

Integrating Data Envelopment Analysis with Goal Programming Model for Sustainable Agricultural Efficiency Enhancement

Ibrahim Zeghaiton Chalooob¹

Jehan Saleh Ahmed²

¹Al-Esraa University, College of
Administration and Economics,
Department of Business
Administration, Baghdad, 10069,
Iraq

Email :

ibrahim.z@esraa.edu.iq

²Fallujah University ,Collage of
Administration Sciences and
Financial, Department of Business
Administration, Anbar 31002, Iraq

Email :

jeihan.saleh.ahmed@uofallujah.edu.iq

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Corresponding Author: Ibrahim Zeghaiton Chalooob

Abstract: Achieving multiple-goal simultaneously can be done by optimising resources efficiently. Sustainable agriculture has several goals to accomplish, including economic, environmental, and social. Integrating Data Envelopment Analysis (DEA) with Goal Programming (GP) improves the decision-making process in sustainable agriculture. Utilising this hybrid approach can address the complexities of multiple objectives in sustainable agriculture. A case study conducted on empirical data has enhanced the efficiency through optimising resource use by balancing the competing goals. The flexibility of this approach makes it adaptable to various scenarios in the agriculture sector.

Keywords: Sustainable Agriculture, Goal Programming (GP), Data Envelopment Analysis (DEA), Multi-objective Optimization, Agricultural Efficiency.

1. Introduction:

Agriculture seeks to balance the three main pillars of sustainability: economic viability, environmental stewardship, and social responsibility. As agriculture faces increasing pressure from constraints on resource and the necessity for higher productivity, achieving sustainable agriculture efficiency become a critical challenge. Traditional decision-making frameworks rarely succeed to incorporate the multi-dimensional aspects of sustainability, focusing on either maximizing yield or minimizing environmental impact, however infrequent both.

To address this challenge, hybridizing Goal Programming (GP) with Data Envelopment Analysis (DEA) is proposed to enhance decision-making for sustainable agriculture. GP allows for the simultaneous optimization of multiple objectives, while DEA evaluates the relative efficiency of decision-making units (DMUs) based on input-output data. Boosting efficiency becomes the basis for optimizing environmental satisfaction and economic performance of sustainable agriculture. Facilitating efficiency in sustainable agriculture can save 10% of energy inputs through constant return to scale. Relying on data envelope analysis (DEA), it can reduce the consumption of resources alongside with other inputs enhancing efficiencies to sustain the optimum agriculture production Hesampour, *et al.* (2022). This integration aims to optimize the use of resource in agriculture while balancing the objectives of environment, economy, and social.

2.Related Work

Goal Programming (GP) and Data Envelopment Analysis (DEA) have widely been applied in variety of sectors; manufacturing, healthcare, and agriculture. GP proven to be an effective tool for optimization when multiple objective detected. The conflicting goals of economic profit and environmental conservation must be balanced. Chaloob, *et al* (2016); Ahmed, *et al* (2017); Visentin, *et al* (2021);Nawawi, *et al* (2022). applied the GP model to optimize crop production with water and fertilizer resources limitation.

Although some methodological issues in data envelopment analysis are detected, multiple criteria DEA (MCDEA) approach formed with a multiple objective perspective. While MCDEA models' objectives are generally conflicting, goal programming (GP) technique proposed to overcome the MCDEA sensitivity Rubem, *et al.* (2017). The DEA employed to scale the agricultural efficiency units by comparing the relationships in their input-output Najafabadi, *et al* (2022) .shown that DEA identified the best practices for resource conservation in agriculture.

3.Goal Programming Model

Scenarios with multi-objective optimization face challenges in balancing several conflicting objectives. However, traditional optimization methods consider only one measurable criterion which is do not adequately address multi-objective problems Olfati, *et al* (2025).The Goal Programming (GP) model is designed to optimise multiple objectives simultaneously. In the context of sustainable agriculture, the objectives are:

1. Economic Goal: Maximising crop yield or farm income.
2. Environmental Goal: Minimising water and fertiliser usage, reducing pesticide applications, and decreasing carbon emissions.
3. Social Goal: Enhancing labour conditions, improving food security, and ensuring equitable resource distribution.

The GP formulation is based on the following structure:

$$\text{Minimise}(Z) = \sum_{g=1}^G w_g^+ d_g^+ + w_g^- w_g^-$$

Objective function for GP

Purpose: This objective function aims to minimize the total weighted deviations from multiple sustainability goals (economic, environmental, and social).

Components:

- ♦ Z represents the total weighted deviation.
- ♦ w_g^+ and w_g^- are weights indicating the importance of over-achieving or under-achieving a particular goal.
- ♦ d_g^+ and d_g^- represent the positive (over-achievement) and negative (under-achievement) deviations from each goal g , respectively.
- ♦ G is the total number of goals being optimised.

Subjected to the constraints

1. Economic Constraints

$$\text{Profit : } P \geq \text{Min Profit}$$

Where: P_i is the profit generated by the i^{th} DMU , and Min Prof it is the minimum acceptable profit.

2. Environmental Constraints

$$\text{Water Usage : } W \leq \text{Max Water}$$

Where W_i is the water used by the i^{th} DMU , and Max Water is the maximum allowable water usage.

3. Social Constraints

$$\text{Labour Conditions : } L_i \geq \text{Min Labour Conditions}$$

Where, L_i represents the social goals such as fair labour practices or food security targets.

Data Collection and Case Study: Malaysian Rice Production

The rice farm was selected to examine the GP model. Challenges faced related to increase in production costs, resource scarcity particularly water, and the required need to meet the local demand.

4.Data Collection

4.1 Data Source, Units, and Scaling

The analysis of this study conducted using data from 50 Malaysian farms, collected from the Agriculture Malaysia's regional statistics Department. Each farm considered as a Decision-Making Unit (DM U) within the GP-DEA model.

More deeply, data on production costs, expected revenues, and resource consumption (land, water, labor) collected targeting three crops: rice, palm oil, and rubber from Malaysian farms. The data was symbolized and coded for ethics purposes. The data of production costs, expected revenues, and resource use combined to build GP model and gauge and analyse the efficiency of the GP-DEA model. The paper concentration was how to enhance model efficiency. This case study tested the ability of GP model's to achieve optimized

production plans while balancing to optimize multiple goals. The detailed key inputs and outputs related to data analysis is presented in Table 1:

Table 1. Data key inputs and outputs used for GP-DEA model

Category	Variable	Unit
Inputs	Land Area	Hectares
	Labor	Number of Workers
	Water Usage	m ³ /Hectare
Outputs	Crop Yield	Tones /Hectare
	Farm Income	MYR ¹ /hectare
	Environmental Index ²	Scale(0–1)

Source: Najafabadi *et al.* (2022)

MYR¹ is the Malaysian Ringgit per hectare.

²Environmental index derived based on farm-level data (e.g., pesticide use, waste management, and energy efficiency) adopting the scoring approach by Najafabadi *et al.*(2022) [6].

4.2 Data Normalization and Weighting in DEA

Different unit measurements is so sensitive in DEA, thus all variables (input and output) were normalized using min–max scaling to be ranged between [0,1]. This normalizing process is done before model estimation. The normalization transformation applied by:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}, y'_{rj} = \frac{y_{rj} - \min(y_r)}{\max(y_r) - \min(y_r)}$$

where

x_{ij} and y_{ij} denote the input and output values for DMU_j

4.3 Model Implementation

LINGO is a widely-used software for solving optimization problems. The results of production plans has reached the optimal solutions which demonstrating how GP supported the viability of the sustainable and economically production planning.

4.4 Model Application and Simulation

The GP-DEA model fed the data from 50 farms of mixed crop-livestock production in Malaysia. Inputs were land area, labor, water, and fertilizer usage. Outputs were crop yield, farm income, and some environmental indicators (e.g., biodiversity and soil health).

Our GP-DEA model designed to optimize triple objectives of sustainability:

1. Economic (profit),
2. Environmental (water usage reduction), and
3. Social (labor conditions)

The following metrics were used for model's effectiveness evaluation:

- ♦ **DEA efficiency Scores:** signalling the farm performance relying on inputs to produce outputs.
- ♦ **Goal Achievement:** a measurement of how closely the farms achieved the goals, predefined earlier in GP model.

- ♦ **Goals Deviation:** it is calculated by subtracting the values of the actual performance from the targeted set in GP.

5. Integrating Data Envelopment Analysis With Goal Programming

The integration of DEA with GP is relatively remaining a novel approach within the sustainable agricultural context. Despite combined two approach has been utilized successfully in other domains, this study has built on previous studies through the strong merging of both GP and EDA models addressing the multi-objective complexity that is inherited in the sustainable agricultural practices. A conceptual framework of combined DEA–GP models for sustainable agricultural efficiency enhancement is shown in Figure 1.

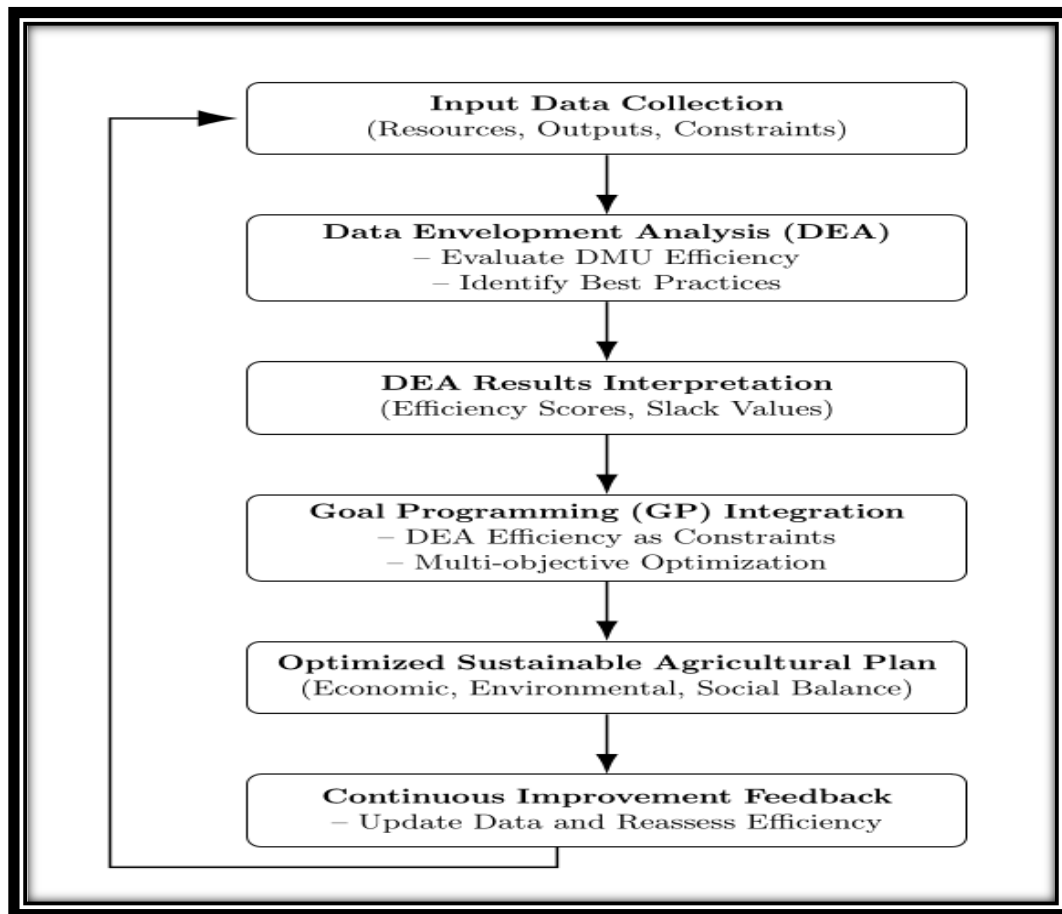


Figure 1: Conceptual framework of DEA–GP model for enhancing sustainable

6. Data Envelopment Analysis

DEA is used to measure the relative efficiency of decision-making units (DMUs) such as farms, where each DMU utilizes inputs like land, water, labour, and fertilizer to produce outputs such as crop yield, income, and environmental improvements (e.g., soil health). The DEA model evaluates efficiency based on the ratio of weighted outputs to inputs. DEA is used to measure the efficiency of each DMU by comparing the ratio of weighted outputs to inputs. The model can be formulated as follows:

• **Objective Function:**

$$\text{Maximize } \Theta = \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m u_i x_{ij}}$$

Where:

- ♦ Θ is the efficiency score of the j th DMU.
- ♦ y_{rj} is the r^{th} output for DMU _{j} (e.g., crop yield, income).
- ♦ x_{ij} is the i^{th} input for DMU _{j} (e.g., land, water, labour).
- ♦ u_r and u_i are the weights assigned to the outputs and inputs, respectively.
- ♦ S is the total number of outputs, m and is the total number of inputs.

• **Constraints: Efficiency Constraint for All DMUs:**

$$\frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m u_i x_{ik}} \leq 1, \forall k$$

This ensures that no DMU exceeds an efficiency score of 1.

• **Non-Negativity Constraint:**

$$u_r, u_i \geq 0, \forall r, i$$

After solving this DEA model, we get efficiency scores Θ for each DMU.

Goal Programming (GP) Model

GP aims to minimize deviations from predefined goals (economic, environmental, and each DMU). The GP model is formulated as:

Objective Function:

$$\text{Minimise } Z = \sum_{g=1}^G w_g^+ d_g^+ + w_g^- d_g^-$$

Where:

- ♦ Z represents the total weighted sum of deviations.
- ♦ d_g^+ and d_g^- are the positive and negative deviations from the g^{th} goal.
- ♦ w_g^+ and w_g^- are the weights representing the relative importance of each deviation.
- ♦ G is the total number of goals (economic, environmental, and social).

7. Integrating DEA Efficiency into GP

The hybrid GP-DEA model integrates the results of DEA into the GP framework ensuring the efficiency of decisions made through the GP model. The DEA efficiency score is used as a constraint in the GP model, ensuring that farms not only meet sustainability goals but also operate at an optimal level of resource use. The GP model applied for optimizing production of these crops. LINGO optimization software employed to run the model, providing an optimal production plan. To integrate the DEA efficiency scores into the GP model, we introduce the following constraint:

7.1. Efficiency Constraint for All DMUs:

$$\Theta_j \geq \text{Min Efficiency}, \forall_j$$

Where Θ_j , is the efficiency score obtained from DEA for the j th DMU, and Min Efficiency is the minimum acceptable efficiency level for each DMU. This constraint ensures that the GP model not only minimises deviations from sustainability goals but also maintains an efficient use of resources a determined by DEA.

7.2. Goal Achievement Constraints: For each g th goal, we have:

$$x_g + d_g^+ - d_g^- = \text{Goal}_g$$

Where: x_g is the actual level of the g^{th} goal, and Goal_g , is the target set for that goal.

- Non-Negativity Constraints:

$$d_g^+, d_g^- \geq 0, \forall_g$$

Where: x_g is the actual level of the g^{th} goal, and Goal_g , is the target set for that goal.

8. Results and Discussion

The simulation results of the integrated GP-DEA model demonstrated a significant improve in both efficiency and sustainability across the 50 farms. Table 2 shows the average performance improvements compared with the baseline efficiency before optimization.

Table 2: Performance Metrics Before and After GP-DEA Implementation

Metric	Baseline	Post GP-DEA Optimization	Improvement (%)
Average Efficiency Score	0.78	0.87	+11.5%
Economic Goal Achievement (%)	73.4	85.2	+16.0%
Environmental Goal Achievement (%)	68.1	82.4	+21.1%
Social Goal Achievement (%)	75.6	86.7	+14.7%

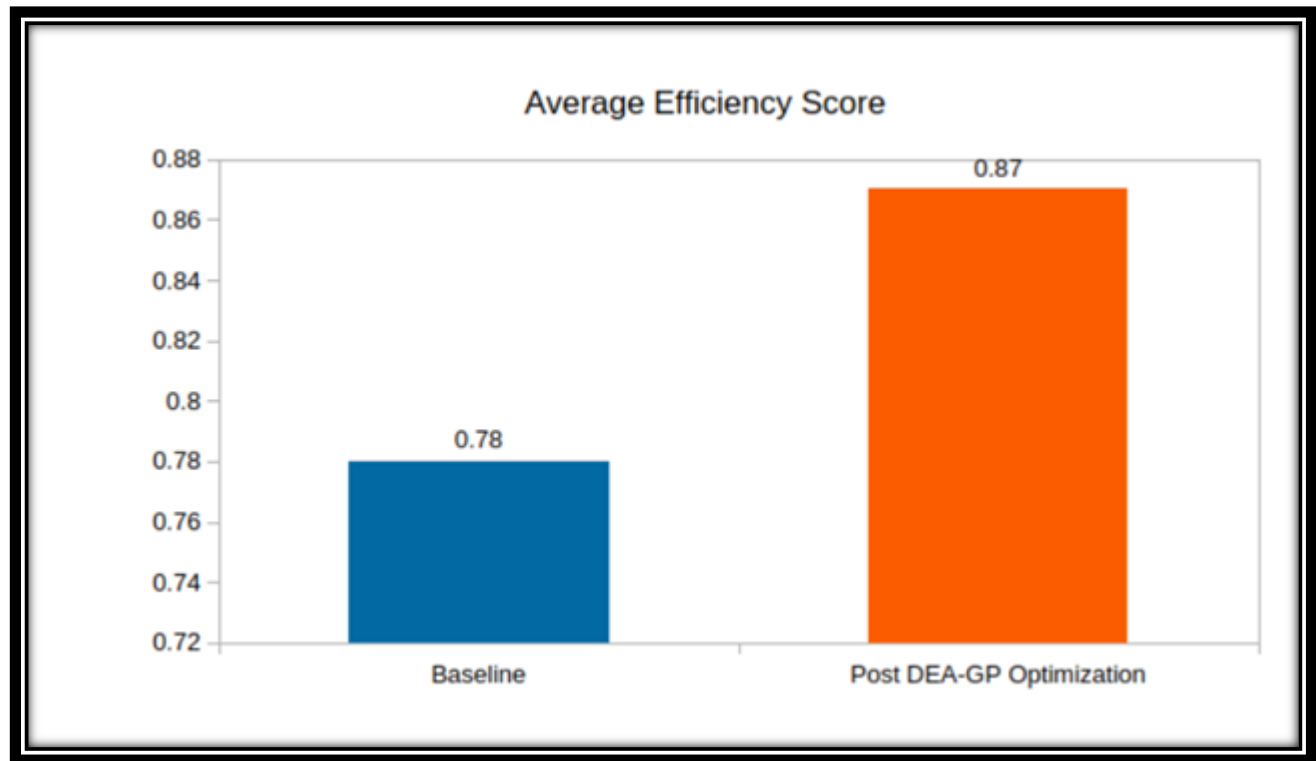


Figure 2: Average Efficiency Score

Table 3: Statistics of Input /Output Data Before Optimization (n = 50 farms)

Variable	Mean	SD	Min	Max
Land Area (hectare)	6.45	2.13	2.0	12.0
Labour (person-hours)	1,250	320	800	1,950
Water Use (m ³ /ha)	3,200	780	2,000	5,100
Energy Input (MJ/ha)	7,850	1,230	5,600	10,500
Output Value (MYR/ha)	8,920	2,450	4,800	13,600

The integrated GP-DEA model has successfully enhanced the average efficiency score by 11.5%, pointing to better resource utilization across farms. Figure 1 illustrates the distribution of efficiency scores before and after the GP-DEA optimization. Farms with low baseline efficiency showed the greatest improvements. Additionally, the GP-DEA hybrid model has assisted the farms under study to achieve a higher percentage of their sustainability goals. For instance, the environmental goal regarding water usage reeducation was improved by 21.1%, while other goals improved by 16% for economic and 14.7% for social. Inefficient farms were able to modify their resource allocations more efficaciously, particularly in reducing water and fertilizer inputs while increasing yield, in Figures (2& 3).

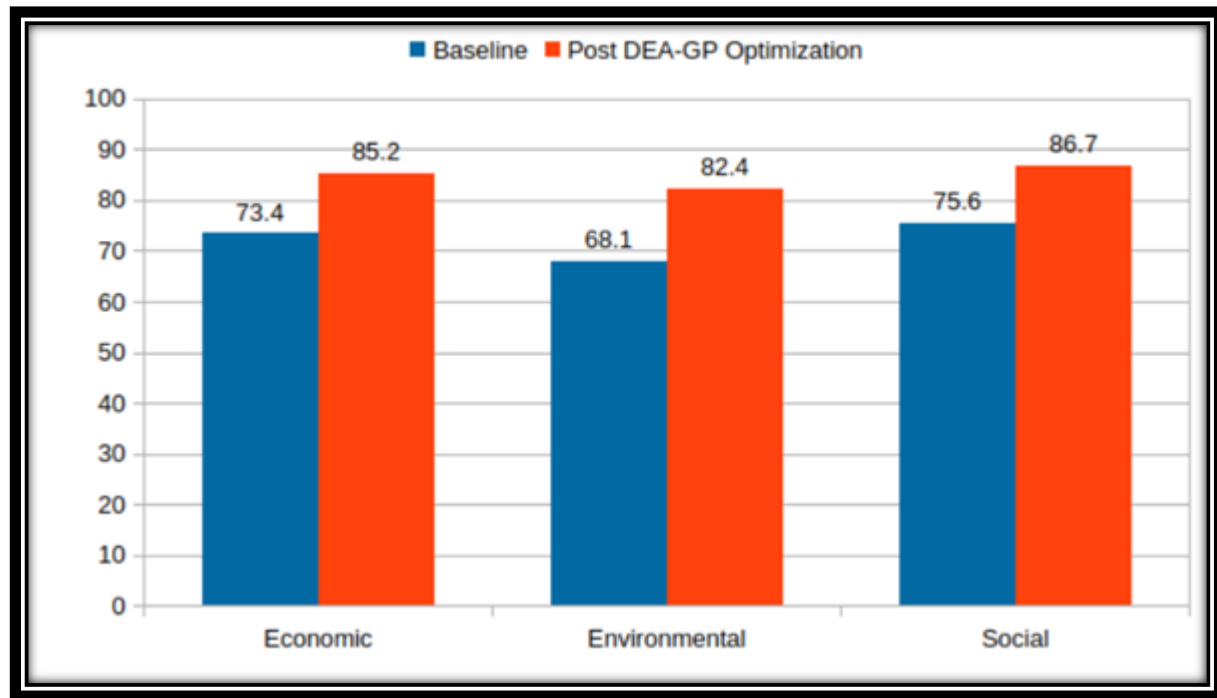


Figure 3: Constraints Achievement Values

Table 4: Goal Deviations by Farm Efficiency Segment

Efficiency Segment	Farm ID / Group	Economic Deviation	Environmental Deviation	Social Deviation
Low Efficiency (DEA < 0.70)	F01–F10	0.145	0.182	0.098
Low Efficiency (DEA < 0.70)	F11–F20	0.132	0.176	0.092
Mean (Low)	–	0.139	0.179	0.095
High Efficiency (DEA ≥ 0.70)	F21–F35	0.072	0.094	0.056
High Efficiency (DEA ≥ 0.70)	F36–F50	0.068	0.089	0.051
Mean (High)	–	0.070	0.092	0.054

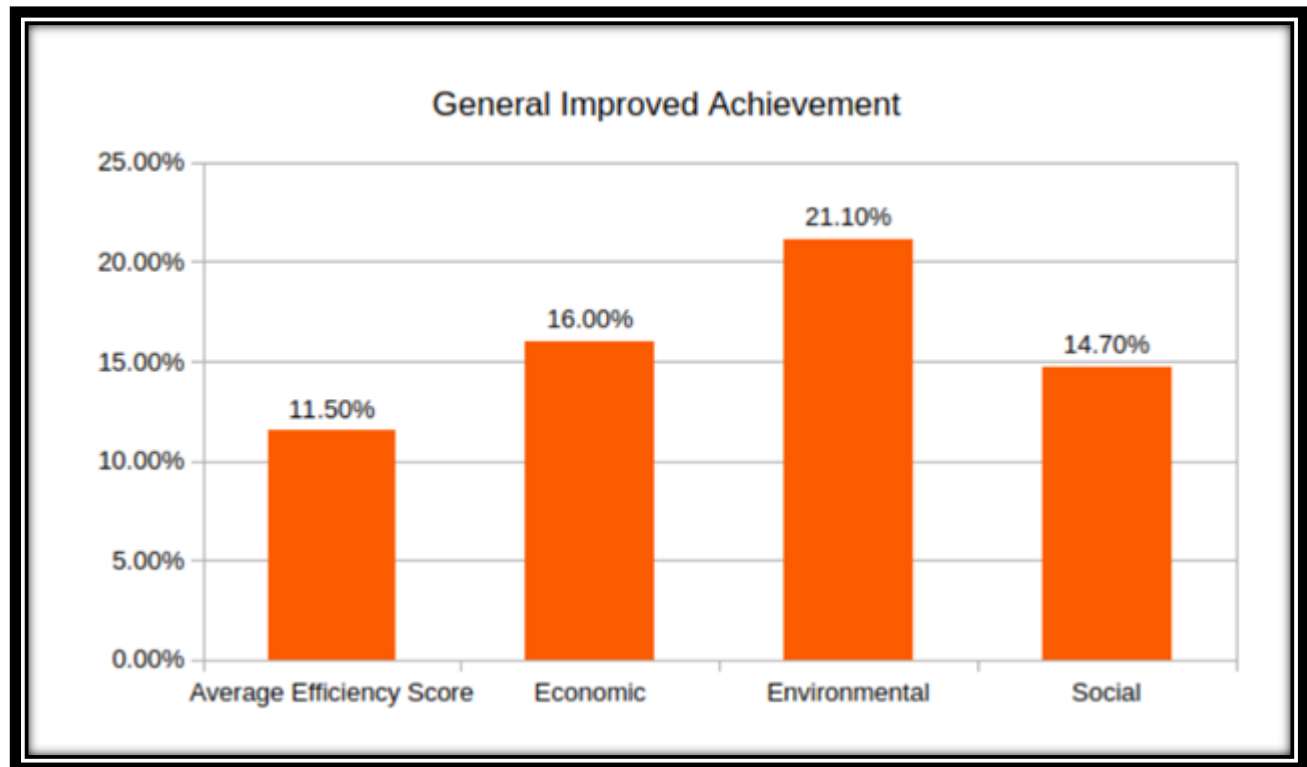


Figure 4: General Percentage of Improved Achievements

Some of limitations of the DEA approach are faced when conducting efficiency analysis. Although DEA is a vigorous approach to measure related variable efficiency, it accumulates several recognized limitations restrictions including sensitivity to outliers, inefficient stochastic treatment, uncertainty in variable relationships (input–output), and high homogeneity requirements.

9. Conclusion

This case study demonstrates that the integration of Goal Programming (GP) with Data Envelopment Analysis (DEA) can provide a powerful and robust instrument to optimize sustainable agricultural practices. This mathematical framework of GP-DEA helps proportion sustainability goals while ensuring efficient use of resources. The GP-DEA hybrid model allows farms to balance their goals related to economy, environment, and social ensuring efficient utilization of resources. The simulation results displayed significant improvements in efficiency and goal achievements across all three sustainability dimensions. Future research will be focusing on expanding GP-DEA model to incorporate additional factors like climate variability and technological innovations in agriculture. Further examination across different agricultural regions and will aid in validating the model's applicability in different settings. To sum up:

- ♦ The Objective Function: is to minimizes the sum of the weighted of deviations from target goals (economic, environmental, and social).
- ♦ The Goal Achievement Constraints: is to ensure that deviations from the predefined goals are scaled to be reduced.

- ♦ The DEA Efficiency Constraint: is to guarantee that the decision-making units operate efficiently relaying on the DEA results.
- ♦ The Non-Negativity Constraints: is to ensure that deviations and DEA weights are always positive so as keeping the model realistic and feasible.

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دمج تحليل تغليف البيانات مع نموذج البرمجة الهدفية لتعزيز كفاءة الزراعة المستدامة

الاستاذ المساعد الدكتور. جهان صالح احمد الاستاذ المساعد الدكتور. ابراهيم زغيتون جلوب

الملخص

يمكن تحقيق أهداف متعددة في آن واحد من خلال الاستخدام الأمثل للموارد. ونسعى في الزراعة المستدامة إلى تحقيق عدة أهداف، منها الاقتصادية والبيئية والاجتماعية. ويسهم دمج تحليل تغليف البيانات (DEA) مع البرمجة الهدفية (GP) في تحسين عملية اتخاذ القرار في الزراعة المستدامة. ويمكن لهذا النهج الهجين معالجة تعقيدات الأهداف المتعددة في الزراعة المستدامة. وقد أظهرت دراسة حالة أجريت على بيانات تجريبية تحسناً في الكفاءة من خلال الاستخدام الأمثل للموارد عبر الموازنة بين الأهداف المتنافسة. وتتيح مرونة هذا النهج إمكانية تطبيقه على مختلف السيناريوهات في القطاع الزراعي.