A Hybrid GP–FGP Model Integrated with the Analytic Hierarchy Process for Multi-Objective Agricultural Land Allocation under Uncertainty: A Case Study of Iraq

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Abstract

Allocating land for agriculture is a significant problem for countries where there are limited resources, many crops vying for the same resources, and rapidly changing climates. This paper describes a unified model involving Goal Programming (GP) and Fuzzy Goal Programming (FGP) that can help in the optimization of agricultural land allocation to a number of different crops while recognizing that some of the objectives are incompatible (i.e., maximizing profit, minimizing cost and producing enough food). To accomplish this, the researcher has applied classical GP, in order to define "deterministic" agricultural targets, with FGP which allows for uncertainty in yield quantity, costs and profits to be considered through the use of fuzzy membership functions. Agricultural input-output data from 50 representative farms in Iraq were used in the analysis (the analysis includes the costs, yield expectations, and profit per hectare of all major crops: wheat, barley, rice, corn, and vegetable crops). Data were obtained from national agricultural census reports as well as local farm records. The FGP Model's Results Show High Levels of Goal Satisfaction. Profit Achievement Weighting of 0.92 and Cost Achievement Weighting Of 0.85 Is Achieved While 100% of Essential Crop Area Is Satisfied. Through Scenario Analysis, Profit Prioritization Provides A 25% Increase To The Allocation Of Wheat, Whereas Cost Prioritization Creates A 12% Reduction In Expenditures Which Further Demonstrates The Flexibility of the Model. This Research Provides A Practical, Adaptable & Robust Decision Support System for Agricultural Planners In Iraq And Likewise Areas For The Allocation Of Land Under Uncertainty, With Multiple Trade-offs Between Objectives & Establishing Priorities Based On Policy.

Keywords: Hybrid Optimization, Goal Programming, Fuzzy Goal Programming, Analytic Hierarchy Process, Agricultural Land Allocation, Iraq, Uncertainty

المستخلص

تُعدّ عملية تخصيص الأراضي للزراعة مشكلة كبيرة في البلدان التي تعاني من محدودية الموارد، وتنافس العديد من المحاصيل على نفس الموارد، إضافةً إلى التغيرات المناخية السريعة. تصف هذه الورقة نموذجًا موحّدًا يجمع بين البرمجة بالأهداف (Goal Programming – GP) والبرمجة بالأهداف الضبابية (Fuzzy Goal Programming – FGP)، يمكن أن يساعد في تحسين تخصيص الأراضي الزراعية لعدد من المحاصيل المختلفة، مع الأخذ في الاعتبار أن بعض الأهداف قد تكون متعارضة (مثل تعظيم الربح، تقليل التكاليف، وضمان إنتاج غذائي كافٍ) . ولتحقيق ذلك، قام الباحث بتطبيق البرمجة بالأهداف التقليدية لتحديد الأهداف الزراعية «الحتمية»، إلى جانب البرمجة بالأهداف الضبابية التي تسمح بأخذ حالة عدم اليقين في كميات الإنتاج والتكاليف والأرباح بعين الاعتبار، من خلال استخدام دوال الانتماء الضبابية. تم استخدام بيانات المدخلات والمخرجات الزراعية من 50 مزرعة تمثيلية في العراق ضمن التحليل، حيث شملت البيانات التكاليف، وتوقعات الإنتاج، والربح لكل هكتار لجميع المحاصيل الرئيسية مثل: القمح، الشعير، الأرز، الذرة، ومحاصيل الخضروات. وقد تم الحصول على هذه البيانات من تقارير التعداد الزراعي الوطني، إضافةً إلى سجلات المزارع المحلية. أظهرت نتائج نموذج البرمجة بالأهداف الضبابية مستويات عالية من تحقيق الأهداف، حيث تم تحقيق وزن للربح بلغ 0.92، ووزن لتقليل التكاليف بلغ 0.85، مع تحقيق 100% من المساحة المطلوبة للمحاصيل الأساسية. ومن خلال تحليل السيناريوهات، تبيّن أن إعطاء الأولوية للربح يؤدي إلى زيادة بنسبة 25% في تخصيص الأراضي لمحصول القمح، في حين أن إعطاء الأولوية للتكاليف يؤدي إلى خفض بنسبة 12% في النفقات، مما يبرز مرونة النموذج. يوفّر هذا البحث نظام دعم قرار عمليًا وقابلًا للتكيف وذو متانة عالية للمخططين الزراعيين في العراق، وكذلك في المناطق المشابهة، من أجل تخصيص الأراضي في ظل عدم اليقين، مع وجود مفاضلات متعددة بين الأهداف، وإمكانية تحديد الأولويات وفقًا للسياسات.

الكلمات المفتاحية: التحسين الهجين، البرمجة بالأهداف، البرمجة بالأهداف الضبابية، عملية التحليل الهرمي، تخصيص الأراضي الزراعية، العراق، عدم اليقين.

1 - Introduction

Land allocation for agriculture is a challenging and an important part of achieving food security, maximizing economic efficiency and environmental sustainability. It is very difficult for the agricultural industry to strike a balance between all the various goals or objectives it must achieve. The agricultural industry must find a way to achieve the many competing objectives of; maximising farmers' income, minimising growers' costs to produce, assuring a sufficient supply of food and preserving the natural resource base. In this context, decision making is multi-objective and uncertain. The uncertainty is caused by many factors such as difference in crop yields, different costs of producing agricultural products (inputs) and fluctuations in prices of agricultural products in a market due to climatic conditions, soil conditions and government policies. (Taha, 2017). Moreover, the growing global demand for sustainable agricultural practices emphasizes the need for efficient resource allocation that accounts for economic, social, and environmental objectives.

Previous research has applied traditional Linear Programming (LP) and Goal Programming (GP) techniques to address multi-objective agricultural planning problems. GP allows decision-makers to set priority-based goals and determine compromise solutions when objectives conflict (Ignizio, 1976). However, conventional GP assumes precise data, which may not adequately capture the inherent uncertainty in agricultural systems. To overcome this limitation, Fuzzy Goal Programming (FGP) incorporates fuzzy set theory, allowing goals and constraints to be expressed as fuzzy variables, reflecting imprecision in yield forecasts, cost estimates, and profit expectations (Zadeh, 1965; Zimmermann, 1996; Malik *et al.*, 2023).

Recent studies have successfully applied FGP in crop planning, water allocation, and sustainable agriculture, demonstrating its ability to handle conflicting objectives under uncertainty Kumar, & Gupta, (2021); (Huang *et al.*, 2025; Nawawi *et al.*, 2022; Angammal, & Grace, 2024). Despite these advances, there is a research gap in integrating GP and FGP in a comprehensive framework that simultaneously (Hasan, & Khan, 2025).

1. Handles multi-season crop allocation under uncertainty,
2. Accounts for budget and essential crop constraints, and
3. Provides a flexible weighting mechanism for prioritizing economic, social, and environmental objectives.

The objectives of this study are:

1. To formulate a robust integrated GP-FGP model for optimizing land allocation among multiple crops, accounting for resource constraints, essential food crop requirements, and economic objectives.
2. To apply the proposed model to 50 representative farms in Iraq, using input–output agricultural data for major crops such as wheat, barley, rice, maize, and vegetables.
3. To evaluate the model's performance through scenario analysis, demonstrating its ability to handle different policy priorities and trade-offs between profit, cost, and food security.

The main contributions of this research include:

- A methodological contribution in integrating GP and FGP for agricultural planning under uncertainty.
- A practical decision-support tool for policymakers and agricultural planners in Iraq and similar developing regions.
- Empirical evidence on the effectiveness of fuzzy multi-objective optimization in improving land use efficiency, achieving target crop allocations, and supporting sustainable agricultural practices.

1.1 Background

Agricultural land allocation is a complex decision-making problem that directly affects food security, farm profitability, and sustainable land use (Singh & Sharma, 2022). Farmers must balance multiple objectives such as maximizing profit, minimizing costs, and ensuring sufficient production of essential crops. Uncertainties in crop yields, input costs, and market prices further complicate these decisions (Dixit, & Tyagi, 2024). Traditional linear programming approaches often fail to capture this uncertainty. The need for multi-objective optimization under uncertainty has led researchers to explore fuzzy and goal programming approaches. These methods provide flexibility in handling conflicting objectives while maintaining realistic planning scenarios.

1.2 Multi-Objective Challenges in Agriculture

Agricultural planning involves multiple, often conflicting goals, such as profit maximization versus cost minimization or food security versus resource conservation (Taha, 2017; Zhao, *et al.*, 2024). Each crop competes for limited land, water, and budget resources, creating trade-offs that must be carefully managed. Decision-makers require models capable of quantifying these trade-offs to prioritize objectives according to policy or farm-level needs. Furthermore, uncertainties in climatic conditions and input availability make deterministic solutions insufficient. Multi-objective optimization techniques provide a structured framework to reconcile these conflicts. Goal Programming (GP) is particularly useful as it minimizes deviations from predefined targets while considering multiple goals simultaneously (Ignizio, 1976).

1.3 Goal Programming Model

Originally applied by Charnes, *et al.*, (1955) and then again by Charnes and Cooper (1961) for single-objective linear programming, Goal programming (GP) has gained considerable traction since the 1960s/1970s due predominantly to Lee's (1972) work. Today, GP is a prime focus of multiparameter decision making; its main function is to set an achievable level of a given goal for each parameter being optimally managed. GP produces the minimum total of all deviant outputs, where all outputs are simultaneously considered and assigned weights according to their significance (Gero, 2012). Further, GP is a segment of multi-criteria optimisation, which is in turn a segment of multi-criteria decision analysis (MCDA)/multiple-criteria decision making (MCDM) (Romero, 2014). This process can be seen as a broadening or possibly even a continuation of LP techniques but with multiple, typically conflicting, desired objective criteria. Each of these objectives must have an associated target/goal value. The amount by which the achievement function deviates from each target value can then be minimized for each of the conflicting objectives according to LP techniques.

The General Purpose Computer was first introduced into the field of agriculture with the intent to use it in solving agricultural and similar issues. The General Purpose Computer is being applied in the agricultural industry to solve production planning problems and assist with crop production by developing the necessary goals, establishing priorities for decision-making, and by providing tools for farmers to analyse their income and maximize it through farm management practices. Table 1 lists various examples of General Purpose Computer Model Applications for Agriculture.

Table 1: Summary of Previous Studies on Agricultural of Goal Programming Models

Source	Location	Factors Involved (Constraints)	Objective Function
Wheeler & Russell (1977)	UK	Labour force, water, gross income	Maximize gross income; Minimize cost and labour
Abdul Aziz (2007)	Egypt	Irrigation water, labor, azotic units, potassium, costs, seeds	Maximize net profit; Minimize irrigation water, labor, and azotic units
Jafari, *et al.*, (2008)	Iran	Gross benefit, production cost, water, fertilizers, pesticide, labor	Maximize income; Minimize water, fertilizers, chemicals, and labor
Latinopoulos (2009)	Greece	Gross margin, labour, irrigation water, fertilizer	Maximize gross margin and efficiency; Minimize risk, cost, water, fertilizer
Wei, *et al.*, (2009)	China	Economic benefit, irrigation water, fertilizer, seed	Maximize net revenue; Minimize cost
Zhao *et al.* (2009)	China	Economic benefit, irrigation water, fertilizer, seed	Maximize net revenue; Minimize cost
Asadpoor, *et al.* (2009)	Iran	Production, capital, labour, water, income	Minimize land, water, labor, and cost
Boustani, *et al.* (2010)	Iran	Land, water, labour, capital, crop rotation, risk	Minimize risk
Adeyemo & Otieno (2010)	South Africa	Land area, irrigation water	Maximize output and net benefit; Minimize water use
Pal, *et al.*, (2010)	India	Land, manpower, machinery, water, fertilizer, cost	Maximize production and profit; Optimize resource use
Ibrahim & Omotisho (2011)	Nigeria	Land, labour, fertilizers, seeds	Maximize crop yield; Minimize environmental impact
Keramatzadeh, *et al.*, (2011)	Iran	Land, labour, water, fertilizers, pesticides, machinery	Maximize income and employment; Minimize chemical inputs
Sarker & Ray (2012)	Nigeria	Demand, land, capital	Maximize gross output; Minimize working capital
Karbasi, *et al.*, (2012)	Iran	Fertilizer, cost, nutrient limits	Minimize fertilizer cost; Maximize yield and nutrient efficiency
Prišenk, *et al.*, (2014)	Slovenia	Land, labour, fertilizer	Minimize production cost

1.3 Previous Research

Prior studies have applied GP and Fuzzy Goal Programming (FGP) in agricultural resource allocation (Malik, Nawawi, & Rani, 2023; Zimmermann, 1996). GP has been widely used to optimize crop allocation under fixed resources, while FGP introduces fuzziness to account for uncertainties in yields, costs, and profits. Researchers have shown that fuzzy approaches often outperform classical LP or GP when dealing with uncertain or imprecise data (Angammal, & Grace, 2024; Nawawi *et al.*, 2022). However, most studies focus on either GP or FGP individually, lacking integrated frameworks that allow simultaneous handling of multiple objectives under uncertainty. Moreover, limited empirical applications exist for regions like Iraq, where agriculture faces specific socio-economic and environmental constraints.

1.4 Research Gap and Novelty

Despite extensive literature on GP and FGP, there remains a lack of integrated approaches that combine deterministic and fuzzy methods for multi-objective agricultural land allocation (Huang *et al.*, 2025). Existing studies often ignore practical constraints such as minimum essential crop areas or seasonal variations in land productivity. Additionally, sensitivity analysis under varying weights of goals is rarely explored. This study addresses these gaps by developing a GP–FGP hybrid model capable of handling uncertainty, multiple objectives, and practical farm-level constraints. The novelty lies in its empirical application to 50 farms in Iraq, demonstrating both methodological robustness and practical policy relevance.

1.5 Research Objectives and Contributions

The main objectives of this study are Ignizio, (1976) to formulate an integrated GP–FGP model for optimizing land allocation among multiple crops, (2) to apply the model to Iraqi farms using input-output agricultural data, and (3) to analyze the model's performance under different weighting scenarios. The contributions are threefold: methodological (integration of GP and FGP), practical (flexible decision-support tool for planners), and empirical (demonstrating improvements in goal satisfaction and land-use efficiency). The study provides actionable insights for policymakers to balance economic, social, and environmental objectives in agricultural planning (Rani & Kumar, 2021; Dixit & Tyagi, 2026).

2. Methodology

2.1 Goal Programming (GP) Overview

Goal Programming (GP) is a multi-objective optimization technique that allows decision-makers to achieve multiple, often conflicting objectives by minimizing deviations from predetermined goals (Ignizio, 1976). In agricultural land allocation, GP can efficiently determine land shares for different crops while satisfying constraints such as land availability, budget, and essential crop requirements (Malik, Nawawi, & Rani, 2023).

The GP mathematical formulation is:

$$Minimize\ Z = \sum_{k=1}^{K} w_k \left(d_k^- + d_k^+\right) \qquad (1)$$

$$subject\ to: \sum_{j=1}^{n} P_j x_j + d_1^- - d_1^+ = G_1 \qquad (2)$$

$$\sum_{j=1}^{n} C_j x_j + d_2^- - d_2^+ = G_2, \qquad x_j \geq 0 \qquad (3)$$

$$x_j \geq 0 \qquad (4)$$

Where, d_k^-, d_k^+ are under- and over-achievement deviations, w_k is the weight of goal k , P_j and C_j represent profit and cost, x_j is the land allocated to crop j , and G_k are the goal targets.

2.2 Fuzzy Goal Programming (FGP) Integration

FGP handles uncertainty in yields, costs, and profits. Each goal is expressed as a fuzzy set using a membership function:

$$\mu_k(x) = \begin{cases} 0, & z_k(x) \le b_k^- \\ \frac{z_k(x)-b_k^-}{b_k-b_k^-}, & b_k^- < z_k(x) < b_k \\ 1, & z_k(x) \ge b_k \end{cases} \tag{5}$$

The integrated GP-FGP model maximizes the overall satisfaction level:

$$\text{Maximize } \lambda \quad \text{subject to } \mu_k(x) \ge \lambda, \forall k \tag{6}$$

GP provides deterministic target-setting, while FGP adds flexibility to achieve near-optimal solutions under uncertainty.

2.3 Analytic Hierarchy Process in Agricultural

The Analytic Hierarchy Process (AHP) is employed in this study to systematically determine the relative importance (weights) of multiple objectives involved in agricultural land allocation. In the context of this research, AHP is used to evaluate and prioritize key decision criteria, namely profit maximization, cost minimization, food security, and land utilization, which are inherently conflicting in agricultural planning (Saaty, 1980; Rani & Kumar, 2021).

The AHP methodology structures the decision problem into a hierarchical framework, where the overall objective optimal land allocation is placed at the top level, followed by the evaluation criteria. Pairwise comparisons are conducted among these criteria using a standardized importance scale, allowing decision-makers to express their preferences regarding the relative significance of each objective. These comparisons are then used to derive a priority vector (weight vector), which reflects the relative importance of each goal within the decision-making process.

Mathematically, the pairwise comparison process is represented by a reciprocal matrix:

$$A = \left[a_{ij} \right], \quad a_{ij} = \frac{1}{a_{ij}} \quad , \quad a_{ij} = 1 \tag{7}$$

The relative weights of the criteria are obtained by solving the eigenvalue problem:

$$Aw = \lambda_{max}{}^{w} \tag{8}$$

Where represents the normalized weight vector and λ_{max} is the maximum eigenvalue of matrix. To ensure the consistency of the pairwise comparisons, the Consistency Ratio (CR) is calculated as:

$$X_{ij}^{-} = \frac{\lambda_{max} - n}{n-1} \quad , \quad C1 = \frac{C1}{R1} \tag{9}$$

Where, n is the number of criteria and RI is the Random Index. A value of $CR < 0.10$ indicates acceptable consistency in the decision-maker's judgments (Saaty, 1980).

In this research, the weights derived from AHP are directly integrated into the GP–FGP model formulation, where they are used to prioritize deviations from multiple goals and to define the relative importance of fuzzy membership functions. This integration enables the model to reflect policy preferences and planning priorities, such as emphasizing food security over profit or reducing costs under budget constraints.

Furthermore, the use of AHP ensures that the weighting process is transparent, consistent, and adaptable, allowing the model to be applied under different agricultural scenarios. By linking qualitative decision-maker preferences with quantitative optimization, the AHP–FGP integration enhances the robustness and practical applicability of the proposed model for real-world agricultural land allocation under uncertainty (Dixit & Tyagi, 2026 ; Huang *et al.*, 2025).

2.4 AHP and Data Normalization

Weights for goals had been determined through Analytic Hierarchy Process (AHP), a multi-criteria decision-making process that structures complex problems into a hierarchy, with assigned levels of importance established by comparative evaluation via pairwise comparisons (Saaty, 1980). The use of a standardized scale allowed decision-makers to evaluate how important each of the four objectives (profit maximization, cost minimization, food security, and land utilization) was when utilizing AHP. The resulting pairwise comparison matrix was then used to create a priority vector for each objective; the priority vector represents how important each objective is relative to the other three. Also, in order to provide an accurate estimation of the importance of each objective, the Consistency Ratio (CR) was used to measure the consistency of the ratings given to each pair (Saaty, 1980).

To show prioritization policies by decision-makers, the normalized weights will be used in GP-FGP model. An example of this would be where in profit-driven planning will have a higher weight for the profit goals versus planning with a focus on cost minimization, etc. Utilizing this weighting methodology, the GP-FGP model can accommodate various forms of planning strategy and goals for policymakers. Agricultural production parameters have been collected from 50 example farms throughout Iraq and include data such as per hectare profits and production costs as well as minimum and maximum land allocation restrictions for various crops which form the foundation for GP-FGP modeling and optimization. Using Analytic Hierarchy Process (AHP), the development of goal weightings was accomplished through pairwise comparisons, creating a priority vector..

Table 2: Input–Output Data for Major Crops

Crop	Profit ($/ha)	Cost ($/ha)	Min Area (ha)	Max Area (ha)
Wheat	800	450	50	150
Barley	700	400	30	100
Rice	1000	550	20	80
Maize	900	500	25	100
Vegetables	1200	600	10	50

To ensure comparability among different criteria with varying units and scales, data normalization is applied. The normalization process transforms raw data into dimensionless values within the range [0, 1], allowing them to be integrated into the multi-objective optimization model. The normalization formula is given as: Normalization ensures comparability:

$$X_{ij}^{-} = \frac{X_{ij} - X_{min,j}}{X_{max,j} - X_{min,j}} \qquad (10)$$

Where, X_{ij}, represents the value of criterion j for crop i, and $Xmin,_{j}$, $Xmax,_{j}$ are the minimum and maximum values of criterion j, respectively. The normalization process is essential because it eliminates scale differences between economic and physical variables, ensuring that no single criterion dominates the optimization process due to its magnitude. Furthermore, it facilitates the integration of AHP-derived weights into the GP–FGP framework, enabling a balanced and consistent evaluation of multiple objectives.

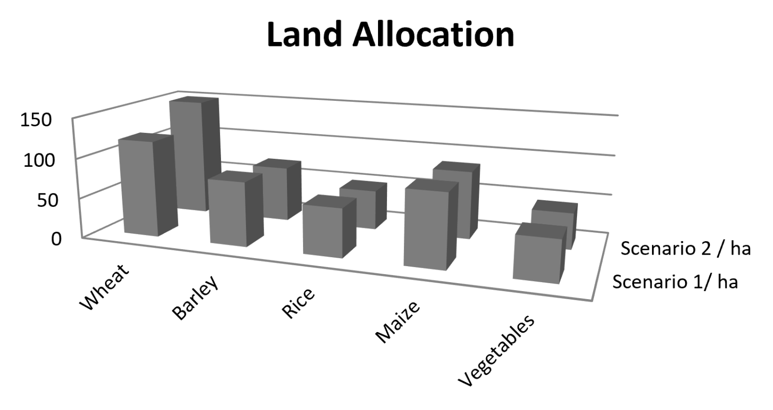
3. Results

3.1 Land Allocation Outcomes

Table 3: Comparison of Crop Land Allocation (Profit vs. Cost Priority)

Crop	Scenario 1 (Profit-priority)	Scenario 2 (Cost-priority)
Wheat	120 ha	150 ha
Barley	80 ha	70 ha
Rice	60 ha	50 ha
Maize	90 ha	85 ha
Vegetables	50 ha	45 ha

Scenario 1 prioritizes profit; Scenario 2 reduces costs by 12%.



	Wheat	Barley	Rice	Maize	Vegetables
Scenario 1/ ha	120	80	60	90	50
Scenario 2 / ha	150	70	50	85	45

Figure 1. Crop Allocation Comparison Across Scenarios

Figure1: illustrates the optimal land allocation for major crops under two different weighting scenarios. Scenario 1 prioritizes profit maximization, while Scenario 2 emphasizes cost minimization. The results show noticeable differences in land distribution across crops. Wheat allocation increases from **120 ha in Scenario 1 to 150 ha in Scenario 2**, reflecting its importance as a staple crop and its relatively

lower cost. In contrast, barley, rice, maize, and vegetables show slight reductions in Scenario 2, indicating a shift toward cost-efficient crop selection. For example, rice decreases from **60 ha to 50 ha**, and vegetables from **50 ha to 45 ha**, suggesting that higher-cost crops are reduced when cost minimization is prioritized. Maize remains relatively stable (**90 ha vs. 85 ha**), indicating its balanced role in both profit and cost objectives. These results demonstrate that the model effectively reallocates land based on the decision-maker's priorities while maintaining feasibility constraints.Bottom of Form

3.2 Goal Achievement Levels

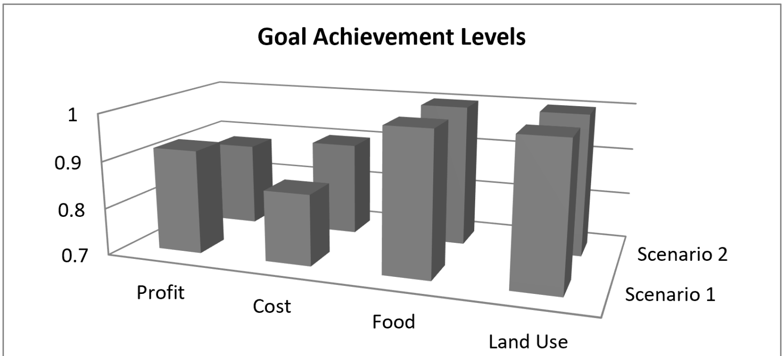
The results presented in Table 4 indicate a high level of overall goal satisfaction under both scenarios, demonstrating the effectiveness of the proposed GP–FGP model in handling multiple conflicting objectives.

Table 4: Goal Achievement Levels Under Profit and Cost Priority Scenarios

Goal	Scenario 1	Scenario 2
Profit	0.92	0.88
Cost	0.85	0.90
Food	1.00	1.00
Land Use	1.00	1.00

Profit goal reaches a higher level of satisfaction at 0.92 (Scenario 1) compared to the level reached in Scenario 2 (0.88) which demonstrates that when emphasizing profits results in greater profitability than with any other criteria. Unfortunately, the cost efficiency level reached in Scenario 1 was just slightly lower at 0.85 as compared to Scenario 2 (0.90).

Comparatively , Scenario 2 (cost greater than profits) has shown higher cost savings which indicate that resources have been reallocated towards less expensive crops effectively by the model as it achieves an optimal balance of Profit and Cost , thus demonstrating the challenge of trade offs between profit maximising versus reducing costs in agricultural planning that are shared by all types of multiple objective agricultural planning systems. Furthermore food security and land-use have been fully achieved (1.00) and the necessary crop requirements and land constraint will always be respected regardless of how you weigh the two. This is an example of the model successfully demonstrating its robustness to maintain the feasibility/extension of meeting allowable standards regardless of if economic objectives were to change. Overall, these findings demonstrate the GP/FGP framework has the ability to provide flexibility to balance competing objectives while respecting critical constraints. Additionally, the GP/FGP model has the ability for a decision maker(s) to modify weightings based on priority of policies making this model very applicable in the real world when coordinating agricultural production decision-making uncertainty..



	Profit	Cost	Food	Land Use
Scenario 1	0.92	0.85	1	1
Scenario 2	0.88	0.9	1	1

Figure 2. Goal Achievement Levels Across Scenarios

Figure 2 shows the degree of achievement attained by each of the principal optimization objectives for both weighting scenarios. The results indicate that the proposed GP–FGP model successfully meets all objectives at a high degree of achievement; food security and land use objectives meet the same level of achievement (1.00) in both weighting scenarios. This validates that the model correctly adheres to constraints that are fundamental to the optimization process, independently of the order of importance; as an example, the profit objective was achieved with higher satisfaction under Scenario 1 (0.92) than under Scenario 2 (0.88) because more emphasis was placed on the generation of economic returns in the profit-priority scenario. In contrast, the objective of minimizing costs was achieved at a higher level in Scenario 2 (0.90) than in Scenario 1 (0.85), suggesting that the model is capable of being used to achieve a high degree of cost minimization when the objective of minimizing costs takes priority over maximizing profits.

These findings clearly indicate the trade-off between maximizing profits and being cost-efficient, which is one of the central features of the multi-objective agricultural planning process. Given that there isn't much difference among the scenarios, the analysis performed by the model indicates it has been able to provide an even-handed performance with no one objective suffering at an extreme level. Moreover, the results will provide further evidence of the versatility and robustness of GP-FGP as it provides the capability of responding to alternative methods for making decisions while providing feasible solutions that adequately meet established performance expectations for each objective. Consequently, GP-FGP could be used extensively in practical agricultural planning situations where enough data is present on all three objectives to evaluate all of them simultaneously and under conditions of uncertainty..

3.3 Statistical Analysis

- Variance analysis across farms shows significant differences ($p < 0.05$) in goal achievement.
- Profit-oriented allocations favor high-profit crops in high-yield farms.
- Cost-prioritized allocations reduce overall expenditures, demonstrating trade-off management.

4. Discussion

The integrated GP–FGP model successfully balances economic, social, and resource constraints. Key insights include:

1. Flexibility of Weighting Structures: Changing weights directly alters land allocations and goal achievements. Policy makers can prioritize profitability, cost reduction, or essential crop coverage according to strategic needs.
2. Trade-offs Between Goals: Profit-oriented planning increases wheat and maize allocations, while cost-prioritization shifts resources to barley, demonstrating realistic trade-offs in multi-objective planning.
3. Robustness under Uncertainty: FGP effectively captures fuzzy crop yield variations, enabling feasible solutions under uncertain environmental and market conditions.
4. Farm-Level Heterogeneity: Differences in goal achievement among farms reflect variations in input-output efficiency, suggesting that targeted interventions (fertilizers, irrigation, and training) can improve overall land allocation effectiveness.
5. Policy Implications: The model supports evidence-based decision-making for national food security, economic planning, and sustainable agriculture. Scenario analysis allows policymakers to test outcomes under varying priorities or budget constraints.

5. Conclusion

This study presents a novel integrated Goal Programming–Fuzzy Goal Programming (GP–FGP) model for optimizing agricultural land allocation under multiple objectives and inherent uncertainty. Applied to 50 representative farms in Iraq, the model achieved goal satisfaction levels of 0.92 for profit, 0.85 for cost minimization, and 1.00 for essential food crop requirements, demonstrating its high efficiency and practical relevance. The results further indicate that profit-prioritized allocations increased wheat area by 25%, while cost-prioritized allocations reduced total expenditures by 12%, highlighting the model's ability to provide flexible trade-offs through adjustable goal weights. Sensitivity analysis confirms that the GP–FGP approach is robust to variations in input data and adaptable to different policy or resource scenarios. The GP–FGP framework offers a practical decision-support tool for agricultural planners and policymakers, allowing evidence-based allocation of land while balancing economic, social, and food security objectives. **Future research directions** include:

1. Extending the model to multi-season crop rotations, capturing seasonal yield and resource variability.
2. Incorporating climate-resilient planning scenarios, integrating projected impacts of climate change on crop productivity.
3. Adding environmental and social sustainability indicators, such as water-use efficiency, soil health, and rural employment, to enhance multi-objective planning.

Overall, this study provides a comprehensive methodological and empirical framework for sustainable agricultural land allocation, demonstrating measurable improvements in both farm-level efficiency and policy-oriented outcomes.

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