices on the overall cost of production.

The paper proceeds in the following way. In the following section, the basic theory of DEA is presented. In Section 3 the results of the DEA analysis are presented. The final section concludes.

## 2. Materials and Methods

DEA, as was mentioned earlier, is a non-parametric model where it is not compulsory to specify the inputs and outputs being used and obtained, respectively, in production function. Each production unit participating in the implementation of this model is called a Decision Making Unit (DMU) which uses $m$ inputs and produces $s$ outputs. The data set of the model consists of $n$ DMUs. The efficiency score for every DMU is calculated by using the following model, following the original approach of Charnes et al. [9]:

Constant Return to Scale (CRS) Model

$$\min\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{1}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j \chi_{ij} + s_i^- = \theta x_{io} \quad i = 1, 2, \ldots, m \tag{2}$$

$$\begin{gathered}\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1, 2, \ldots, s \\ \lambda_j \geq 0 \quad j = 1, 2, \ldots, n\end{gathered} \tag{3}$$

Variable Return to Scale (VRS) Add

$$\sum_{j-1}^{n} \lambda_j = 1 \tag{4}$$

where $j$ is the number of observations of the DMUs. Each observation DMU$_j$ ($j$ = 1, 2, ... $n$), uses $m$ inputs $x_{ij}$ ($i$ = 1, 2, ... $m$) to produce $s$ outputs $y_{rj}$ ($r$ = 1, 2, ... $s$). The efficient frontier is determined by these $n$ observations. $\theta$ is the efficiency score of each DMU. There are two properties to ensure that a piecewise linear approximation has been developed to the efficient frontier and the area dominated by the frontier. $\sum_{j=1}^{n} \lambda_j \chi_{ij}$ ($i$ = 1, 2, ... $m$) and $\sum_{j=1}^{n} \lambda_j y_{rj}$ ($r$ = 1, 2, ... $s$) are the possible inputs and outputs achievable by the DMU$_j$, where $\lambda_j$ ($j$ = 1, 2, ... $n$) are nonnegative scalars that $\sum_{j=1}^{n} \lambda_j = 1$. The same $y_{rj}$ can be obtained by using $\hat{x}_{ij}$, where $\hat{x}_{ij} \geq x_{ij}$ and the same $x_{ij}$ can be used to obtain $\hat{y}_{ij}$, where $\hat{y}_{ij} \geq y_{ij}$.

$s_i^-$ and $s_j^+$ represent input and output slacks, respectively. The efficiency target is

$$\hat{x}_{ij} = \theta^* x_{io} - s_i^{-*} \; i = 1,\ 2,\ \ldots\ m \tag{5}$$

$$\hat{y}_{ij} = y_{io} + s_r^{+*} \; r = 1,\ 2,\ \ldots\ s \tag{6}$$

If $\theta^* = 1$ then the DMU under evaluation is a frontier point. If $\theta^* < 1$ then the DMU under evaluation is inefficient and has to decrease its input levels. The non-zero optimal $\lambda_j^*$ represents the benchmarks for a specific DMU under evaluation. The efficiency target demonstrates how inputs can be decreased to make the DMU under evaluation efficient.

Both the CRS and VRS DEA models are considered radial. One of the most applied versions of radial measure is that which is slack-based [46,47]. Additionally, the directional distance function model provides the ability to project the evaluated DMU by assigning a vector in the Euclidean space. The major advantage of this approach is the ability to clarify the direction of decreasing inputs and increasing outputs and include in such surveys undesirable outputs being obtained during the production process [48–50]. Finally, Banker and Thrall [51] have extended the Return to Scale estimation for a single-output estimation to multiple output cases, utilizing the benefits obtained by applying DEA.

In this paper, the input-oriented model has been applied, assuming VRS. This model allows variations in return to scale, which is usually an issue in agriculture because it is not appropriate to assume perfect competition, elimination of constraints, easy access to finance, and so on The input-oriented model was chosen because the target of this research was to propose ways of cost-of-production minimization, instead of production maximization.

The place of research was southern Greece, or more specifically, the regions of Peloponessos and Crete, where the vast majority of glasshouse agricultural holdings are located due to mild weather conditions (Figure 1). In both regions cultivating practices are similar. The time period of our research was autumn 2016–spring 2017, because during summer glasshouses are not used for cultivation purposes. Both regions are quite important for the national economy, accounting, in the year 2017, for Crete 13,773 € per capita and for Peloponessos 13,134 € per capita, which is above the national medium [52].

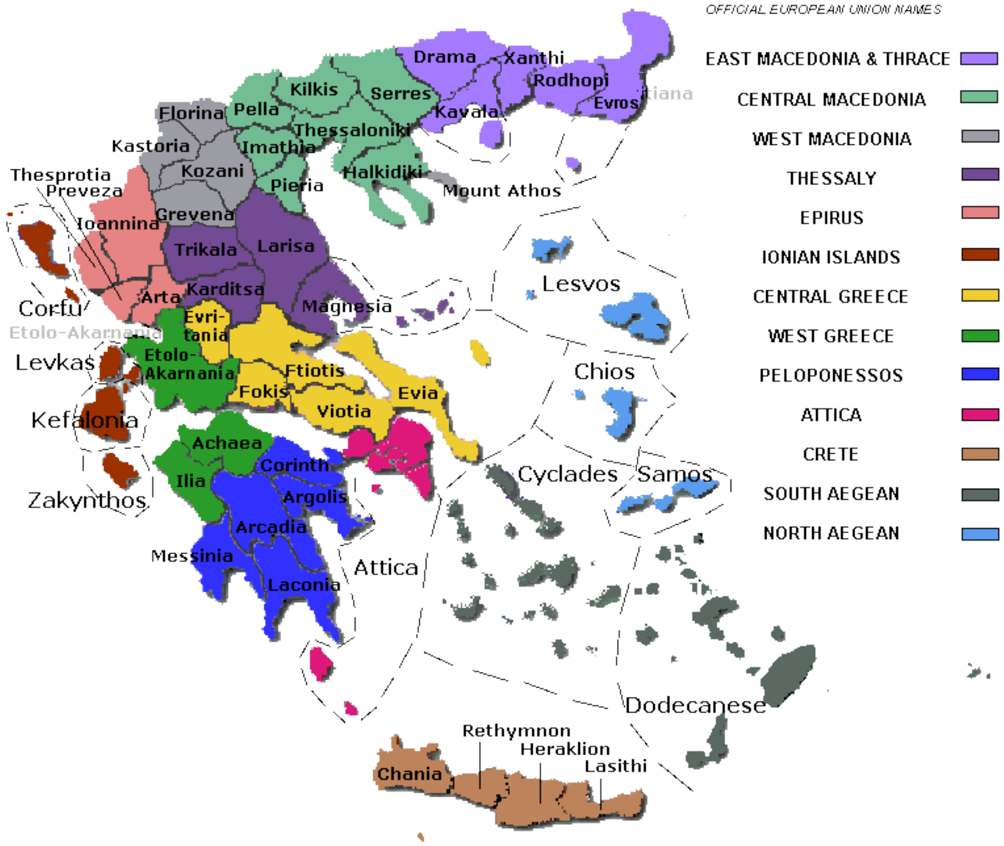


**Figure 1.** Place of research. Source: Own Elaboration.

The crops selected for this study are the main ones produced in Greece as offseason vegetables [52]. A questionnaire was used to collect all information related to production costs and the turnover of each holding. These data referred to each product, and the crops included in this work were tomato, cucumber, eggplant, and pepper. They were collected via face-to-face interviews by a group of five interviewers who had been trained previously on this topic. Ninety-eight DMUs were examined which refer to equal agricultural holdings, with the descriptive statistics of these described in the following table. The inputs used were the acreage of each cultivation, the working hours, and all kind of costs related to each cultivation, like crop protection (the value of fungicides and insecticides), fertilizers, energy, plants, and other costs (e.g., maintenance). The output was considered to be the turnover of each crop. This selection was based on previous similar projects which have verified their suitability for such assessments [43,44]. Every glasshouse cultivated all four crops by its being divided appropriately. Three interviewers collected data in Crete and two of them in Peloponnese. All of them were agronomists or postgraduate students, having the necessary background for such surveying. The sample can be considered as representative because a stratified sampling methodology was followed. The Ministry of Food and Rural Development, in collaboration with the statistics authority, has formulated a database providing information about the structural characteristics of agricultural holdings, including glasshouse holdings. The total acreage covered with glasshouses is nearly 6000 Ha. Fifty percent of this is located in the regions of Peloponnese and Crete. The classification of glasshouses in these regions, based on their acreage, is presented in Table 1. The sample used represents, with the same ratio, these agricultural holdings, having as criteria their size and the technology level they apply. The structural characteristics of the sample are presented in Table 2.

**Table 1.** Glasshouse holdings' structural characteristics in Peloponnese and Crete.

| Acreage/Holding (Ha) | (%) of Holdings | Acreage Covered (Ha) |
|---|---|---|
| <0.1 | 16.3 | 486.8 |
| 0.1–0.2 | 53.5 | 1597.9 |
| 0.21–0.3 | 21.0 | 627.2 |
| >0.3 | 9.2 | 274.8 |

**Table 2.** Structural characteristics of the sample.

| Acreage/Holding (Ha) | (%) of Holdings | Acreage Covered (Ha) |
|---|---|---|
| <0.1 | 16.3 | 2.77 |
| 0.1–0.2 | 53.5 | 9.10 |
| 0.21–0.3 | 21.0 | 3.57 |
| >0.3 | 9.2 | 1.56 |

From the above data (Table 3) it is obvious that the sizes of the agricultural holdings are rather small; this still is their main characteristic. Additionally, it is worth mentioning that the majority of them do not use energy for heating, instead taking advantage of the mild weather conditions during winter in these regions. Their main disadvantage is that they do not use cooling infrastructure during summer, this being the main reason for cultivating only off-season vegetables. The software used for this analysis was Microsoft Excel Solver 2007.

**Table 3.** Descriptive Statistics.

| | Area (Ha) | Crop Protection (€) | Fertilizers (€) | Labor (Hrs/year) | Energy (€) | Plants (€) | Other Costs (€) | Turnover (€) |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.173 | 751.27 | 1278.36 | 2595.19 | 756.38 | 973.31 | 1070.25 | 14,108.89 |
| SD | 0.117 | 680.05 | 1277.16 | 2395.75 | 1650.04 | 736.61 | 1030.17 | 9164.96 |
| MIN | 0.025 | 75.00 | 160.00 | 619.00 | 12.00 | 214.00 | 83.88 | 2459.42 |
| MAX | 0.6 | 2823.50 | 7052.36 | 12,577.00 | 7449.00 | 3240.00 | 6160.00 | 41,669.54 |

## 3. Results

The application of the DEA VRS model provided the following results, which are described in Tables 4 and 5.

**Table 4.** Data Envelopment Analysis (DEA) Variable Return to Scale (VRS) results.

| | Decision Making Units (DMUs) |
|---|---|
| Mean | 0.87 |
| SD | 0.20 |
| MIN | 0.32 |
| MAX | 1.00 |

**Table 5.** Detailed DEA scores.

| DEA Score Range | Number. of Holdings |
|---|---|
| >0.9 | 53 |
| 0.8–0.9 | 6 |
| 0.7–0.79 | 3 |
| 0.6–0.69 | 8 |
| 0.5–0.59 | 11 |
| 0.4–0.49 | 3 |
| 0.3–0.39 | 14 |

Despite the fact that the average efficiency scores can be characterized as satisfactory, the variation in efficiency scores is significant because the minimum efficiency score for a DMU was only 0.32. That means that for this specific one that there was excessive usage of all the inputs already mentioned by 68%. Due to the fact that several cultivations were included in this model, it is quite useful to identify the efficiency scores for each cultivation separately. The following table illustrates these results.

Table 6 provides useful information for the efficiency scores of each cultivation process. Based on this, the eggplant appears to be the cultivation with the highest efficiency scores in a homogenous way because its standard deviation score is zero. This outcome appears due to the fact that all farmers follow similar production protocols, which are proposed by agronomists and lead to consumption of similar quantities of inputs. The second-ranked cultivation is pepper, which achieved quite satisfactory scores. The third is the cucumber cultivation and the forth cultivation appears to be that of the tomato, which achieved the lowest efficiency score. Additionally, the same cultivation appears to have the largest variation in efficiency scores among all the cultivations, as the SD indicates. This illustrates the significant differences in input usage existing among farmers, providing hints for further research on why this is happening only within tomato cultivation and not for other crops.

**Table 6.** DEA VRS results per cultivation.

| | Cucumber | Eggplant | Pepper | Tomato |
|---|---|---|---|---|
| Mean | 0.86 | 0.98 | 0.95 | 0.70 |
| SD | 0.17 | 0.00 | 0.14 | 0.22 |
| MIN | 0.42 | 0.98 | 0.59 | 0.32 |
| MAX | 1.00 | 0.99 | 1.00 | 1.00 |

## 4. Discussion

Based on the above results, and keeping in mind similar research findings, it is evident that this methodological approach has the potential to provide useful information regarding the decision making process. It is evident that there is considerable variation in input usage among farmers in two dimensions. The first refers to efficiency scores per DMU, where there are different levels of homogeneity. The second refers to efficiency differences among the four vegetable production protocols which were examined. This methodological approach provides information on a DMU level about excess input usage, specifying the directional distance of each inefficient DMU from the frontier line (which is formulated by the efficient DMUs). Additionally, which production protocols are on an optimum level has been clarified. This quantification of excess usage of resources can be utilized by farmers and, in a very short period of time, lead them to adjust their production process in such a way that leads to increased profitability without jeopardizing their yields. This is very important for such cultivations which are characterized by increased production costs and very high entrepreneurial risks. It is also known that glasshouse infrastructure is used for several cultivations. The four vegetables assessed in this study to a large extent require similar inputs. A successful entrepreneurial approach to these production activities requires the maximum utilization of them, as basic economic theory implies [53]. The DEA application provides all the necessary information to farmers about which cultivation and which production protocol utilizes in a relatively efficient way the inputs being consumed. This information provides evident incentives for successful decision making on land management, being applicable even during the following cultivating period. The most significant advantage of this methodological approach is that its non-parametric nature formulates operational road maps leading to increased profitability by simply following basic management principles [53].

These results also signify future research directives. Having identified considerable efficiency differences, and having in mind specific criteria for foodstuff selection, it is necessary this assessment be implemented for environmental and energy incentives. More specifically, it would be rather interesting to implement the same model with the inclusion as an undesirable output the GHG emissions of each production process. These findings will help both farmers and traders to diminish their carbon footprints. It has already been mentioned that energy costs have a great impact on the overall cost of production for vegetables being produced in glasshouses. The implementation of DEA, on a pure energy level, will provide quite important information about possible relative energy misuses, with the quantification of them leading to both operational and environmental improvement. This was not possible to assess in this analysis because the collection of data was made in an anonymous and non-spatial way. It would also be quite interesting to apply the life cycle assessment methodology to quantifying the energy balance, providing at the same time ways for reducing the environmental footprint and thus improving energy utilization, satisfying in this way a continuous consumer demand.

## 5. Conclusions

In this paper, Data Envelopment Analysis was employed in a sample of ninety-eight glasshouse agricultural holdings in southern Greece in the regions of Peloponnese and Crete. The implementation of DEA methodology for glasshouse vegetable production provided quite important and significant findings at the farm level, quantifying relative deficiencies. This approach verified the utility of DEA in providing directives for more successful operational protocols, advancing in this way their managerial skills and increasing their competitiveness as well. The close interrelationship of vegetable production with market forces creates a demanding framework for implementing innovative and reliable assessment models for both operational and environmental performance. This specific DEA model has verified its own utility, providing at the same time incentives for continuing its use in glasshouse farming monitoring and evaluation. A second insight concerns the land management of glasshouse vegetable production because glasshouse infrastructure is used for several cultivations. Based on the fact that the inputs used for producing every vegetable evaluated in this analysis are similar, DEA provides a simple way to calculate the efficiency of all cultivations and informs farmers about which cultivation utilizes in a relative efficient way the inputs being consumed. Additionally, this approach provides directives for improving the efficiency of land, one of the most important production factors in agriculture. This is also important for policy analysis when such results need to be generalized. Future research may explore whether and how DEA can be used in efficiency assessment of vegetables produced in glasshouses in northern regions of the country, where adverse weather conditions require advanced glasshouse infrastructure, as well as the environmental impact of such production processes.

**Author Contributions:** Conceptualization, T.B. and G.V.; Methodology, T.B.; Software, C.M.; Validation, G.V.; Formal Analysis, C.M.; Investigation, C.M.; Resources, C.M. and T.B.; Data Curation, T.B.; Writing—Original Draft Preparation, G.V.; Writing—Review & Editing, T.B., G.V. and C.M.; Visualization, C.M.; Supervision, T.B.; Project Administration, G.V.

**Funding:** This research received no external funding.

**Acknowledgments:** We would like to thank two reviewers, who would like to remain anonymous, for their advice provided during the reviewing process.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References


1. Gollin, D.; Parente, S.L.; Rogerson, R. Farm work, home work and international productivity differences. *Rev. Econ. Dyn.* **2004**, *7*, 827–850. [CrossRef]
2. Pratley, J. The workforce challenge in horticulture. *Agric. Sci.* **2012**, *24*, 26–29.
3. Detsis, V.; Briassoulis, H.; Kosmas, C. The Socio-Ecological Dynamics of Human Responses in a Land Degradation-Affected Region: The Messara Valley (Crete, Greece). *Land* **2017**, *6*, 3. [CrossRef]
4. Hospido, A.; Canals, L.I.; McLaren, S.; Truninger, M.; Edwards-Jones, G.; Clift, R. The role of seasonality in lettuce consumption: A case study of environmental and social aspects. *Int. J. Life Cycle Assess.* **2009**, *14*, 381–391. [CrossRef]
5. Chan, C.; Sipes, B.; Ayman, A.; Zhang, X.; LaPorte, P.; Fernandes, F.; Pradhan, A.; Chan-Dentoni, J.; Roul, P. Efficiency of Conservation Agriculture Production Systems for Smallholders in Rain-Fed Uplands of India: A Transformative Approach to Food Security. *Land* **2017**, *6*, 58. [CrossRef]
6. Simoes, P.; Marques, R. On the economic performance of the waste sector. A literature review. *J. Environ. Manag.* **2012**, *106*, 40–47. [CrossRef]
7. Nastis, S.A.; Bournaris, T.; Karpouzos, D. Fuzzy data envelopment analysis of organic farms. *Oper. Res.* **2017**, 1–14. [CrossRef]
8. Farrell, M.J. The Measurement of Productive Efficiency. *J. R. Stat. Soc. Ser. A* **1957**, *120*, 253–290. [CrossRef]
9. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
10. Boussofiane, A.; Dyson, R.G.; Thanassoulis, E. Applied data envelopment analysis. *Eur. J. Oper. Res.* **1991**, *52*, 1–15. [CrossRef]
11. Paradi, J.C.; Asmild, M.; Simak, P.C. Using DEA and Worst Practice DEA in Credit Risk Evaluation. *J. Product. Anal.* **2004**, *21*, 153–165. [CrossRef]
12. Cook, W.D.; Seiford, L.M. Data envelopment analysis (DEA)—Thirty years on. *Eur. J. Oper. Res.* **2009**, *192*, 1–17. [CrossRef]
13. De Witte, K.; Marques, R.C. Influential observations in frontier models, a robust non-oriented approach to the water sector. *Ann. Oper. Res.* **2010**, *181*, 377–392. [CrossRef]
14. Sharma, K.R.; Pingsun, L.; Zaleski, H.M. Productive efficiency of the swine industry in Hawaii: Stochastic frontier vs. data envelopment analysis. *J. Prod. Anal.* **1997**, *8*, 447–459. [CrossRef]
15. Vlontzos, G.; Niavis, S. Assessing the Evolution of Technical Efficiency of Agriculture in EU Countries: Is There a Role for the Agenda 2000? In *Agricultural Cooperative Management and Policy. Cooperative Management*; Zopounidis, C., Kalogeras, N., Mattas, K., van Dijk, G., Baourakis, G., Eds.; Springer: Cham, Germany, 2014; pp. 339–351, ISBN 978-3-319-06634-9.
16. Lozano, S.; Villa, G.; Brannlund, R. Centralized reallocation of emission permits using DEA. *Eur. J. Oper. Res.* **2009**, *193*, 752–760. [CrossRef]
17. Thanassoulis, E. Data Envelopment Analysis and Its Use in Banking. *Interfaces (Providence)* **1999**, *29*, 1–13. [CrossRef]
18. Ferrier, G.D.; Lovell, C.A.K. Measuring cost efficiency in banking: Econometric and linear programming evidence. *J. Econom.* **1990**, *46*, 229–245. [CrossRef]
19. Smith, P.; Mayston, D.J. Measuring efficiency in the public sector. *OMEGA* **1987**, *15*, 181–189. [CrossRef]
20. Thanassoulis, E.; Dunstan, P. Guiding schools to improved performance using dataenvelopment analysis: An illustration with data from a local education authority. *J. Oper. Res. Soc.* **1994**, *45*, 1247–1262. [CrossRef]
21. Cullinane, K.; Wang, T.-F.; Song, D.-W.; Ji, P. The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis. *Transp. Res. Part A Policy Pract.* **2006**, *40*, 354–374. [CrossRef]
22. Liu, C.H.; Lin, S.J.; Lewis, C. Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. *Energy Policy* **2010**, *38*, 1049–1058. [CrossRef]
23. De Koeijer, T.J.; Wossink, G.A.A.; Struik, P.C.; Renkema, J.A. Measuring agricultural sustainability in terms of efficiency: The case of Dutch sugar beet growers. *J. Environ. Manag.* **2002**, *66*, 9–17. [CrossRef]
24. Malana, N.M.; Malano, H.M. Benchmarking productive efficiency of selected wheat areas in Pakistan and India using data envelopment analysis. *Irrig. Drain.* **2006**, *55*, 383–394. [CrossRef]

25. Azad, M.A.; Ancev, T. Using ecological indices to measure economic and environmental performance of irrigated agriculture. *Ecol. Econ.* **2010**, *69*, 1731–1739. [CrossRef]
26. Wang, K.; Yu, S.; Zhang, W. China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Math. Comput. Model.* **2013**, *58*, 1117–1127. [CrossRef]
27. Niavis, S.; Tamvakis, N.; Manos, B.; Vlontzos, G. Assessing and explaining the efficiency of extensive olive oil farmers: The case of Pelion peninsula in Greece. *Agriculture* **2018**, *8*, 25. [CrossRef]
28. Vasquez-Rowe, I.; Iribarren, D.; Moreira, M.T.; Feijoo, G. Combined application of life cycle assessment and data envelopment analysis as a methodological approach for the assessment of fisheries. *Int. J. Life Cycle Assess* **2010**, *15*, 272–283. [CrossRef]
29. Silva, E.; Stefanou, S.E. Nonparametric Dynamic Production Analysis and the Theoryof Cost. *J. Prod. Anal.* **2003**, *19*, 5–32. [CrossRef]
30. Mohammadi, A.; Shahin, R.; Jafari, A.; Dalgaard, T.; Knudsen, M.T.; Keyhani, A.; Mousavi-Avval, S.H.; Hermansen, J.E. Potential greenhouse gas emission reductions in soybean farming: A combined use of Life Cycle Assessment and Data Envelopment Analysis. *J. Clean. Prod.* **2013**, *54*, 89–100. [CrossRef]
31. Vasquez-Rowe, I.; Villanueva-Rey, P.; Iribarren, D.; Moreira, M.T.; Feijoo, G. Joint lifecycle assessment and data envelopment analysis of grape production for vinification in the Rías Baixas appellation (NW Spain). *J. Clean. Prod.* **2012**, *27*, 92–102. [CrossRef]
32. Khoshnevisan, B.; Rafiee, S.; Omid, M.; Mousazadeh, H. Applying data envelopment analysis approach to improve energy efficiency and reduce GHG (greenhouse gas) emission of wheat production. *Energy* **2013**, *58*, 588–593. [CrossRef]
33. Mobtaker, H.G.; Akram, A.; Keyhani, A. Energy use and sensitivity analysis of energy inputs for alfalfa production in Iran. *Energy Sustain. Dev.* **2012**, *16*, 84–89. [CrossRef]
34. Cassidy, E.; West, P.C.; Gerber, J.S.; Foley, J.A. Redefining agricultural yields: From tonnes to people nourished per hectare. *Environ. Res. Lett.* **2013**, *8*, 1–8. [CrossRef]
35. Toma, E.; Dobre, C.; Dona, I.; Cofas, E. DEA Applicability in Assessment of Agriculture Efficiency on Areas with Similar Geographically Patterns. *Agric. Agric. Sci. Procedia* **2015**, *6*, 704–711. [CrossRef]
36. Iribarren, D.; Vasquez-Rowe, I.; Moreira, M.T.; Feijoo, G. Further potentials in the joint implementation of life cycle assessment and data envelopment analysis. *Sci. Total Environ.* **2010**, *408*, 5265–5272. [CrossRef]
37. Song, M.; An, Q.; Zhang, W.; Wang, Z.; Wu, J. Environmental efficiency evaluation based on data envelopment analysis: A review. *Renew. Sustain. Energy Rev.* **2012**, *16*, 4465–4469. [CrossRef]
38. Zhou, H.; Yang, Y.; Chen, Y.; Zhu, J. Data envelopment analysis application in sustainability: The origins, development and future directions. *Eur. J. Oper. Res.* **2018**, *264*, 1–16. [CrossRef]
39. Reig-Martínez, E.; Picazo-Tadeo, A.J. Analysing farming systems with Data Envelopment Analysis: Citrus farming in Spain. *Agric. Syst.* **2004**, *82*, 17–30. [CrossRef]
40. Gómez-Limón, J.A.; Picazo-Tadeo, A.J.; Reig-Martínez, E. Eco-efficiency assessment of olive farms in Andalusia. *Land Use Policy* **2012**, *29*, 395–406. [CrossRef]
41. Iribarren, D.; Hospido, A.; Moreira, M.T.; Feijoo, G. Benchmarking environmental and operational parameters through eco-efficiency criteria for dairy farms. *Sci. Total Environ.* **2011**, *409*, 1786–1798. [CrossRef]
42. Pahlavan, R.; Omid, M.; Akram, A. Energy use efficiency in greenhouse tomato production in Iran. *Energy* **2011**, *36*, 6714–6719. [CrossRef]
43. Khoshnevisan, B.; Rafiee, S.; Omid, M.; Mousazadeh, H. Reduction of $CO_2$ emission by improving energy use efficiency of greenhouse cucumber production using DEA approach. *Energy* **2013**, *55*, 676–682. [CrossRef]
44. Pahlavan, R.; Omid, M.; Rafiee, S.; Mousavi-Avval, S.H. Optimization of energy consumption for rose production in Iran. *Energy Sustain. Dev.* **2012**, *16*, 236–241. [CrossRef]
45. Färe, R.; Lovell, C.A.K. Measuring the technical efficiency of production. *J. Econ. Theory* **1978**, *19*, 150–162. [CrossRef]
46. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
47. Chambers, R.G.; Chung, Y.; Färe, R. Benefit and Distance Functions. *J. Econ. Theory* **1996**, *70*, 407–419. [CrossRef]
48. Chambers, R.G.; Chung, Y.; Färe, R. Profit, directional distance functions, and Nerlovian efficiency. *J. Optim. Theory Appl.* **1998**, *98*, 351–364. [CrossRef]

49. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
50. Banker, R.D.; Thrall, R.M. Estimation of returns to scale using Data Envelopment Analysis. *Eur. J. Oper. Res.* **1992**, *62*, 74–84. [CrossRef]
51. Greek Stitistic Authority. Available online: www.statistics.gr (accessed on 17 December 2018).
52. Caves, R.E.; Caves, R.E. *Multinational Enterprise and Economic Analysis*; Cambridge University Press: Cambridge, UK, 1996.
53. Kay, R.D.; Edwards, W.M. *Farm Management*; McGraw-Hill: New York, NY, USA, 1994.


© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).