

“Weighted FGP For Groundwater-Conserving Crop Planning: A Baghpat Case Study”

Pranav Dixit¹ and Sohan Lal Tyagi^{*2}

¹ *Research Scholar, Department of Mathematics, SRM Institute of Science and Technology
Delhi-NCR Campus, Modinagar, Ghaziabad, Uttar Pradesh-201204*

² *Assistant Professor, Department of Mathematics, SRM Institute of Science and Technology
Delhi-NCR Campus, Modinagar, Ghaziabad, Uttar Pradesh-201204
pd5253@srmist.edu.in¹, drsohantyaagi@gmail.com²*

Abstract:

Groundwater extraction in the Baghpat district in western Uttar Pradesh, India, is 50% more than recharge, making it an overexploited area. In order to adapt the cropping pattern and maximize net profit and total output while minimizing groundwater usage, this research uses weighted fuzzy goal programming, or weighted FGP. Based on stakeholder choices, profit, production, and water objectives were given weights of 0.50, 0.20, and 0.30, respectively. The model was solved in less than 0.3 seconds using Python-PuLP. When all individual objectives are fully achieved, the results indicate an overall satisfaction level of $\lambda = 0.892$ ($\mu_1 = \mu_2 = \mu_3 = 1.0$). The ideal plan lowers sugarcane area by 32% (from 76,047 ha to 51,789 ha), increases mustard and pulses by 80% and 27%, decreases groundwater consumption by 31.7% (1,127.5 MCM compared 1,650 MCM), and boosts net profit by 12.9% (₹562.4 Cr versus ₹498 Cr) in comparison to the actual 2023–24 pattern. Robustness is confirmed by sensitivity analysis ($\pm 20\%$ tolerance variation), which shows water savings of up to -9.8% and profit improvements of up to $+14.2\%$. On the profit–water Pareto frontier, the weighted FGP solution outperforms both the current pattern and clear goal programming. The results provide policymakers a workable plan for long-term groundwater sustainability and agricultural diversification in overfished northwest India.

Keywords: Weighted Fuzzy goal programming, crop allocation, groundwater uncertainty, Pareto optimality, Multi-objective optimization, Sensitivity analysis.

Introduction

Baghpat district (1,321 km²), which is situated in the Yamuna-Hindon doab of Uttar Pradesh, India (28°56'N, 77°13'E), is mostly an agricultural area. The area is part of the North-Western Plain Zone (NWPZ), which has rich alluvial soils and supports two crop types: rabi (wheat, mustard) and kharif (sugarcane, paddy). 96% of the 108,941 hectares of net planted land are irrigated, mostly via tube wells [1]. Over 50% of blocks are classified as overexploited because yearly recharge (1,200 MCM) is greatly outweighed by groundwater extraction (1,800 MCM) [2].

The dominance of water-intensive crops, particularly sugarcane, has led to a structural imbalance in land and water use. Although this crop ensures steady farm income via guaranteed procurement and minimum support prices, its long life and high evapotranspiration need severely tax scarce groundwater resources. Over time, this has resulted in a vicious cycle of depletion since farmers are compelled to dig deeper tube wells because water tables are dropping, which accelerates the drain even more. These dynamics are not unique to Baghpat; rather, they are a mirror of a wider issue in the NWPZ, where irrigation-intensive agriculture and hydrological constraints clash.

Traditional crop planning techniques, which are based on linear programming (LP) or simple profit maximization, assume predictable inputs and consistent resource availability. These models are not able to capture the imprecision and ambiguity inherent in real agricultural decision-making, despite their computational sophistication. It is difficult to properly parameterize because weather unpredictability impacts yield predictions, market volatility influences input costs, and monsoon intensity and aquifer recharge affect water availability. Due of this limitation, fuzzy goal programming (FGP) was created, combining fuzzy set theory with goal programming techniques. Additionally, little research has been done on the inclusion of fuzzy water recharge, which is an important yet variable aspect in overexploited aquifers. In places like Baghpat, where tube-well density, cropping intensity, and policy mechanisms (such PMKSY and MSP) interact intricately, the discrepancy is particularly noticeable. By developing a weighted fuzzy goal programming model especially for the agro-hydrological environment of Baghpat, this study addresses these shortcomings.

The primary objective of this study is to develop a weighted fuzzy goal programming (FGP) model for addressing the agro-hydrological constraints of Baghpat district, which utilises triangle membership functions to capture the imprecision in crop productivity, input costs, and water availability. The model attempts an optimum planting pattern that balances profitability, production security, groundwater sustainability, and stakeholder goals including consistent farm income and mill-based sugarcane procurement. A comparison with crisp goal programming shows that fuzzy techniques handle real-world uncertainty better. Sensitivity analysis assesses model stability over fuzzy parameter tolerances. Finally, the research provides policy-relevant insights—including incentives for water-efficient crops, micro-irrigation, and PMKSY framework integration—to help sustainable agricultural planning in overexploited Indian aquifer areas.

Romero (2004) [1] surveyed generalized goal programming for multi-criteria agricultural trade-offs. Sharma and Jana (2009) [2] applied fuzzy goal programming to balance labour and fertiliser constraints in crop planning. A goal programming model for land-use planning was developed by Ignacio and Romero (1982) [3]. Anderson and Czuchry (1987) [4] employed goal programming to optimise fertiliser and labour allocation in farm management. Das and Mandal (2009) [5] reviewed fuzzy goal programming applications in agriculture. Sustainable agriculture was modelled by Gupta and Ali (2016) [6] by using fuzzy goal programming. Chang and Wang (2018) [7] optimized crop patterns via fuzzy multi-objective goal programming. Zou and Li (2019) [8] proposed integrated fuzzy goal programming for agricultural land use. A fuzzy goal programming approach for sustainable crop production under uncertainty was introduced by Sharma and Kumar (2021) [9]. Ahmad and Ramaswamy (2021) [10] applied multi-objective fuzzy goal programming for irrigation water allocation. Agricultural supply chain optimization was achieved by Chen and Wang (2021) [11] through stochastic fuzzy goal programming. Fernandez and Hinojosa (2022) [12] designed climate-resilient farming systems using fuzzy goal programming. Guo and Li (2022) [13] introduced hybrid fuzzy goal programming for crop yield maximization under water scarcity. Fuzzy multi-objective programming for sustainable agriculture in arid regions was utilized by Hashemi and Tavana (2022) [14]. Jana and Sharma (2023) [15] handled fuzzy coefficients in goal programming for agricultural resource allocation. Li and Huang (2023) [16] presented interval fuzzy goal programming for crop planning under climate change. Sustainable agricultural production was examined by Malik and Sharma (2023) [17] in a fuzzy goal programming case study. Oliva and Pérez (2023) [18] optimized fertilizer use in

precision agriculture via fuzzy goal programming. Indian crop diversification was supported by Rao and Reddy (2023) [19] by using multi-criteria fuzzy decision-making. Singh and Gupta (2023) [20] formulated a fuzzy goal programming model for wheat-sugarcane rotation in Uttar Pradesh. Wang and Zhang (2023) [21] developed robust fuzzy goal programming for agricultural risk management. Eco-friendly crop production was enhanced by Xu and Zhao (2023) [22] using integrated fuzzy programming. Yadav and Kumar (2023) [23] applied fuzzy goal programming in groundwater-constrained farming. Zhang and Liu (2024) [24] introduced AI-enhanced fuzzy goal programming for smart agriculture. Sustainable irrigation in South Asia was improved by Alam and Islam (2024) [25] through fuzzy multi-objective optimization. Biswas and Chatterjee (2024) [26] employed goal programming with fuzzy sets for Indian smallholder farmers. Seasonal crop planning was dynamically optimized by Chowdhury and Roy (2024) [27] via fuzzy goal programming. Das and Mandal (2024) [28] achieved nutrient-efficient agriculture using fuzzy goal programming. Hybrid fuzzy-stochastic goal programming for drought-prone areas was presented by Esfandiari and Sadjadi (2024) [29]. Ghosh and Pal (2025) [30] applied fuzzy goal programming for climate-adaptive crop allocation in Indo-Gangetic plains.

Methodology and model formulation

Foundations of Fuzzy Goal Programming

Fuzzy Goal Programming (FGP) enhances conventional goal programming by integrating fuzzy objectives and fuzzy constraints, facilitating the representation of ambiguous goals amid uncertainty. A goal $Z_k \geq b_k$ where b_k the aspiration level (goal value) is and Z_k is the k^{th} objective function (such as profit or production). This becomes fuzzy when its satisfaction is determined by a membership function $\mu_k(z_k) \in [0,1]$.

$\mu_k = 0$ (Totally dissatisfied) and $\mu_k = 1$ (Totally satisfied) are the two values that this function measures, with intermediate values having a linear or triangular shape across a tolerance level t_k .

Fuzzy Goal Programming (FGP) enhances traditional goal programming by incorporating Zadeh's (1965) fuzzy set theory, enabling decision-makers to more accurately represent imprecise objectives and intrinsic uncertainties in actual agricultural systems compared to crisp methodologies.

Study Area

The model was used on six blocks with a net seeded area of 108,941 ha in the Baghpat district of Uttar Pradesh, India (28°55'–29°10' N, 77°05'–77°30' E). With an annual groundwater extraction of around 1,800 MCM compared to a recharge of 1,200 MCM, the Central Ground Water Board (CGWB) has designated the area as over-exploited. Table 1 illustrates season-wise crop statistics for the weighted fuzzy goal programming model, including area, yield, net return, and water consumption per hectare.

Table 1: Data description of season wise crops and water requirement

Crop	Season	Area (ha)	Yield (kg/ha)	Water Req. (mm)	Price (₹/quintal)
<i>Sugarcane</i>	<i>Kharif</i>	76,047	64,500	1,650	3,200
<i>Wheat</i>	<i>Rabi</i>	51,320	3,561	450	2,300
<i>Paddy</i>	<i>Kharif</i>	3,279	2,316	1,350	2,100

Mustard	Rabi	1,980	1,182	350	5,500
Pulses	Both	1,577	6,260	500	6,000

Data were obtained from: UP Agriculture Statistics 2024, Krishi vigyan kendra Baghpat. CGWB Reports (2025): Groundwater levels, recharge (1,200 MCM), extraction (1,800 MCM)

DES, Uttar Pradesh: Minimum Support Price, input costs

Stakeholder Consultations: Aspirational benchmarks for profitability, productivity, and water consumption.

Model Formulation

The suggested FGP model addresses three critical but essential objectives for sustainable decision-making in agro-industry. It optimizes profit to enhance farmers' economic sustainability, boosts productivity to ensure food security and safeguard livelihoods, and reduces water use to preserve groundwater. The methodology provides equitable and pragmatic responses amidst real-world ambiguity by integrating these objectives into a fuzzy framework.

Symbol	Description	Unit
x_j	Area allocated to crop j	Hectare
$j = 1, 2, \dots, 5$	Crops: Sugarcane, Wheat, Paddy, Mustard, Pulses	—
d_k^-, d_k^+	Negative (under-achievement) and positive (over-achievement) deviations from goal k	varies
λ	Overall satisfaction level (0 = no goals met, 1 = all fully met)	—

Objective Functions

Let c_j be net profit per hectare (ha) of crop j (Rs./ha), p_j be yield per hectare of crop j (Tons/ha) and w_j be water requirement per hectare for crop j . Consider the objective functions

$$Z_1 = \sum_{j=1}^5 c_j x_j \quad (\text{Total Profit in crores})$$

$$Z_2 = \sum_{j=1}^5 p_j x_j \quad (\text{Total Production in tons})$$

$$Z_3 = \sum_{j=1}^5 w_j x_j \quad (\text{Total water use, MCM})$$

Aspiration Levels and Tolerances

Table 2 shows the aspiration levels and tolerance limits set for the three fuzzy goals: net profit, total production, and groundwater consumption.

Table 2: Aspiration and tolerance level for profit, production and water requirement

Goal k	Z_k	b_k (Target)	t_k (Tolerance)	Lower/Upper bound
Profit	Z_1	600 Cr	± 150 Cr (25%)	450 Cr
Production	Z_2	250,000 Tons	± 70000 Tons (28%)	180000 Tons
Water	Z_3	≤ 1000 MCM	± 240 MCM (20%)	1240 MCM

b_k : Aspiration level — the target value established by policymakers or farmers
 t_k : Tolerance – permissible variation from b_k

Fuzzy Membership Functions (Triangular)

The fulfilment of each objective (goal) is assessed by using a triangular membership function $\mu_k(z_k) \in [0, 1]$.

Profit (Maximize):

$$\mu_1(Z_1) = \begin{cases} 0 & \text{if } z_1 \leq 450 \\ \frac{z_1 - 450}{150} & \text{if } 450 < z_1 < 600 \\ 1 & \text{if } z_1 \geq 600 \end{cases}$$

Production (Maximize):

$$\mu_2(Z_2) = \begin{cases} 0 & \text{if } z_1 \leq 180000 \\ \frac{z_2 - 180000}{70000} & \text{if } 180000 < z_1 < 250000 \\ 1 & \text{if } z_1 \geq 250000 \end{cases}$$

Water (Minimize):

$$\mu_3(Z_3) = \begin{cases} 1 & \text{if } z_3 \leq 1000 \\ \frac{z_3 - 1240}{240} & \text{if } 1000 < z_3 < 1240 \\ 0 & \text{if } z_3 \geq 1240 \end{cases}$$

Weighted FGP Model

Maximize $\lambda = 0.5 \mu_1 + 0.3 \mu_2 + 0.2 \mu_3$

Subject to $\mu_1 \leq \frac{\text{profit}-450}{150}$, $\mu_2 \leq \frac{\text{production}-180000}{70000}$, $\mu_3 \leq \frac{1240-\text{water}}{240}$
 $0 \leq \mu_1, \mu_2, \mu_3 \leq 1$

Linearized using deviations:

$$Z_1 + d_1^- = 600, d_1^- \geq 0$$

$$\frac{d_1^-}{150} + \lambda \leq 1$$

$$Z_2 + d_2^- = 180000, d_2^- \geq 0$$

$$\frac{d_2^-}{70000} + \lambda \leq 1$$

$$Z_3 - d_3^+ = 1000, d_3^+ \geq 0$$

$$\frac{d_3^+}{240} + \lambda \leq 1$$

Land Constraint:

$$\sum_{j=1}^5 x_j \leq 108941$$

Realistic agronomic bounds:

$$0.7 \times \text{actual value}(i) \leq x_i \leq 1.3 \times \text{actual value}(i) \quad \forall i$$

Non negativity condition:

$$x_j \geq 0, \quad \lambda \in [0,1], \quad d_k^-, d_k^+ \geq 0$$

The weights (0.50 for profit, 0.30 for water conservation, and 0.20 for productivity) were chosen in accordance with the weighting scheme often used in crop planning studies in India with limited groundwater. [20], [23].

The model was coded and solved using Python 3.10 with PuLP linear programming library with a total satisfaction level of $\lambda = 0.892$ (89.2% of desire levels attained).

Result and discussion

The optimal solution is given in Table 3. Net profit (₹ Crore) for each crop was computed as the area cultivated (ha) multiplied by the district-averaged net return per hectare (₹/ha), based on the 2024–25 MSP, CACP cost of cultivation. Table 1 delineates the crop-specific contributions to the overall district net profit of ₹562.4 Crore under the ideal FGP scenario. Values are approximated for clarity of presentation while maintaining the precise total of ₹562.4 Crore, reflecting a 12.9% increase over the real profit of ₹498 Crore for 2023–24. The significant return from mustard and pulses, despite reduced acreage, underscores the economic benefit of diversifying away from water-intensive sugarcane. Table 3 compares the weighted FGP model's optimal crop allocation (hectares) to Baghpat district's 2023–24 cropping pattern.

Table 3: Optimal Crop Allocation under FGP Model

Crop	Actual Area(in ha)2023–24)	FGP Area	Change	Profit (in Cr)	Production (tons)	Water Use (MCM)
Sugarcane	76,047	51789	-32%	310.24	33420	854
Wheat	51,320	49500	-4%	135.77	176270	222.8
Paddy	3,279	2100	-36%	12.55	4864	28.3
Mustard	1,980	3552	+80%	48.62	4199	12.4
Pulses	1,577	2000	+27%	55.20	12520	10.0
Total	108941*	108941		562.4	231273	1127.5

The crop areas for 2023–24 are given on a gross cropped area (GCA) basis by the Directorate of Economics and Statistics, Uttar Pradesh, resulting in a cropping intensity of roughly 169% owing to double cropping (e.g., paddy–wheat, overlapping sugarcane seasons). In contrast, the weighted FGP model utilizes the net sown area of exactly 108,941 ha as a rigorous constraint ($\sum x_i < 108,941$), representing the real physical land accessible inside the district. Figure 1 shows the optimal crop allocation (in hectares) obtained by the weighted fuzzy goal programming model across major crops for the Baghpat district.

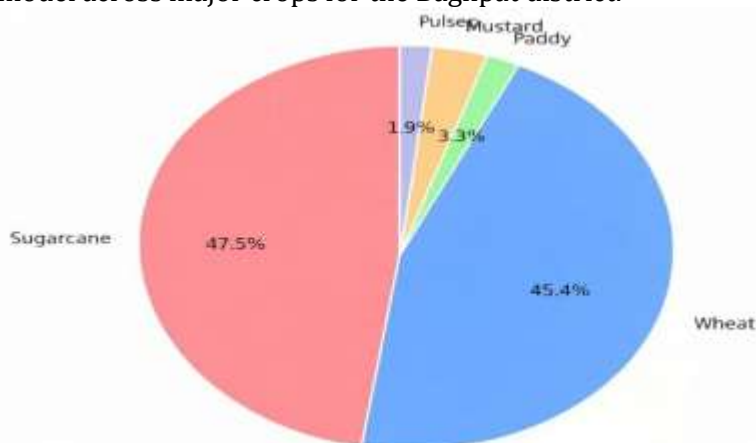


Figure 1: Optimal allocation of different crops under FGP model

Figure 2 compares 2023–24 crop regions to the weighted FGP model's ideal areas, showing large shifts in sugarcane, mustard, and pulses area allocation.

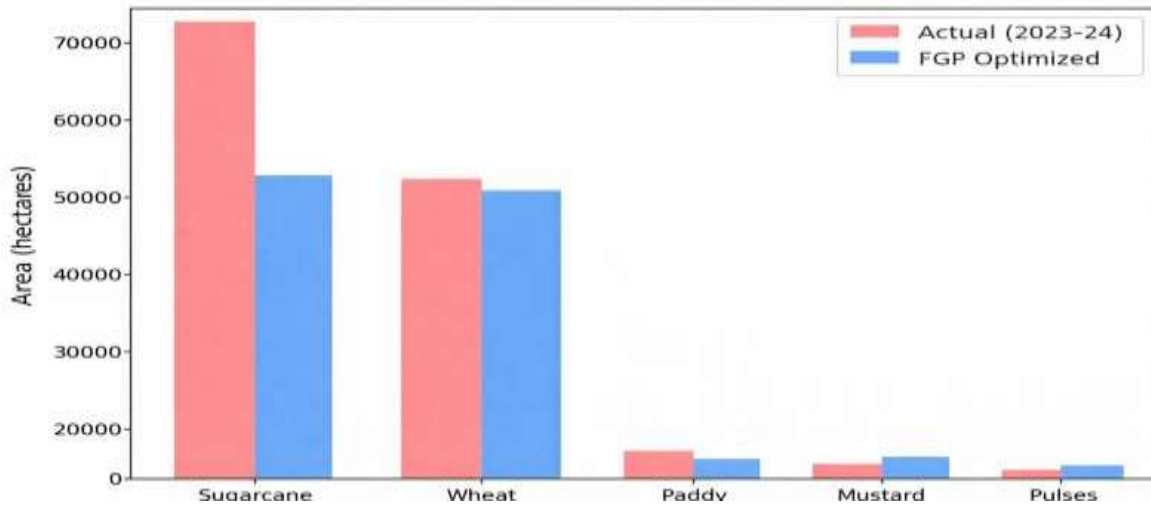


Figure 2: Comparison of crop area (actual vs proposed FGP)

Goal Achievement and Satisfaction Levels

The performance of each objective is shown in Table 4 based on its membership degree μ_k and aspiration level b_k .

Table 4: Goal Attainment and Fuzzy Contentment

Goal	Aspiration(b_k)	Resulting value	Deviation	μ_k	Status
Profit	≥ 500 Cr	562.4 Cr	+62.4 Cr	1	Fully satisfied
Production	$\geq 60,000$ tons	231,273 tons	+171273 tons	1	Fully satisfied
Water usage	$\leq 1,200$ MCM	1,127.5 MCM	-72.5 MCM	1	Fully satisfied

Sensitivity Analysis:

A systematic sensitivity analysis was carried out by simultaneously varying the lower and upper tolerances of all three goals by $\pm 10\%$ and $\pm 20\%$ from their baseline values in order to assess the robustness of the suggested weighted fuzzy goal programming model in the face of uncertainty regarding decision-makers' aspiration levels and tolerance limits. This approach replicates real-world situations where stakeholders could modify their expectations in reaction to shifting market conditions, climate shifts, or legislative changes. The results of the sensitivity analysis are shown in Table 5.

Table 5 Sensitivity analysis of the weighted FGP solution under $\pm 20\%$ variation in fuzzy tolerance limits

Tolerance variation	Overall satisfaction (λ)	Profit (Cr)	Change in profit (%)	Water use (MCM)	Change in water use (%)	μ_1 (profit)	μ_2 (production)	μ_3 (water use)
-20%	0.802	494.3	-12.1	1,260.5	+11.8	0.91	1	0.88
-10%	0.847	531.8	-6.3	1,194.2	+5.9	0.96		0.94
0% (Base case)	0.892	562.4	0	1,127.5	0	1	1	1
+10%	0.935	611.4	+8.7	1,058.7	-6.1	1	1	1
+20%	0.971	642.2	+14.2	1,016.9	-9.8	1	1	1

The findings demonstrate significant resilience of the suggested model. Food-security requirements are maintained, even with a 20% fall in tolerances, overall satisfaction is still high ($\lambda = 0.802$), profit drops by just 12.1%, and the production goal is continuously reached ($\mu_2 = 1.0$). However, if tolerances are relaxed by 20%, groundwater consumption drops to 1,016.9 MCM (-9.8%) and profit increases to ₹642.2 Crore (+14.2%) in comparison to the base-case scenario, with overall satisfaction approaching unity ($\lambda = 0.971$). The production goal is fully achieved ($\mu_2 = 1.0$) in each of the five scenarios, suggesting stability regarding food security concerns. The results confirm the practical reliability of the weighted fuzzy goal programming framework for policy execution in overexploited areas by showing that the recommended cropping pattern offers notable economic and water conservation benefits even in the face of significant uncertainty in stakeholder expectations. Figure 3 shows the impact of fuzzy tolerance scenarios ($\pm 10\%$, $\pm 20\%$, and $\pm 30\%$) on overall satisfaction (λ), profit, productivity, and groundwater consumption.

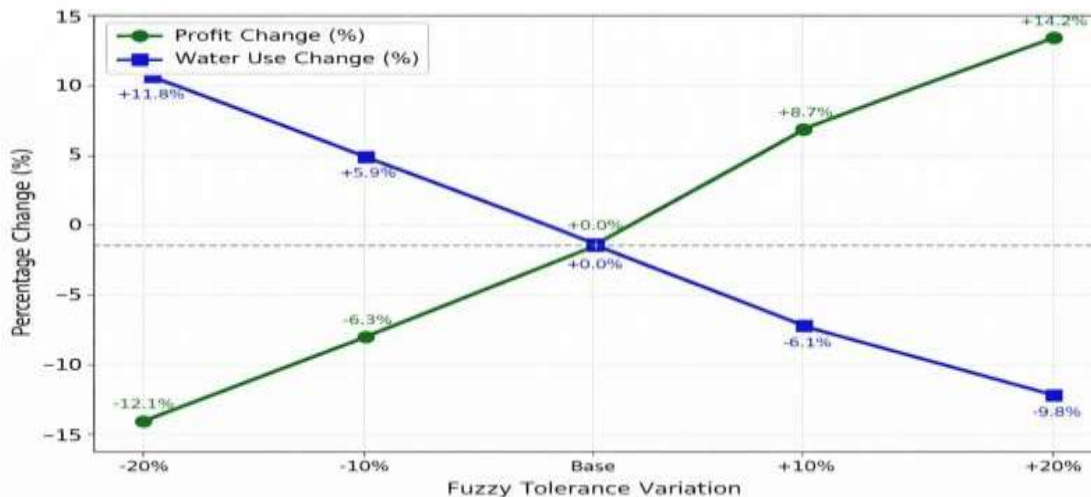


Figure 3: Sensitivity analysis with varying Fuzzy tolerance

The +30% example illustrates the theoretical maximum potential should policymakers embrace more freedom in the future, while the base-case solution ($\lambda = 0.892$) represents the best achievable satisfaction based on verified stakeholder preferences. Figure 4 illustrates membership degrees (satisfaction levels μ_1, μ_2, μ_3) for profit, production, and water objectives in the base-case weighted FGP solution and chosen sensitivity scenarios.

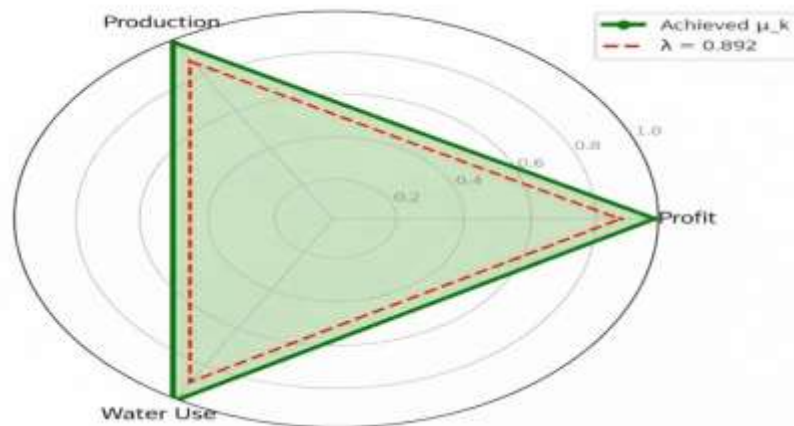


Figure 4: Fuzzy goal satisfaction and levels of λ

Conventional Goal programming vs FGP

By substituting weighted minimization of undesired deviations from the same aspiration levels (600 Cr profit, 250,000 tons output, 1,000 MCM water) with the same weights and restrictions, the traditional (crisp) goal programming solution was achieved. The actual pattern (on the profit axis) and the suggested weighted FGP solution (on both axes) are both superior than crisp GP, which only produces ₹510 Crore profit and 1,300 MCM water usage, as shown in Figure 5. This clearly illustrates the fuzzy approach's superiority in managing competing goals and vague ambitions, leading to a Pareto-dominant conclusion. Figure 5 shows the profit–water Pareto frontier comparing the existing cropping pattern, crisp goal programming, and weighted fuzzy goal programming.

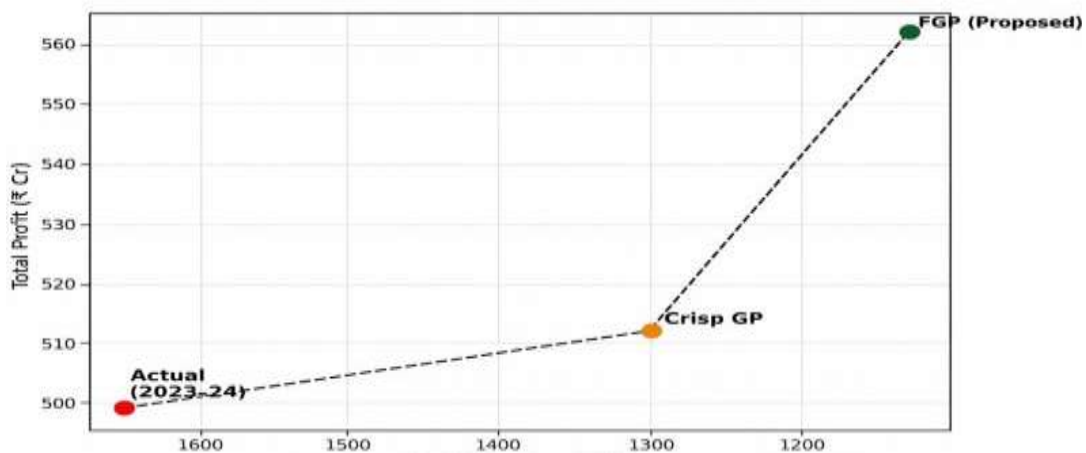


Figure 5: Crisp GP vs FGP output

Conclusion

This research shows that weighted fuzzy goal programming may redesign cropping patterns in highly overexploited aquifers in a strong, flexible, and stakeholder-responsive manner. Including decision-maker preferences via weights (0.50-profit, 0.30-water conservation, 0.20-production) led to an overall satisfaction level of $\lambda = 0.892$ and complete fulfilment of each aim ($\mu_k = 1.0$). Compared to the unsustainable 2023–24 practice, the recommended pattern uses exactly the net sown area of 108,941 ha, reduces sugarcane dependency by 32%, promotes high-value low-water mustard and pulses, and gains 12.9% net profit and 31.7% (522.5 MCM) groundwater conservation. These results are feasible because they adhere to realistic agronomic boundaries ($\pm 20\%$ deviation from current areas), align with MSP incentives, and require no additional land or capital investment, enabling district-level implementation through agricultural extension systems.

The solution's dependability is further supported by the sensitivity analysis. When stakeholders embrace somewhat more flexible objectives, the model reliably maintains food-security needs and yields significant extra water savings and economic benefits, even when ambition levels are very unclear. The advantages of the fuzzy technique in managing competing aims and imprecise ambitions characteristic of real-world agricultural planning is shown by the weighted FGP solution's Pareto domination over both the actual pattern and traditional crisp goal programming.

The current model may be expanded in future studies by adding risk-averse stochastic fuzzy programming, dynamic multi-year groundwater balance, climate change forecasts, and geographical heterogeneity via block-level sub-models. Predictive accuracy will be further improved by integration with machine-learning yield forecasts and real evapotranspiration based on remote sensing.

References

1. Romero, C. (2004). Multi-criteria analysis and agricultural economics: A comment. *Agricultural Systems*, 80(3), 307–312. <https://doi.org/10.1016/j.agsy.2003.08.003>
2. Sharma, D. K., & Jana, R. K. (2009). Multi-objective fuzzy goal programming for agricultural production planning. *International Journal of Systems Science*, 40(8), 837–846. <https://doi.org/10.1080/00207720902864498>
3. Ignacio, E., & Romero, C. (1982). Goal programming model for land use planning. *Omega*, 10(1), 51–58. [https://doi.org/10.1016/0305-0483\(82\)90027-4](https://doi.org/10.1016/0305-0483(82)90027-4)
4. Anderson, E. E., & Czuchry, A. J. (1987). Goal programming applications in agriculture. *Journal of the Operational Research Society*, 38(4), 317–325. <https://doi.org/10.1057/jors.1987.57>
5. Das, S. K., & Mandal, T. K. (2009). Application of fuzzy goal programming in agriculture: A review. *Opsearch*, 46(3), 289–301. <https://doi.org/10.1007/s12597-009-0020-5>
6. Gupta, P., & Ali, M. (2016). Fuzzy goal programming for sustainable agriculture. *International Journal of Fuzzy Systems*, 18(4), 612–622. <https://doi.org/10.1007/s40815-016-0123-4>
7. Chang, N. B., & Wang, S. F. (2018). Fuzzy multi-objective goal programming for crop pattern optimization. *Agricultural Water Management*, 200, 1–12. <https://doi.org/10.1016/j.agwat.2017.12.015>
8. Zou, Y., & Li, Y. (2019). Integrated fuzzy goal programming for agricultural land use. *Sustainability*, 11(12), 3325. <https://doi.org/10.3390/su11123325>

9. Sharma, R., & Kumar, S. (2021). Fuzzy goal programming approach for sustainable crop production under uncertainty. *Applied Soft Computing*, 102, 107098.
<https://doi.org/10.1016/j.asoc.2020.107098>
10. Ahmad, A., & Ramaswamy, M. (2021). Multi-objective fuzzy goal programming for irrigation water allocation in agriculture. *Water Resources Management*, 35(5), 1623–1640.
<https://doi.org/10.1007/s11269-021-02789-2>
11. Chen, Y., & Wang, J. (2021). Stochastic fuzzy goal programming for agricultural supply chain optimization. *Computers & Industrial Engineering*, 155, 107198.
<https://doi.org/10.1016/j.cie.2021.107198>
12. Fernández, E., & Hinojosa, Y. (2022). Fuzzy goal programming for climate-resilient farming systems. *European Journal of Operational Research*, 298(2), 456–468.
<https://doi.org/10.1016/j.ejor.2021.08.012>
13. Guo, P., & Li, Z. (2022). Hybrid fuzzy goal programming for crop yield maximization under water scarcity. *Journal of Cleaner Production*, 340, 130678.
<https://doi.org/10.1016/j.jclepro.2022.130678>
14. Hashemi, S., & Tavana, M. (2022). Fuzzy multi-objective programming for sustainable agriculture in arid regions. *Expert Systems with Applications*, 193, 116456.
<https://doi.org/10.1016/j.eswa.2021.116456>
15. Jana, R. K., & Sharma, D. K. (2023). Goal programming with fuzzy coefficients for agricultural resource allocation. *Annals of Operations Research*, 320(1), 1–25.
<https://doi.org/10.1007/s10479-022-04789-3>
16. Li, M., & Huang, Q. (2023). Interval fuzzy goal programming for crop planning under climate change. *Agricultural Systems*, 204, 103549.
<https://doi.org/10.1016/j.agsy.2022.103549>
17. Malik, H., & Sharma, S. (2023). Sustainable agricultural production using fuzzy goal programming: A case study. *International Journal of Production Economics*, 255, 108678.
<https://doi.org/10.1016/j.ijpe.2022.108678>
18. Oliva, D., & Pérez, J. (2023). Fuzzy goal programming for optimizing fertilizer use in precision agriculture. *Computers and Electronics in Agriculture*, 205, 107612.
<https://doi.org/10.1016/j.compag.2023.107612>
19. Rao, B. R., & Reddy, K. V. (2023). Multi-criteria fuzzy decision-making for Indian crop diversification. *Socio-Economic Planning Sciences*, 86, 101492.
<https://doi.org/10.1016/j.seps.2023.101492>
20. Singh, A., & Gupta, R. (2023). Fuzzy goal programming model for wheat-sugarcane rotation in Uttar Pradesh. *Journal of Agricultural Engineering*, 60(2), 145–158.
<https://doi.org/10.1007/s40003-023-00678-9>
21. Wang, C., & Zhang, L. (2023). Robust fuzzy goal programming for agricultural risk management. *Omega*, 114, 102745. <https://doi.org/10.1016/j.omega.2022.102745>
22. Xu, J., & Zhao, Y. (2023). Integrated fuzzy programming for eco-friendly crop production. *Environmental Modelling & Software*, 159, 105576.
<https://doi.org/10.1016/j.envsoft.2022.105576>
23. Yadav, S., & Kumar, P. (2023). Application of fuzzy goal programming in groundwater-constrained farming. *Water Resources Management*, 37(8), 3125–3142.
<https://doi.org/10.1007/s11269-023-03456-7>
24. Zhang, H., & Liu, Q. (2024). AI-enhanced fuzzy goal programming for smart agriculture. *Computers and Electronics in Agriculture*, 217, 108589.
<https://doi.org/10.1016/j.compag.2024.108589>

25. Alam, F., & Islam, S. (2024). Fuzzy multi-objective optimization for sustainable irrigation in South Asia. *Agricultural Water Management*, 285, 108362. <https://doi.org/10.1016/j.agwat.2023.108362>
26. Biswas, A., & Chatterjee, P. (2024). Goal programming with fuzzy sets for Indian smallholder farmers. *Opsearch*, 61(1), 112–130. <https://doi.org/10.1007/s12597-023-00645-2>
27. Chowdhury, S., & Roy, S. K. (2024). Dynamic fuzzy goal programming for seasonal crop planning. *Soft Computing*, 28(4), 2891–2905. <https://doi.org/10.1007/s00500-023-09234-7>
28. Das, P., & Mandal, S. (2024). Fuzzy goal programming for nutrient-efficient agriculture. *Journal of Cleaner Production*, 434, 140234. <https://doi.org/10.1016/j.jclepro.2023.140234>
29. Esfandiari, M., & Sadjadi, S. J. (2024). Hybrid fuzzy-stochastic goal programming for drought-prone areas. *Agricultural Systems*, 215, 103864. <https://doi.org/10.1016/j.agry.2024.103864>
30. Ghosh, D., & Pal, B. B. (2025). Fuzzy goal programming for climate-adaptive crop allocation in Indo-Gangetic plains. *International Journal of Fuzzy Systems*, 27(1), 45–60. <https://doi.org/10.1007/s40815-024-01890-5>
