STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **15**, June 2026, pp 4963–4974.
Published online in International Academic Press (www.IAPress.org)

Applying Goal Programming Model and Data Envelopment Analysis to Enhance Sustainable Agricultural Efficiency

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Abstract Utilising the resource in an optimum manner hides significant challenges in sustainable agricultural development, specifically when addressing multiple goals such as economic, environmental, and social. This study aims to develop a combined hybrid framework of Multiple Goal Programming with Data Envelopment Analysis (MGP-DEA) to enhance the sustainability of agricultural efficiency. Methodologically, DEA is used to assess the relative farm efficiency. This method is implemented to increase the efficiency standards based on inputs and outputs. The results of applying the DEA are then integrated into the goals for programming as a guideline for efficiency. The goals are to improve resource allocation reducing deviations from defined economic, environmental, and social objectives. The input and output data are retrieved from 50 Malaysian agricultural farms. The input variables are land, labour, water and fertiliser, farm inputs and environmental indicators, and the output variables are crop grain. The analysed results show that the proposed MGP-DEA model has an increased average efficiency from 0.78 to 0.87, representing an 11.5% increase in efficiency. In addition, the levels of achievement of sustainability goals increase by 16.0% for economic goals, 21.1% for environmental goals, and 14.7% for social goals compared to the baseline scenario. The above outcomes confirm that combining efficiency evaluation based on data envelopment analysis (DEA) with optimisation based on multiple goal programming (MGP) provides a powerful decision-making tool for sustainable agricultural planning and policy formulation.

Keywords Sustainable Agriculture, Multiple Goal Programming (MGP), Data Envelopment Analysis (DEA), Optimisation, Agricultural Efficiency

DOI: 10.19139/soic-2310-5070-3310

1. Introduction

Achieving sustainable agricultural has major challenge for the stakeholders of policymakers, farm managers, and researchers worldwide. Historically, agriculture has been required to ensure food security and economic viability. Its importance lies in reducing environmental degradation and enhancing social well-being. The main factors have intensified the need for efficient and sustainable resource optimisation in agricultural systems: 1) increased pressure of population growth due to the opposite emigration, 2) limited resources, and 3) the enforcement of new environmental regulations [1].

Agricultural planning approaches are conventionally considered single objective, maximising crop yield or farm income. Such approaches ignore the environmental impacts or social constraints. Sustainable agriculture, however,

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

has multiple goals dealing with food security, water and fertiliser conservation, profitability, while somehow conflicting with environmental pollution, and improvement of labour conditions [3]. The necessity of balancing competing objectives requires analytical tools that are capable of capturing to optimise while ensuring efficiency.

In this context, optimisation techniques for multi-objective have increasingly trended in agricultural research. Among these techniques, Goal Programming (GP) have widely been applied to address problems of multiple objective priorities. GP has been promoted by the decision-makers who minimise the deviations from predefined targets. It has been successfully used in agricultural applications such as crop planning, water allocation, fertiliser management, and sustainable land-use optimisation [5, 7–9]. These studies have exhibited GP effectiveness that integrated the economic, environmental, and social factors in a single framework.

In conjunction with GP, Data Envelopment Analysis (DEA) has largely been applied to evaluate the relative efficiency of agricultural Decision-Making Units (DMU) based on multiple inputs and outputs. As the DEA is a non-parametric benchmarking technique, best-performing units are identified without the need for a predefined production function [10]. A considerable number of studies have applied the DEA technique to measure the agricultural efficiency (e.g., technical, economic, and environmental), providing valuable insight into resource-use inefficiencies and improvement potential [8–10, 13].

Researchers have attempted to integrate the GP with the DEA. This integration has exploited the complementary strengths. In consolidating these approaches, DEA traditionally assesses the data efficiency by generating benchmarks, while GP optimises the resource allocation, weighing multiple objectives. This integrated approach has been successfully applied in fields such as energy systems, environmental management, and industrial optimisation [2, 6, 11]. However, applying GP–DEA models in sustainable agriculture remains small-scale and underdeveloped.

Combining GP and DEA approaches often lacks a clear and systematic integration mechanism in the existing agricultural studies. In many cases, DEA is used as a tool for performance evaluation. Independently, GP is applied for optimising only. This results disconnecting between efficiency measurement and the decision-making process [4, 12]. The implemented mechanism is that the DEA efficiency scores are incorporated into the weighted GP model.

This gap highlights a missed structured framework that hybridises DEA efficiency scores to be explicitly embedded within the GP optimisation process. Integrating the constraints of efficiency into the GP model enables decision-makers to ensure sustainability goals are achieved while maintaining efficiency at acceptable levels that are relatively close to best-performing peers. The connected relationship between performance evaluation and operational optimisation can be strengthened by applying this hybrid approach, and it also supports informed decision-making.

Consequently, hybridising Goal Programming–Data Envelopment Analysis (GP–DEA) methods has been proposed in this study. To describe the above approach, the DEA efficiency scores, therefore, have become one of the constraints in the GP framework. This research has encountered three objectives, mainly:

1. DEA approach used to evaluate the relative efficiency of each farm based on the input–output data
2. Develop GP model to address economic, environmental, and social sustainability objectives;
3. Integrate DEA efficiency scores into the GP model to optimise resource allocation, considering sustainable efficiency.

The main contributions of this paper are twofold. Methodologically, it provides a mechanism of systematic integration between GP and DEA. This bridges the gap between efficiency assessment and multi-objective optimisation. Empirically, the proposed GP–DEA model is applied to Malaysian agriculture, demonstrating the effectiveness in improving sustainability performance and showing practical insights for policymakers and farm managers.

1.1. Related Work

Goal Programming (GP) and Data Envelopment Analysis (DEA) have been widely applied in a variety of sectors: manufacturing, healthcare, and agriculture. GP has proven to be an effective tool for optimisation when multiple objectives are detected. The conflicting goals of economic profit and environmental conservation must be balanced. Several researchers [1, 3, 5, 8] have applied the GP model to optimise the crops production with water and fertiliser resource limitations. Although some methodological issues in data envelopment analysis are detected, the multiple criteria DEA (MCDEA) approach was formed with a multiple objective perspective. While MCDEA models' objectives are generally conflicting, the goal programming (GP) technique is proposed to overcome the $MCDEA$ sensitivity [3]. The DEA employed to scale the agricultural efficiency units by comparing the relationships in their input-output. Najafabadi (2022)[9] showed that DEA identified the best practices for resource conservation in agriculture.

1.2. Novelty and Contribution

This study presents a structurally integrated framework combining Objective Programming and Data Envelopment Analysis (GP-DEA), where DEA efficiency scores are explicitly incorporated as binding constraints within the GP-DEA model, rather than being used solely for post-implementation efficiency assessment. The proposed approach formalises the integration mechanism between GP-DEA, enhancing transparency, reproducibility, and practicality. Thus, the model ensures that all decisions of resource allocations have to meet both sustainability objectives and optimal efficiency criteria. By addressing the efficiency criteria, the framework will simultaneously achieve the study objectives (economic, environmental, and social), reflecting the multidimensional nature of sustainable agriculture. The proposed GP-DEA model, therefore, has achieved tangible improvements in both efficiency and optimisation performance.

2. Methodology

The GP-EDA approach has been adopted to evaluate efficiency scores and optimise resource allocation in the Malaysian agricultural sector. Three phases were sequenced:

1. using DEA for efficiency score evaluation,
2. using GP for multi-objective optimisation, and
3. integrating DEA efficiency scores into the GP model.

2.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric measurement used to evaluate the performance of a set of homogeneous decision-making units $(DMUs)$ across multiple inputs and outputs. DEA compares each DMU against a best-practice frontier constructed from the observed data. This process is to identify the efficient and inefficient units without requiring a predefined functional form of the production process. The DEA is engaged to evaluate technical efficiency for agricultural farms considering multiple inputs (e.g., land, labour, water, and fertiliser) and outputs (e.g., crop yield, farm income, and environmental indicators). Obtaining DMUs' efficiency score can reflect the ability to maximise outputs given a set of relative inputs to the best-performing farms.

2.1.1. DEA Formulation An input-oriented DEA model adopted the assumption of constant returns to scale (CRS). The objective is to minimise resource usage while maintaining output levels. The DEA model for the i^{th} DMU is formulated as follows:

Objective function:

$$Max_{(u,v)}\ \ \theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \qquad ....(1)$$

Subjected To:

$$\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1, \quad k = 1, 2, 3...n \qquad ...(2)$$

$$u_r \geq 0, \quad r = 1, 2, 3...s$$

$$u_i \geq 0, \quad i = 1, 2, 3...m$$

Where

- θ_j is the efficiency score of $DMUs$
- y_{rj} denotes the amount of output r produced by $DMUs$
- y_{ij} denotes the amount of input i used by $DMUs$
- u_r and u_i are the weights assigned to outputs and inputs,respectively
- s and m represent the number of outputs and inputs;
- is the total number of $DMUs$

The efficiency score θ_j ranges between two values (0 and 1), where 1 indicates that the DMU is technically efficient and lies on the efficiency frontier.

2.2. Goal Programming (GP) Formulation

Goal Programming (GP) is an optimisation technique for multi-objective purposes. It is designed to minimise deviations from predefined target levels associated with multiple conflicting objectives. Simultaneously, GP is used to address sustainable agriculture goals (economic, environmental, and social) for profit maximisation, water reduction and optimise fertiliser usage, and improvement of labour conditions.

The general GP objective function is expressed as:

$$Min \;\; Z = \sum_{g=1}^{G} (w_g^- d_g^- \; + \; w_g^+ d_g^+) \qquad ...(3)$$

Subjected To:

$$f_g(x) \;\; + \;\; d_g^- \;\; - d_g^+ \;\; = T_g, \quad g = 1, 2, 3, ...G \qquad ...(4)$$

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

Where

- Z is the total weighted deviation from all goals;
- d_g^- and d_g^+ represent underachievement and overachievement deviations from the g^{th} goal;
- w_g^- and w_g^+ denote the relative importance of each deviation;
- T_g is the target value of the g^{th} goal;
- G is the number of goals.

2.3. Integrating Data Envelopment Analysis with Goal Programming

The integration of DEA with GP remains a novel approach within the sustainable agricultural context. Despite the combined two approach having been utilised 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 inherent in the sustainable agricultural practices. A conceptual framework of combined DEA–GP models for sustainable agricultural efficiency enhancement is shown in Figure 1. The core methodological contribution of this study is integrating DEA and GP. The proposed hybrid framework used DEA to evaluate the relative efficiency of farms and generate efficiency scores. The best-practice resource utilisation is reflected in the quantitative benchmark scores. The DEA efficiency scores are then explicitly incorporated into the GP model as efficiency constraints, ensuring that the optimisation process does not produce solutions that are inefficient relative to the DEA frontier. Integrating performance evaluation with optimisation can be explained as transforming the DEA results into concentrates (i.e., actionable decision variables) within the GP model.

The DEA-based efficiency constraint is formulated as:

$$\theta_j \geq \theta^{min}, \quad j = 1, 2, 3, ...n \qquad ...(5)$$

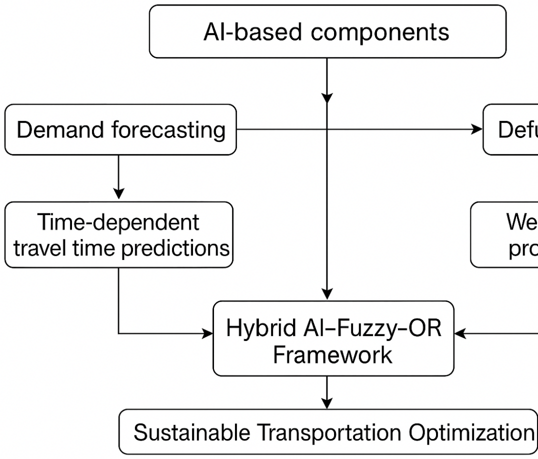


Figure 1. Conceptual framework of DEA–GP model for enhancing sustainable

Where

- θ_j denoted as the efficiency score of $DMUs$ obtained by the DEA method;
- θ^{min} the minimum acceptable efficiency threshold.

Incorporating the efficiency scores constraint within the GP model can simultaneously minimises the deviations from the set goals. This ensures that each DMU operates the accepted efficiency level.

2.4. *Goal Programming Model*

Balancing conflicting multi-objectives is the main challenge faced in optimisation. In traditional optimisation methods with individual criterion may not address multi-objective problems properly [10]. Goal Programming models designed to optimise multiple objectives simultaneously. The objectives in agriculture context are:

- **The economic goals** are to maximise the crop yield leading to increase the farms income.
- **The environment goals** are to reduce water and fertiliser consumption leading to decrease the pesticide applications and carbon emissions.
- **The social goals** are to promote the labour work-condition leading to improving food security ensuring equitable resource distribution.

The formulation of GP model is structured as follow:
Objective function for GP

$$Minimise \ \ (Z) = \sum_{g=1}^{G} w_g^+ \, d_g^+ \ + w_g^- \, d_g^- \qquad ...(6)$$

Purpose: This objective function aims to minimise 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:

$$Profit : P \geq Min - Profit \qquad ...(7)$$

   Where: P is the profit generated by the i^{th} DMU, and $MinProfit$ is the minimum acceptable profit.

2. Environmental Constraints:
$$WaterUsage : W \geq Max - Water \qquad ...(8)$$
Where: W is the water used by the i^{th} DMU, and $MaxWater$ is the maximum allowable water usage.
3. Social Constraints:
$$Labour\ Conditions : L \geq Min\ Labor\ Conditions \qquad ...(9)$$
Where: L represents the social goals such as fair labour practices or food security targets.

3. Data Collection and Case Study: Malaysian Rice Production

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

3.1. DEA Data and Normalization Procedure

3.1.1. DEA Input–Output Data The DEA analysis is based on input–output data collected from 50 farms (DMUs) in Malaysia. The inputs and outputs selected to reflect the economic, environmental, and operational characteristics of sustainable agricultural production. Table 1 presents the variables used in the DEA model.

Table 1. The DEA Input–Output Variables

Category	Variable	Description	Unit
Inputs	X_1	Land area	Hectares
	X_2	Labour	Man-days
	X_3	Water consumed	Cubic meters
	X_4	Fertiliser use	Kilograms
Outputs	Y_1	Crop yield	Tons
	Y_2	Farm income	Monetary units
	Y_3	Environmental performance indicator (soil, biodiversity index)	Index value

Each DMU represents an individual farm that utilises the above inputs to produce agricultural and environmental outputs. Malaysian agriculture data has constructed the DEA efficiency frontier and benchmarking farm performance.

3.2. Data Normalisation in DEA

Input and output variables measured by units and magnitudes (hectares, cubic meters, kilograms, monetary values, and index scores). Using DEA approach without normalisation might cause numerical instability, leading to biased weight allocation. Thus, using heterogeneous data of variables with large numerical ranges misguide the optimisation process. This issue can be treated by normalising the data. Normalisation ensures all variables (inputs and outputs) are within the same scale, preserving the relative proportions across $DMUs$.

Input variables are expressed as:
$$x_{ij}^{norm} = \frac{x_{ij} - min(x_i)}{max(x_i) - min(x_i)} \qquad ...(10)$$
Output variables are expressed as:
$$y_{rj}^{norm} = \frac{y_{rj} - min(y_r)}{max(y_r) - min(y_r)} \qquad ...(11)$$
Where

- x_{ij} and y_{rj} are the original input and output variables of $DMU's\ j$
- x_{ij}^{norm} and y_{rj}^{norm} are considered the normalised input and output values;
- min and max represent the minimum and maximum of input and output values of each variable across all $DMUs$.

After the normalisation process is completed, the values of all input and output variables will lie between the interval [0, 1].

3.3. Relationship Between Data and DEA Weighting

After the data normalised, DEA model assigns the weights to the relative performance, rather than the actual values. This process allows each variable to contribute meaningfully to the efficiency evaluation. The inputs and outputs then assigned the weights endogenously while determined through optimisation that maximise $DMU's$ efficiency score. The GP objective function and constraints are ensuring:

- No single variable dominates because of the differences in scales,
- Efficiency scores are reflecting the proportional relationships between input–output variables,
- Comparison scores among $DMUs$ remain valid and interpretable.

The reliability of efficiency scores derived from DEA are strengthened by the normalising process. The scores afterwards used when integrating DEA within GP.

3.4. Justification for Data Normalisation

Normalisation process employed in this analysis mainly for three reasons:

- **Scale compatibility**
  Agricultural variables (inputs and outputs) are expressed in heterogeneous units/ranges, and normalisation ensures comparability.
- **Numerical stability and Fair weights**
  Normalising the data improves the performance of DEA through avoiding extreme coefficient values. Normalisation prevents the DEA approach from assigning excessive weights to variables solely due to heterogeneous measurement units.

With normalisation, the DEA model will provide a robust and transparent efficiency assessment. This is essential for subsequent integration into the Goal Programming framework.

3.5. Conceptual Framework: Stepwise DEA–GP Integration Algorithm

As the DEA–GP integrated approach has been adopted in this study, the integration process consists of the following steps:

1. **First step:** Identifying the $DMUs$, and input and output variables step.
   Each $DMUs$ is characterised by the vector:
   $$x_j = (x_{1j}, x_{2j}, \dots, x_{mj}) \qquad ...(12)$$
   and the outputs vector:
   $$y_j = (y_{1j}, y_{2j}, \dots, y_{sj}) \qquad ...(13)$$
   Where input variables represent resource consumption, including land, labour, water, and fertiliser. While the output variables represent the economic and environmental performance indicators, including crop yield, income, and sustainability indices.
2. **Second step:** Data Normalising step. To remove scales variation effects, all input and output variables have been normalised. The normalised dataset has been frequently used in DEA and GP models, ensuring numerical comparability and stability.
3. **Third step:** DEA Efficiency Assessment step. DEA is constructing the efficiency scores frontier through computing technical efficiency for each $DMUs$. Each efficiency score (θ_j) has been obtained. These scores have quantified the relative performance of each farm by transforming inputs into outputs.
4. **Fourth step:** Efficiency Benchmarks Determination step. The results of the DEA are the reference units showing the identified benchmark performance levels. θ_{min} is the minimum acceptable efficiency threshold that represent efficiency level to satisfy all $DMUs$ during the optimisation process in this step. These benchmarks are the thresholds reflecting the best-practice standards and policy objectives.
5. **Fifth step:** Integrating DEA Results into the GP Model step. Efficiency scores are directly integrated to GP model through efficiency constraints:
   $$\theta_J - \theta_{min}, \quad j = 1, 2, 3, ...n \qquad ...(14)$$
   This constraint ensures the generated solution of GP model satisfies the sustainability goals.

6. **Sixth step:** Goal Programming Optimisation step. Optimisation in the GP model is to minimise the weighted deviations subject to constraints and the DEA efficiency constraint. An optimal resource allocation is balancing sustainability objectives while maintaining efficiency constraints.
7. **Seventh step:** Performance Evaluation and Interpretation step. Post-optimisation analysis compares the outcomes (baseline and optimised) in terms of efficiency scores and goal achievement levels. This step aims to improve the attributable integrated DEA–GP framework and validate its effectiveness.

Key Contribution of the Framework The proposed stepwise DEA–GP integration algorithm transforms DEA from a descriptive evaluation instrument into an active constraint-generating component. By explicitly embedding DEA efficiency results into the GP formulation, this approach provides a reproducible and operational decision-support methodology for sustainable agricultural planning.

3.6. DEA Model Specification and Returns-to-Scale Assumption

This study has adopted an input-oriented Data Envelopment Analysis (DEA) model assuming Constant Returns to Scale (CRS), that referred to as the CCR model. The CCR specification assumes that output levels change proportionally with input levels and is appropriate when decision-making units $DMUs$ are assumed to operate at or near an optimal scale. The CCR model has been chosen as the study objective motivation. It focuses on overall technical efficiency and resource-use optimisation across agricultural farms operating under similar production technologies and regulatory conditions. Since the projected framework aims to optimise the input resources, maintaining output levels, the input-oriented CCR model provides a suitable representation of efficiency performance.

Under the assumptions of CCR, the obtained efficiency score for each DMU reflects the overall technical efficiency. It is capturing pure technical efficiency and scale efficiency effects. An efficiency score is equal to 1; this indicates all DMUs lie on the efficiency frontier and operate efficiently relative to best-performing peers. Nevertheless, scores below 1 indicate proportional input reductions that could be achieved without reducing output. The efficiency scores from CCR are subsequently integrated into GP model as binding efficiency constraints. The integration process guarantees the optimisation stage enforces minimum acceptable levels of efficiency, consistent with the CCR method.

3.7. Data Consistency and Variable Harmonisation

The inconsistencies of crop types have been addressed by thoroughly reviewing the entire dataset. This treatment has harmonised and corrected the internal consistency and improved data credibility.

Crop Type Consistency
The study's simulated analysis is limited to the Malaysian agricultural context. This is to serve the homogeneous set of decision-making units (DMUs) using DEA and GP–DEA models. Any previous references to multiple crop types (e.g., rice, palm oil, rubber) have been removed or clarified where they were used only for descriptive background purposes. This rearrangement ensures all $DMUs$ operate under the same comparable production technologies, input–output structures, and environmental conditions, which is a fundamental requirement for valid DEA efficiency assessment.

4. Model Implementation

LINGO is a widely used software for solving optimisation problems. The results of production plans have reached the optimal solutions, which demonstrate how GP supported the viability of the sustainable and economic production planning.

4.1. 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, labour, water, and fertiliser usage. Outputs were crop yield, farm income, and some environmental indicators (e.g., biodiversity and soil health). Our GP-DEA model is designed to optimise the triple objectives of sustainability:

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

The following metrics were used for the 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. Results and Discussion

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

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%

The integrated GP-DEA model has successfully enhanced the average efficiency score by 11.5%, pointing to a better resource utilisation across farms. Figure 1 illustrates the distribution of efficiency scores before and after the GP-DEA optimisation. Farms with low baseline efficiency showed the greatest improvements. Additionally, the GP-DEA hybrid model has assisted the farms under study in achieving 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 fertiliser inputs while increasing yield, in Figures 2,3.

Table 3. Statistics of Input/Output Data Before Optimisation (n = 50 farms)

Variables	Mean	ST.D	Min	Max
Land Area (hectare)	6.45	2.13	2.0	12.0
Labour (person-hours)	1,250	320	800	1950
Water Use (m^3/ha)	3200	780	2000	5100
Energy Input (MJ/ha)	7850	1230	5600	1500
Energy Input (MJ/ha)	8920	2450	4800	13600

Table 4. Goal Deviations by Farm Efficiency Segment

Efficiency Segment	Farm ID/Group	Economic Deviation	Environmental Deviation	Social Deviation
Low Efficiency ($DEA\ > 0.70$)	F1 – 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 ($DEA \geq 0.70$)	F21–F35	0.072	0.094	0.056
High Efficiency ($DEA \leq 0.70$)	F36–F50	0.068	0.089	0.051
Mean (High)		**0.070**	**0.092**	**0.054**

From Figure 4, some of the 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 recognised limitations, including sensitivity to outliers, inefficient stochastic treatment, uncertainty in variable relationships (input–output), and high homogeneity requirements.

6. Summary of the provided Results Interpretation and Discussion

The results show that the integrated GP–DEA model improves efficiency and sustainability across farms, with larger gains observed among initially inefficient farms due to better input reallocation guided by DEA benchmarks. The improvements

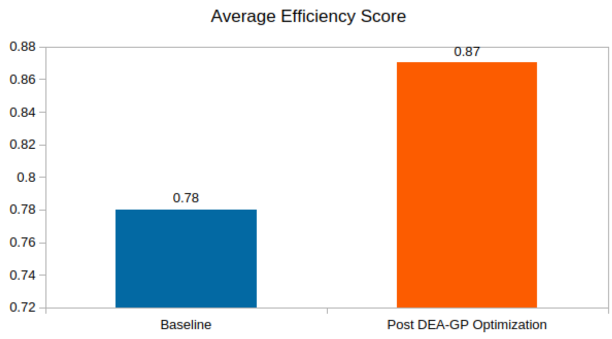
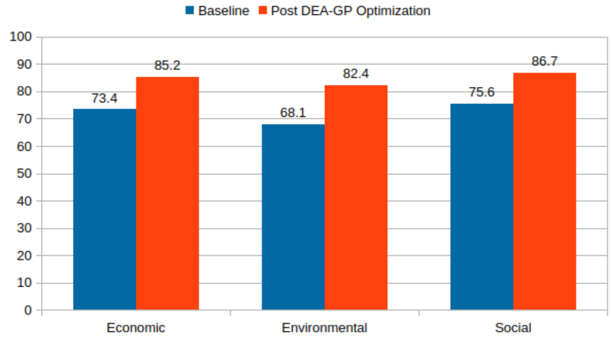


Figure 2. Average Efficiency Score



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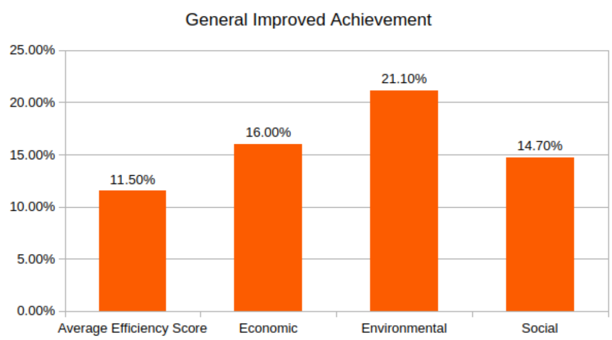

Figure 4. General Percentage of Improved Achievements

have basically shown reductions in input waste (water and fertiliser) that enhanced cost efficiency and profitability, in addition to increasing output. Some farms have contributed with smaller gains, as the operations were closer to the efficiency frontier. This can confirm the validity of the DEA benchmarking process, while avoiding artificial efficiency inflation. The consistent aggregated improvement across farms has indicated systematic optimisation effects. The future directions have to utilise more statistical tests for model robustness and further efficiency differences validations.

6.1. Integration of DEA Limitations within the Results

Results interpretations require considering DEA limitations. Scores of DEA efficiency are relative and depend on the sample collected. They are measured against the best-performing farms from the same dataset, but not against the absolute technological benchmark. This limitation has been mitigated by binding the DEA efficiency scores within the formulation of GP optimisation. Therefore, the final performance indicators become constraints guiding the resource allocation decisions.

The minimum acceptable efficiency level represents a threshold. Ensuring the integration consistency, the efficiency threshold ($\theta \geq 0.70$) has been applied uniformly for all analyses. Integrating GP-DEA reduces over-interpreting of DEA scores and strengthens the approach's relevance.

6.2. Contribution of the GP–DEA Hybrid Approach

The paper's main contribution lies not only in reporting higher efficiency scores but in demonstrating how evaluating the efficiency while optimising sustainability can be operationally integrated. Targeted DEA studies identify only the inefficient farms without prescribing optimal corrective actions. However, the proposed GP–DEA approach translates efficiency allocations into solid optimisation decisions.

Similarly, standalone GP models may generate sustainability-optimal but inefficient solutions. Nevertheless, our integrated framework ensures all solutions satisfy the requirements of explicit efficiency. DEA efficiency results have been embedded as controlling constraints within the GP model. This hybrid approach has clarified how the objectives of efficiency, economic performance, and sustainability have been addressed simultaneously. The previous studies have been enriched by treating these elements separately. Thus, this study introduces to the existing literature a more robust decision-support tool for sustainable agricultural planning.

7. Conclusion

This paper has demonstrated that the integration of Goal Programming (GP) with Data Envelopment Analysis (DEA) can provide a robust approach to optimise sustainable agricultural planning. The formulated framework of $GP - DEA$ has achieved sustainability goals while ensuring efficient use of resources. The $GP - DEA$ hybrid model allows farms to balance their goals (economy, environment, and social), ensuring efficient resource utilisation. The simulated results have displayed significant improvements in efficiency and goal achievements across the above sustainability dimensions. Future research will focus on expanding the $GP - DEA$ model to incorporate additional factors such as climate variability or technological innovations within agriculture planning. Further examination across different agricultural regions will aid in validating the model's applicability in different settings and regions.

To sum up:

- The $GP - DEA$approaches' objective function is to minimise the sum of all weighted deviations from sustainability targets (economic, environmental, and social).
- The constraints are to ensure all deviations from the predefined goals are scaled to be reduced.
- The DEA efficiency constraints within the GP model are to operate efficiently for decision-making units.
- The Non-negativity constraints are set to ensure all deviations from DEA weights are always positive, keeping the model realistic and feasible.

Declarations

All authors declare that they have no conflicts of interest.

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