

Analysis of Production Efficiency Indicators in Horticultural Enterprises

Akbarov Husan Uzbekkhonovich

Associate Professor, Department of Digital Technologies, Tourism and Humanities,
Samarkand Agroinnovations and Research University

Abstract:

This study investigates the efficiency of resource utilization in horticultural enterprises through the application of the Data Envelopment Analysis (DEA) model. A total of 48 farms were evaluated based on input variables (labor force, land area, water usage, fertilizer application, and energy expenditures) and output indicators (crop yield and income). The analysis enabled the classification of farms into efficient and inefficient categories, with optimal input levels calculated for each unit to achieve maximum efficiency. The findings highlight that labor, water, organic fertilizers, and energy costs are the most influential factors affecting performance. Graphical diagnostics were employed to identify sources of resource overuse across individual farms.

Keywords: efficiency, DEA model, horticulture, linear programming, resource analysis, agriculture.

Introduction

In recent years, enhancing the economic efficiency of agricultural enterprises-particularly horticultural farms-has emerged as a pressing issue. The growing demand for food products, expansion of export potential, and the adoption of intensive horticultural technologies have made the rational and efficient use of available resources a critical concern in today's agricultural landscape.

However, practical observations reveal that horticultural farms often fail to optimize the use of key resources such as land, water, fertilizers, and labor. This inefficiency directly affects both the volume and quality of agricultural output. Consequently, there is an increasing need to evaluate farm performance not only through aggregate indicators but also by analyzing resource utilization efficiency.

This study assesses the performance of horticultural enterprises using the Data Envelopment Analysis (DEA) model, which is grounded in linear programming theory. This approach enables the

individual evaluation of each farm, providing insights into how effectively they utilize their available resources. A key advantage of the DEA model lies in its ability to simultaneously account for multiple input and output variables, thereby determining relative efficiency and identifying either excess resource usage or shortages in inefficient farms.

Within the scope of this article, the current state of efficiency in horticultural farms is analyzed, empirical results based on linear programming are presented, and practical recommendations for improving resource efficiency are formulated.

Literature Review

In recent years, the Data Envelopment Analysis (DEA) model has been widely adopted by researchers for evaluating efficiency. For instance, N. Krasniqi et al. (2023) conducted a study on horticultural farms in Kosovo, analyzing 779 observations using the DEA method. Their findings revealed that the majority of farms exhibited technical efficiency levels below 50%. Similarly, M. Ramezani et al. (2022) examined saffron cultivation in Iran and found that crop density negatively affects efficiency. Although dense planting may yield short-term gains, it ultimately reduces land productivity and technical efficiency over time.

Nuambu Mwikamba et al. (2024) employed a two-stage analysis combining DEA and Tobit models to demonstrate that the use of mobile communication tools significantly enhances technical efficiency (TE) and crop yield. Hajime Kamiyama et al. (2016) explored irrigated and non-irrigated orchards using DEA and SFA models, assessing the impact of water usage on technical efficiency in Tunisian olive production. Giuseppe Timpanaro et al. (2018) investigated technical efficiency in Italian horticultural nurseries, concluding that management quality, worker skills, production scale, and strategic practices strongly influence efficiency outcomes.

Research Methodology

Efficiency analysis is considered one of the key approaches in economic theory for evaluating the degree of resource utilization. Several methods exist for measuring efficiency. The ratio method relies on simple input-output ratios; regression analysis explores statistical relationships but does not assess individual unit performance; the Stochastic Frontier Analysis (SFA) accounts for random errors but is model-dependent; and the Data Envelopment Analysis (DEA) method, based on linear programming, evaluates the relative efficiency of units using multiple input and output indicators.

In multi-factor production environments, models capable of jointly assessing input and output variables are essential. From this perspective, the DEA model-developed by Charnes, Cooper, and Rhodes in 1978-offers a robust framework for evaluating efficiency in multi-criteria settings.

Using DEA, each horticultural enterprise is treated as a distinct Decision Making Unit (DMU). The model compares each DMU against all others, identifying those that achieve maximum output as efficient, while others are deemed inefficient in relative terms. A notable advantage of DEA is its non-reliance on predefined weights; the data itself determines optimal weightings.

DEA models are generally categorized into two types: the CCR model (Charnes, Cooper, Rhodes), which assumes constant returns to scale, and the BCC model (Banker, Charnes, Cooper), which accommodates variable returns to scale. Given the variability in resource efficiency across horticultural farms, the BCC model is more appropriate and was therefore employed in this study.

The DEA framework enables a deep analysis of resource utilization in horticultural enterprises, helping to identify optimal production points and areas of inefficiency or misallocation. In this research, the activities of 48 horticultural farms were evaluated using the DEA model. Each farm was treated as a DMU, with selected input and output indicators used to calculate relative efficiency scores.

Input variables included cultivated area (ha), labor input (person-days), organic fertilizer (kg/ha), mineral fertilizer (kg/ha), pesticides (kg/ha), water usage (m³/ha), and energy costs (million UZS/ha). Output variables consisted of crop yield (centners/ha) and annual income (million UZS/ha).

The BCC model was applied due to the variable nature of resource efficiency in horticulture. Modeling was conducted using Python, specifically the pyDEA and PuLP libraries. Efficiency scores were calculated for each farm, and units were classified as efficient (eff = 1) or inefficient (eff < 1).

Additionally, for inefficient farms, graphical analysis was used to determine the extent of resource overuse by calculating benchmark input levels corresponding to efficient performance.

Analysis and Results

Based on the DEA model, 48 horticultural enterprises were analyzed. The results indicate that only a small portion of these farms operated efficiently (efficiency score = 1.0), while the majority were classified as inefficient (efficiency score < 1.0). Graphical analysis revealed that most farms were positioned below the efficiency frontier, with some units exhibiting efficiency scores as low as 0.94.

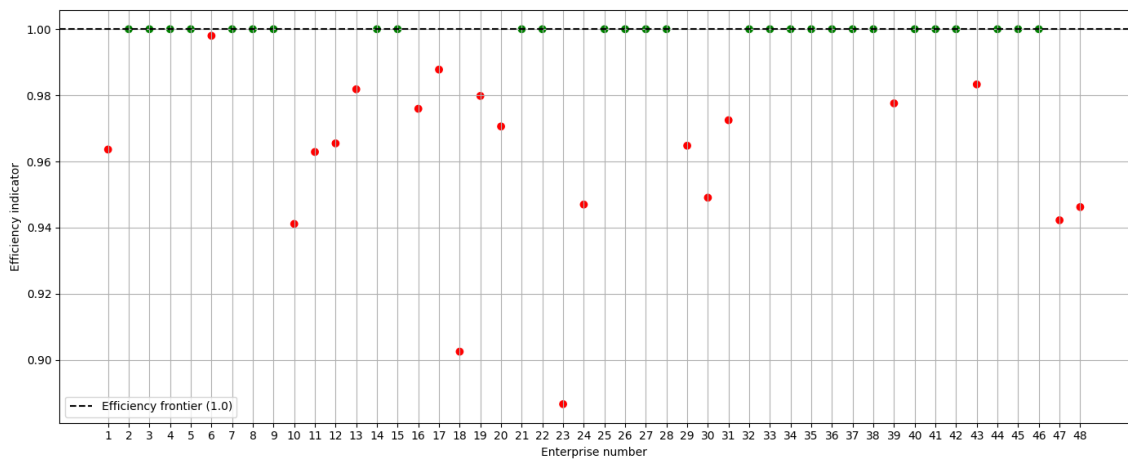


Figure 1. Positioning of horticultural enterprises relative to the efficiency frontier

The graph reveals that out of 48 horticultural enterprises, 26 have achieved full efficiency, with scores equal to 1.0. This indicates that these farms have managed their resources in an optimal manner. The red markers are predominantly located within the 0.90–0.99 efficiency range, signifying a noticeable level of inefficiency among those units. Notably, farms numbered 23 and 48 exhibit the lowest efficiency scores, approaching 0.89–0.90, which suggests substantial overutilization of resources in these cases.

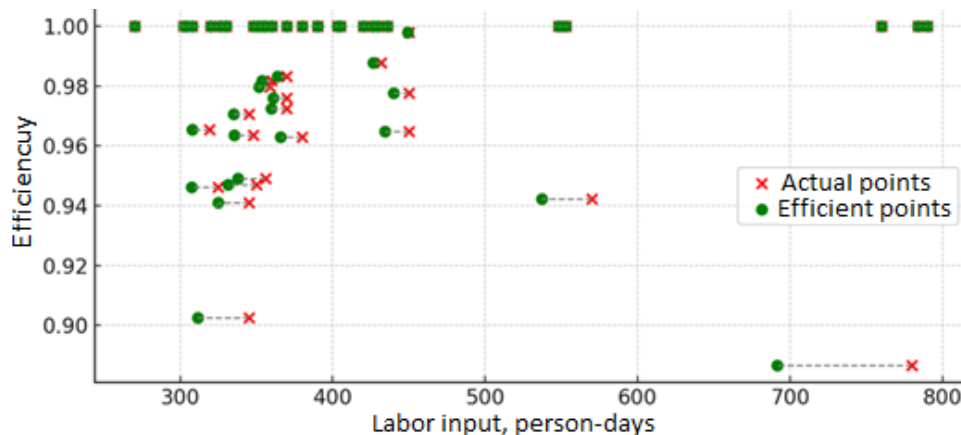


Figure 2. Efficiency indicators based on labor input in horticultural enterprises

The graph clearly demonstrates that optimizing labor input is essential for achieving efficiency. In farms with lower efficiency scores, excessive labor usage, misallocation of resources, and underutilization of production potential are evident. Efficient farms, characterized by high efficiency levels ($\theta = 1.0$), tend to operate with relatively lower labor input—typically around 300–400 person-days. In contrast, inefficient farms often employ significantly more labor (up to 700–800 person-days) while exhibiting lower efficiency scores ($\theta < 0.95$).

The horizontal distance between actual and efficient points on the graph reflects the extent of labor overuse. The greater this distance, the stronger the need for labor resource optimization. Labor input is a critical factor directly influencing efficiency, and it is closely tied to management quality, planning effectiveness, and the degree of mechanization.

Farms with higher efficiency scores have achieved better outcomes with fewer labor resources, indicating a higher level of labor productivity in their production processes.

Conclusion and Recommendations

The analysis confirms that a significant portion of horticultural enterprises are unable to fully and efficiently utilize their available production resources. Efficiency scores derived from the Data Envelopment Analysis (DEA) model indicate that certain farms exhibit excessive consumption of labor, water, fertilizers, and energy inputs. This inefficiency contributes to increased production costs, reduced income, and a decline in overall profitability.

Moreover, the practices of efficient farms offer valuable benchmarks for developing model-based approaches applicable to others. To optimize resource utilization across all farms, the following strategic directions are recommended:

- Enhance mechanization and restructure labor resources based on assessments of workforce productivity.
- Apply agro-technical standards in accordance with soil analysis to ensure precise input usage.
- Introduce drip irrigation systems and water monitoring technologies to improve water efficiency.
- Utilize energy-saving equipment and integrate renewable energy sources to reduce operational costs.

By implementing these strategies, farms can better leverage their internal capacities, improve economic efficiency, and strengthen their competitiveness in the agricultural sector.

References

1. **Akbarov Husan Uzbekkhonovich.** “FACTORS AFFECTING THE PRODUCTIVITY OF FRUIT GROWING ON FARMS”. *ResearchJet Journal of Analysis and Inventions* 2.08 (2021): 50-56.
2. **Krasniqi N., Blancard S., Gjokaj E., Ottaviani Aalmo G.** (2023). Modelling technical efficiency of horticulture farming in Kosovo: An application of data envelopment analysis. *Bio-based and Applied Economics* 12(3):183-195. doi: 10.36253/bae-14693
3. **Ramezani, M.; Dourandish, A.; Jamali Jaghdani, T.; Aminizadeh, M.** The Influence of Dense Planting System on the Technical Efficiency of Saffron Production and Land Use Sustainability: Empirical Evidence from Gonabad County, Iran. *Agriculture* 2022, 12, 92. <https://doi.org/10.3390/agriculture12010092>

4. **Jimson Nyambu Mwikamba, David Jakinda Otieno, Willis Oluoch-Kosura.** Effect of using a mobile phone on technical efficiency and productivity of climate-smart horticulture farmers in Taita-Taveta County, Kenya. *Heliyon* 10 (2024) e36917. www.cell.com/heliyon.
5. **Hajime Kamiyama, Kenichi Kashiwagi, and Mohamed Kefi.** Technical efficiency among irrigated and non-irrigated olive orchards in Tunisia. *Vol. 11(45), pp. 4627-4638, 10 November, 2016.* DOI: 10.5897/AJAR2016.10835. <http://www.academicjournals.org/AJAR>
6. **Giuseppe Timpanaro, Arturo Urso, and Vera T. Foti.** Technical and Scale Efficiency in Nursery Enterprises in an Area of Significant Widespread Horticulture in Italy. *HORTSCIENCE* 53(2):208–216. 2018. <https://doi.org/10.21273>
7. **Battese, G. E., & Coelli, T. J.** (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20(2), 325–332. <https://doi.org/10.1007/BF01205442>
8. **Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E.** (2005). *An Introduction to Efficiency and Productivity Analysis*. Springer. <https://doi.org/10.1007/1-4419-0983-9>
9. **Aigner, D. J., Lovell, C. A. K., & Schmidt, P.** (1977). Formulation and Estimation of Stochastic Frontier Production Models. *Journal of Econometrics*, 6(1), 21–37. [https://doi.org/10.1016/0304-4076\(77\)90052-5](https://doi.org/10.1016/0304-4076(77)90052-5)
10. **Charnes, A., Cooper, W. W., & Rhodes, E.** (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 2(6), 429-444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
11. **Zhu, J.** (2009). *Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets*. Springer. <https://doi.org/10.1007/978-1-4419-1660-7>
12. **Färe, R., Grosskopf, S., & Lovell, C. A. K.** (1985). *The Measurement of Efficiency of Production*. Springer. <https://doi.org/10.1007/978-1-4613-2187-6>
13. **Alhassan, H., & Jena, P. R.** (2019). Technical Efficiency of Cocoa Farmers in Ghana: A Stochastic Frontier Approach. *Agricultural Economics Research Review*, 32(2), 231–240. <https://doi.org/10.22004/ag.econ.297114>
14. **Li, X., & Li, Z.** (2017). Measuring the Technical Efficiency of the Chinese Agricultural Industry Using the Stochastic Frontier Approach. *China Agricultural Economic Review*, 9(4), 497–515. <https://doi.org/10.1108/CAER-03-2017-0040>
15. **Hossain, M. D., & Rahman, M. M.** (2020). Assessing the Technical Efficiency of Rice Production in Bangladesh: A Data Envelopment Analysis. *Agricultural Economics*, 51(5), 705–715. <https://doi.org/10.1111/agec.12563>