https://doi.org/10.56093/JISAS.V79I3.7
Available online at http://isas.org.in/isa/jisas
JOURNAL OF THE INDIAN SOCIETY OF AGRICULTURAL STATISTICS 79(3) 2025 267–278

Multi-objective Crop Plan for Optimal Groundwater using Non-dominated Sorting Genetic Algorithms

Kamalika Nath[1], Rajni Jain[2], Ranjit Kumar Paul[1] and Himadri Shekhar Roy[1]
[1]ICAR-Indian Agricultural Statistics Research Institute, New Delhi
[2]ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi

Received 16 December 2025; Revised 23 January 2026; Accepted 06 February 2026

SUMMARY

Agriculture plays an exceedingly pivotal role in the future growth and development of a nation, relying heavily on its water and land resources. To achieve maximum agricultural productivity, it is crucial to ensure timely and adequate supply of both land and water for irrigated farming. This necessitates precise planning and execution of water resource management, coupled with the incorporation of modern technologies to optimize the utilization of available resources. A significant task in economic and sustainable agricultural decision-making involves optimizing resource constraints within a given planting period. Considering the socioeconomic conditions, the present study tackles a multi-objective optimization problem to identify an optimal crop plan that simultaneously maximizes profit while minimizing groundwater usage. In single-objective optimization problems, determining the superior solution was straightforward by comparing objective function values, whereas in multi-objective optimization, dominance criteria are employed for determination. The study focuses on the genetic algorithm based NSGA-II and NSGA-III algorithms, comparing their performance and effectiveness through result analysis. Additionally, graphical comparisons are presented to showcase the Pareto fronts. The findings indicate that NSGA-III is a more viable tool for addressing optimal crop planning problems compared to NSGA-II.

Keywords: Crop planning; Genetic algorithm; NSGA; Optimization; Pareto optimal.solution.

1. INTRODUCTION

Agriculture sustains the livelihoods of a significant portion of India's population, but it faces complexity and uncertainty due to various production factors. Thus, enhancing farmers' income becomes a paramount concern for decision-makers, researchers, and policymakers. Advancing techniques and appropriate management practices contribute to achieving the objectives of agricultural planning and policy development. Optimization of limited resources has become indispensable to maximize profit, production, and productivity. Several factors impact farmers' earnings, including crop yield, resource efficiency, cropping intensity, and more. Crop planning encompasses numerous considerations such as land suitability, weather conditions, precipitation, irrigation systems, groundwater availability, agricultural inputs (machinery, fertilizers, capital, labor), production costs, and others. In addition to agricultural water management, crop planning plays a crucial role in determining the allocation of water to different crop areas, aiming to attain specific objectives, such as maximizing profit within the constraints of limited land and water resources (Zeng *et al.* 2010).

Danapour*et al.* (2021) described the importance of optimimal allocation of of groundwater abstraction at multiple catchment scales using linear programming. Utilization of several nature-inspired metaheuristic techniques, namely Differential Evolution (DE), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), are investigated by Nath*et al.* (2019) to identify the most efficient crop plan to maximise net farm benefits. Several researchers (Kuo *et al.* 2000; Raju and Kumar, 2004; Olakulehin and Omidiora, 2014 and

Corresponding author: Himadri Shekhar Roy
E-mail address: himadriiasri@gmail.com

Mansourifar *et al.* 2013) used Genetic Algorithm (GA) to maximize benefit from different cropping patterns. Sarma *et al.* (2006), Annepu *et al.* (2011), and Sadati *et al.* (2014) investigated GA to identify optimal crop plans by considering the several constraints to maximize net profit.

Multi-objective optimization involves tackling problems that encompass multiple objective functions. In the optimization process, the aim is to find the best solutions that optimize more than one objective, considering both maximum and minimum values. Multi-objective optimization poses challenges across diverse fields, such as mathematics, engineering, social sciences, economics, agriculture, aviation, and the automotive industry. In agriculture, it is crucial to not only optimize a single objective but also strive for optimal crop planning that effectively utilizes resources by simultaneously optimizing multiple objectives. The presence of multiple objectives adds complexity to the decision-making process. Consequently, agricultural systems and crop planning become intricate, necessitating the simultaneous consideration of multiple conflicting objectives (Xevi and Khan, 2005). Solving such problems differs from addressing single-objective optimization problems, as multi-objective optimization problems typically yield a set of solutions, all of which are equally favorable.

A wide variety of nature-inspired and evolutionary algorithms (EA's) have been used to solve optimization problems consisting of only one objective function. In recent years, nature-inspired optimization algorithms gained popularity to tackle multi-objective problems due to their profound efficiency to solve numerous complex problems in several fields of science. A non-dominated sorting genetic algorithm-II (NSGA-II) was developed to overcome various issues (Deb *et al.,* 2002) related to Multi-Objective Evolutionary Algorithms (MOEA). NSGA (Jarin *et al.,* 2006) was also applied for the crop planning model to maximize total net benefit and minimize total cost. NSGA-II (Pal *et al.,* 2009; Lalehzari *et al.,* 2016; Sarker and Ray, 2009; Yusoff *et al.,* 2011 and Fanuel *et al.* 2018) gains much popularity to solve multi-objective crop planning problems, water irrigation problems, etc. and in contrast to the strategy of single-objective optimization, NSGA-II optimizes every objective independently. To tackle some disadvantages of NSGA-II, related to mainly two and three objectives, Deb, K. and Jain, H. (2013) and Jain, H. and Deb, K. (2013) introduced reference-point based NSGA-III algorithm. NSGA-III (Mwiya *et al.,* 2020), an advanced version of NSGA-II, was investigated to maximize net benefits and water use efficiency and minimization of risk.

Recent studies highlight the growing role of multi-objective optimization in sustainable agricultural land and water management. Integrated land–water frameworks improve resource-use efficiency in agriculture-dominated basins (Buri *et al.,* 2025), while fuzzy multi-objective models effectively address uncertainty in water-scarce and arid regions (Mirzaie, 2024). GIS-based optimization using NSGA-II has shown strong potential for spatial crop allocation by balancing productivity and resource constraints (Krityakierne *et al.,* 2025), and improved NSGA-II variants further enhance basin-scale water allocation under severe scarcity (Cheng *et al.,* 2025). Expanding this scope, NSGA-III based approaches support collaborative optimization of the water–energy–grain nexus, with digital twins strengthening decision reliability in irrigation systems (Huang *et al.,* 2025). At the methodological level, systematic reviews emphasize the flexibility and robustness of multi-objective evolutionary algorithms (Pătrăușanu *et al.,* 2024), while survey studies on search strategies provide essential guidance for selecting suitable algorithms for complex agricultural and water resource decision-making problems (Wang *et al.,* 2023).

The paper is arranged accordingly. A mathematical model for the crop planning problem is presented in section 2.1. Section 2.2 and 2.3 provide a short description of the features of multi-objective methods employed. Section 3describes the data used in the study and its sources. Section 4 provides the results and discussions. In the final section, we summarize the findings and future directions for research.

2. MATERIALS AND METHODS

2.1 Model formulation

In the present section, the required mathematical formulation of the model is presented. An objective function and a set of constraints are described below.

2.2 Objective functions

The problem of crop planning formulated for the study has two goals. At the same time, the model maximizes profit and minimizes groundwater use that irrigates crops. The goal is to use the limited resources effectively to determine the allocation of land for several crops to be planted annually. The objectives and constraints of the optimization model are:

Objective function 1:

Maximization of profit:

$$\text{Maximize } Z_1 = \sum_{i}^{n}\left[\left(Y_i * P_i * A_i\right) - \left(C_i * A_i\right)\right] \quad (1)$$

Objective function 2:

Minimization of irrigation water: The volume of groundwater to be used for irrigating the crops will be minimized due to the shortage of water in the study area.

$$\text{Minimize } Z_2 = \sum_{i=1}^{n}(W_{ri} * A_i) \quad (2)$$

2.3 Constraints

i. Ground-water constraints:

$$\sum(W_{ri} * A_i) \le W_t \quad (3)$$

The groundwater usage should be less than or equal to groundwater available for agriculture.

ii. Constraint regarding total available area for cultivation:

$$\sum A_i \le A_t \quad (4)$$

The sum of land area used for the cultivation of all crops in a given season must be less than or equal to the total available land area

iii. Non-negative constraints:

$$A_i \ge 0 \quad (5)$$

iv. Min-max area constraints:

$$L_{bi} \le A_i \le U_{bi} \quad (6)$$

Crop area must fall within a given boundary.

2.4 Notations

i = 1, 2 … n

n = Number of crops considered in the study area; n= 14 (for kharif season) and n=11 (for rabi season)

Z_1 = Net profit (Rs)

Z_2 = groundwater use

Y_i = Yield of i^{th} crop per unit area (kg/ha)

P_i = Price of each crop in the market (both main product and by-products) (Rs/kg)

$$C_i = (\text{costofseed})_i + (\text{costofhumanlabour})_i + (\text{costofmachines})_i + (\text{costofanimallabour})_i + (\text{costoffertilizersandmanures})_i + (\text{miscellaneouscosts})_i$$

W_{ri} = Water requirement for each Crop (cubic meter)

W_t = Total available water (cubic meter)

A_i = Area under ith crop (thousand hectares)

A_t = Total available area for cultivation (thousand hectares)

L_{bi} = Lower bound of area for each crop (thousand hectares)

U_{bi} = Upper bound of area for each crop (thousand hectares)

2.5 Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

The purpose of conventional single-objective optimisation is to identify a single best solution that minimises or maximises a particular objective function. Nevertheless, there are frequently conflicts between the several objectives that must be optimised at once in many real-world problems. When constructing an automobile, for instance, one goal would be to maximise speed while another might be to reduce fuel consumption. The NSGAII may be a second-generation MOEA developed by Deb *et al.* (2002) which improved upon the original NSGA by employing a more efficient non-domination sorting scheme, removing the sharing parameter, and adding an implicitly elitist method of selection that greatly helps to capture Pareto surfaces (Wang *et al.* 2011). The problem becomes more complicated because of these competing goals.

In addition, the NSGA-II can handle both real and binary representations (Wei *et al.,* 2009). NSGA-II was used in earlier crop planning studies successfully (Sarker and Ray 2009). The concept of Pareto-dominance is employed to assign fitness values to the sampling solutions. For instance, X1 dominates X2 if and only if it performs as well as X2 in all objectives and better in at least one objective. The fast-non-domination sorting approach of the NSGA-II ranks each solution consistent with the number of solutions that dominate it. Once fitness is assigned, a two-step crowded binary tournament selection is performed. In cases where two solutions have different ranks, the individual with the inferiority is preferred. Alternatively, if both solutions possess an equivalent rank, then the answer with the larger crowding distance is preferred. Solutions with higher crowding distances add more diversity to the answer population, which helps to make sure that the NSGA-II finds solutions along with the complete extent of the Pareto surface. The workflow of the algorithm is summarized as follows:

a. Initialization: Create an initial population of potential solutions at random or by applying a heuristic technique.

b. Fitness evaluation: Evaluate of objective function of each candidate solution in the population.

c. Non-Dominated Sorting: Sorting the population into various non-dominated fronts in accordance with the dominance relationship is known as non-dominated sorting. If one solution is superior to another in at least one area while not doing worse in any other area, then it is superior overall.

d. Crowding Distance Assignment: Give each answer in each front a crowding distance by using the crowding distance assignment method. The crowding distance calculates the density of solutions in the area of the objective space that surround a specific solution.

e. Selection: Based on non-dominance level and crowding distance, choose individuals from the existing population to produce the next generation.

f. Crossover and mutation: Genetic operators like crossover and mutation can be used to produce offspring solutions from the chosen individuals.

g. Replacement: Create the following population by combining the solutions for the parents and offspring.

h. Until a termination requirement (such as a maximum number of generations or a suitable collection of solutions) is fulfilled, repeat Steps 2 through 7 as necessary. A detailed step-by-step procedure is given in Fig. 1.

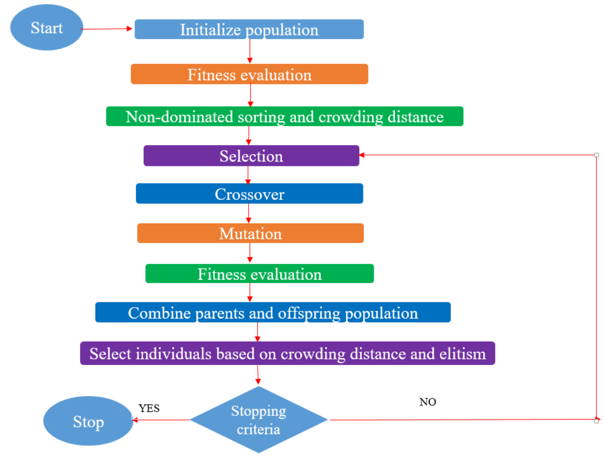

Fig. 1. Flowchart of NSGA-II algorithm.

2.6 Non-dominated sorting algorithm-III

NSGA-II is extended and modified to NSGA-III (Deb & Jain, 2014; Jain & Deb, 2014) to improve the performance and efficiency of the algorithm. NSGA-II provides a set of Pareto optimal solutions which becomes problematic when the number of objective functions increases. Both NSGA-II and NSGA-II generate an initial random population of size N. In the case of NSGA-III, every solution represents a feasible scaling plan as described by Yannibelli *et al.* 2020. During the initial phase, both algorithms use similar kinds of evolutionary cycles such as the crossover and mutation operators. An offspring population is generated by NSGA-II using the same stage of mutation and crossover as NSGA-II. But in the case of selection mechanism, NSGA-III uses a different mechanism to create a new population for the next generation. A new population is created using for the successive generation from the combined current and offspring population. The termination criterion followed in NSGA-III is similar to NSGA-III. After achieving the termination criterion, NSGA-III generates a Pareto set of population corresponding to the final generation.

2.7 Data description

The study is mainly constructed on data composed from the "Comprehensive Scheme for Studying the Cost of Cultivation (CoC) of Principal Crops", Directorate of Economics and Statistics, Ministry of Agriculture, Government of India (https://eands.dacnet.nic.in/

Cost_of_Cultivation.htm). Beneath this scheme, data were assembled from a sample of 300 farm households in 30 tehsils spread across three agro-climatic zones of Punjab. The other secondary data sources used in this study are- Central Ground Water Board (CGWB) (http://cgwb.gov.in/gw_profiles/st_Punjab.htm); Statistical abstracts of Punjab (https://www.esopb.gov.in/static/Publications.html), various issues.

3. RESULTS AND DISCUSSION

3.1 Parameter settings

Simulation experiments were performed to determine the best values of parameters for better performance in the investigated algorithms. The control parameter for NSGA-II and NSGA-III includes crossover probability (CR) and mutation probability =1/D (D is the number of decision variables). The maximum number of iteration for NSGA-II and NSGAIII was set at 100 and the population size was 40. The parameter settings for both algorithms are summarized in table 1.

Table 1. NSGA-II and NSGA-III parameter settings

NSGA-II		NSGA-III	
Population size	40	Population size	40
Maximum number of iterations	100	Maximum number of iterations	100
Crossover constant	0.8	Crossover constant	0.8
		Number of reference directions	92

4. EXPERIMENTAL RESULTS

NSGA-II and NSGA-III are used to decipher the multi-objective optimal crop plan problem that has been formulated in the current study. To assess the performance of the model in this work, the results of the algorithms are compared with each other. The NSGA-II and NSGA-III were implemented in PyCharm IDE using the Python programming language.

When considering multi-objective optimization, a graphical comparison should always be taken into account (Coello and Cortes, 2005). Two key assessment criteria (Adekanmbi *et al.,* 2014) should be considered in particular in evaluating the Pareto fronts produced from a metaheuristic: (i) the placement of the solutions on the true Pareto front and (ii) uniform distribution of solutions across the Pareto front. The degree to which the points on the Pareto front are linearly correlated is the first evaluation criterion. The metaheuristic that produces a Pareto front with more linearly connected points is deemed the best at solving the multi-objective crop planning problem. This method is useful because it may reveal a linear relationship between groundwater consumption and net profit. The Pearson correlation coefficient can be used to measure the strength of a linear relationship between two variables such as groundwater and profit. The correlation coefficient is a value between -1 and 1 that reflects how strong the linear relationship between two variables, such as groundwater use and net profit, is. A higher positive score indicates a strong linear association in the same direction. As a result, we should expect increasing groundwater consumption to result in higher profit values. According to the second evaluation criterion, Pareto solutions should be evenly distributed.

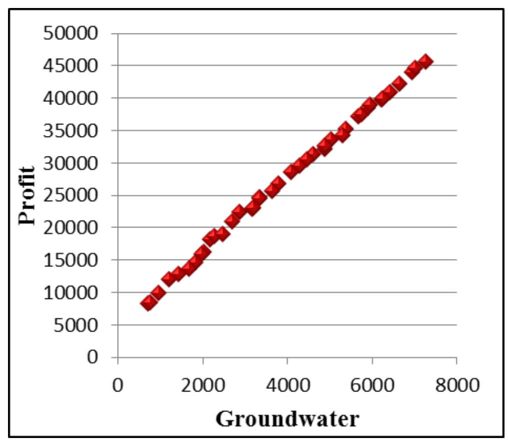

Fig. 2. Pareto optimal front produced by NSGA-II for the crop planning model of Kharif crops when maximizing profit (Rupees per hectare) and minimizing groundwater use (cubic meter per hectare)

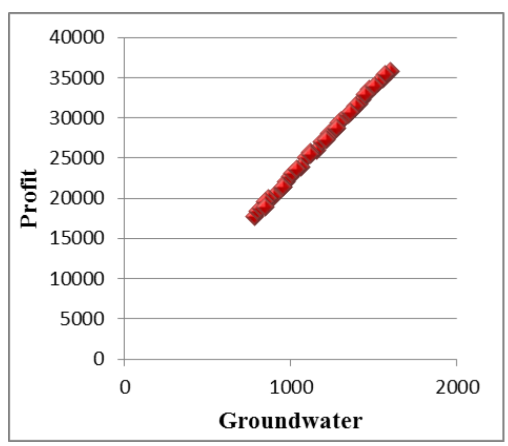

Fig. 3. Pareto optimal front produced by NSGA-II for the crop planning model of rabi crops when maximizing profit (Rupees per hectare) and minimizing groundwater use (cubic meter per hectare)

The Pareto fronts for the meta-heuristics explored in this study are shown in Fig.s 2, 3, 4, and 5. The figures show that NSGA-III discovered a good distribution of solutions, and the correlation coefficient estimated for the Pareto front of NSGAs-III is 0.9936, which is somewhat higher than the correlation value calculated for NSGA II, which is 0.9811. As a result, NSGA-III had the best results, both in terms of solution distribution and placement on the Pareto front of the multi-objective optimal crop planning issue.

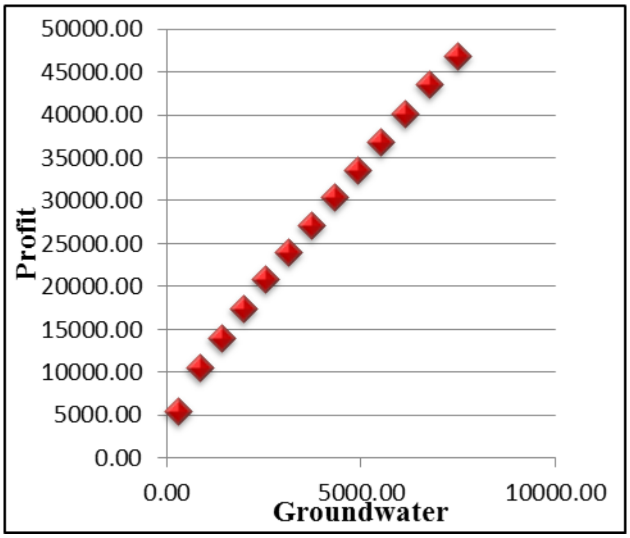

Fig. 4. Pareto optimal front produced by NSGA-III for the crop planning model of Kharif crops when maximizing profit (Rupees per hectare) and minimizing groundwater use (cubic meter per hectare)

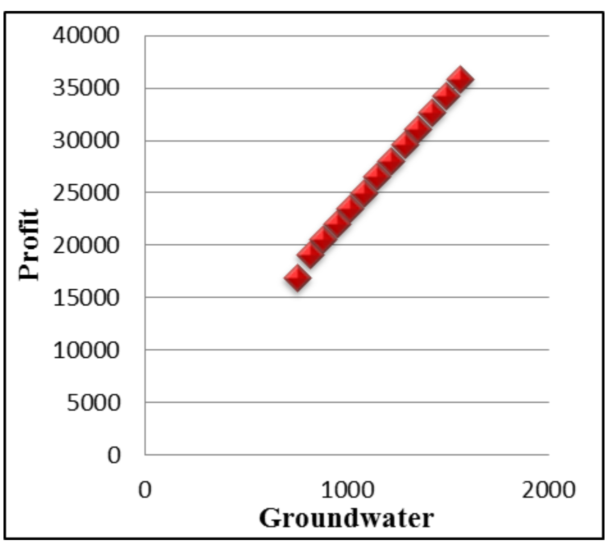

Fig. 5. Pareto optimal front produced by NSGA-III for the crop planning model of rabi crops when maximizing profit (Rupees per hectare) and minimizing groundwater use (cubic meter per hectare)

In cases where the solutions fail to converge to the true Pareto front of the problem, the significance of possessing a satisfactory distribution of solutions becomes irrelevant (Raju *et al.,* 2012). Fig.s 2, 3, 4, and 5 demonstrate the convergence of solutions onto the Pareto front. On this Pareto optimal front, all outcomes are equally favorable. The model allows for the simultaneous fulfillment of all objectives, and when one objective improves, the value of the other objective also fluctuates. From this assortment of solutions, a decision-maker must deliberate and select a single solution for implementation.

There can't be a single solution that achieves all of the goals in multi-objective optimization, but there exist sets of solutions that agree on non-dominated solutions as an alternative. When all of the goals are taken into account, the solutions are optimum in the sense that no other solution in the search space is better than them. Higher-level decision-makers will be able to choose the best option based on factors such as water availability, the number of personnel available, equipment availability, capital available, and land acreage.

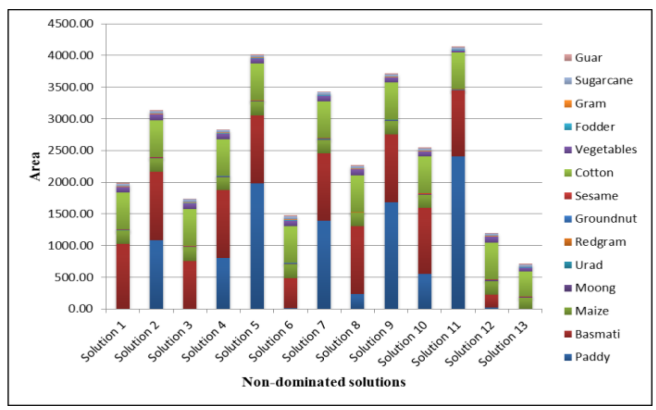

Fig. 6. Planting areas (thousand hectares) as allocated to Kharif crops in the non-dominated solutions by NSGA-III

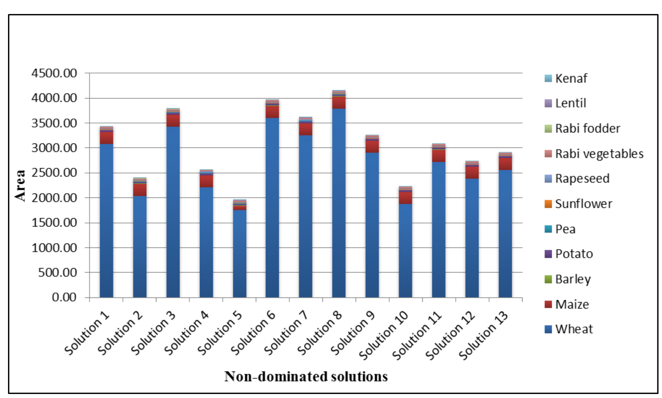

Fig. 7. Planting areas (thousand hectares) as allocated to rabi crops in the non-dominated solutions by NSGA-III

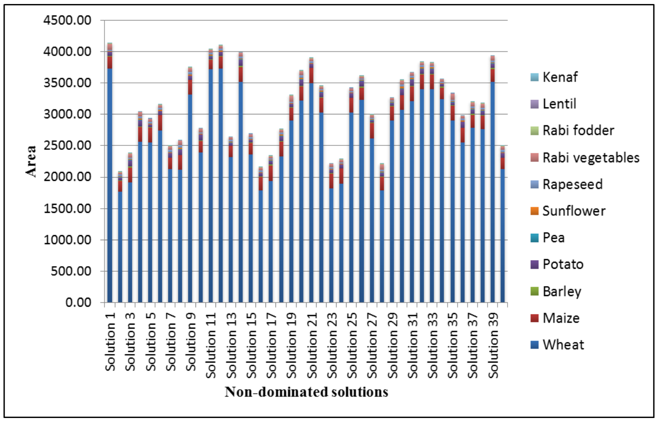

Fig. 8. Planting areas (thousand hectares) as allocated to rabi crops in the non-dominated solutions by NSGA-II

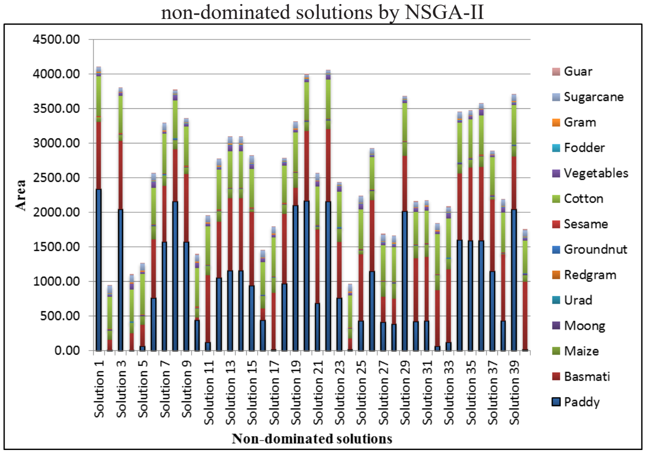

Fig.9. Planting areas (thousand hectares) as allocated to Kharif crops in the non-dominated solutions by NSGA-II

It is also clear from Fig.s 6, 7, 8 and 9 that the number of items in the Pareto front of NSGA-II (39 non-dominated solutions) is more than that of NSGA-III (13 non-dominated solutions). The number of non-dominated solutions indicates how good the algorithm is in producing desired results. Too many vectors (Van Veldhuizen and Lamont, 2000) may overwhelm the decision-makers while choosing from fewer solutions is easier.

The result section presents a detailed analysis of the performance and outcomes achieved by the two meta-heuristic algorithms, NSGA-II and NSGA-III, in the context of crop planning optimization. The study aimed to evaluate the solution distribution, convergence, and effectiveness of these algorithms in generating non-dominated solutions for a multi-objective crop planning problem.

To begin with, the Pareto fronts obtained by NSGA-II and NSGA-III are depicted in Fig.s 2, 3, 4, and 5. These figures provide a visual representation of the distribution of solutions along the Pareto fronts for both algorithms. It is evident that NSGA-III has achieved a superior solution distribution compared to NSGA-II, as indicated by the higher correlation coefficient of 0.9936 for NSGA-III in contrast to 0.9811 for NSGA-II. The correlation coefficient serves as a measure of how well the solutions are spread across the Pareto front. Therefore, NSGA-III exhibits a better ability to explore the trade-offs between maximizing profit and minimizing groundwater use.

Furthermore, the convergence of solutions onto the true Pareto front is a critical aspect of multi-objective optimization. Fig.s 2, 3, 4, and 5 demonstrate that both NSGA-II and NSGA-III have successfully converged solutions onto the Pareto front. This convergence indicates that the algorithms have effectively identified solutions that provide optimal trade-offs between the conflicting objectives. On the Pareto front, each solution is equally favorable, and improvements in one objective are accompanied by fluctuations in the value of the other objective. This characteristic allows decision-makers to make informed choices based on their priorities and preferences.

In the realm of multi-objective optimization, it is essential to recognize that a single solution cannot simultaneously optimize all objectives. Instead, a set of non-dominated solutions is obtained, which represents the best possible trade-offs between the objectives. These non-dominated solutions are considered optimal since no other solution in the search space can outperform them. In the present study, decision-makers are provided with a range of solutions that lie on the Pareto front, enabling them to consider multiple perspectives and make decisions based on factors such as water availability, personnel and equipment availability, capital resources, and land acreage.

To offer a comprehensive analysis, the authors have examined the planting areas allocated to Kharif and rabi crops in the non-dominated solutions obtained by NSGA-II and NSGA-III. The corresponding figures (Fig.s 6, 7, 8, and 9) showcase the allocation of planting areas to specific crops for each algorithm. It is observed that NSGA-II produces a larger number of non-dominated solutions (39 solutions) compared to NSGA-III (13 solutions). While a larger number of solutions may provide decision-makers with more alternatives, it can also introduce complexity and potential difficulties in selecting the most suitable solution. Conversely, a smaller number of solutions simplifies the decision-making process by reducing the number of options to consider.

In conclusion, the enlarged result section provides a comprehensive analysis of the study's findings. It highlights the superior solution distribution and correlation coefficient achieved by NSGA-III. Additionally, it emphasizes the importance of convergence onto the true Pareto front and the generation of non-dominated solutions in multi-objective optimization. The analysis of planting area allocations further elucidates the trade-offs and decision-making challenges involved in selecting the optimal crop planning solution.

5. CONCLUSION

The present study employs genetic algorithms to tackle linear constrained multi-objective crop planning problems using nature-inspired models for multi-objective optimization. The study offers a comprehensive analysis of the solutions generated through population-based techniques. Specifically, the research utilizes NSGA-II and NSGA-III methods to optimize the fundamental linear, constrained crop planning problem and analyze the outcomes of the multi-objective optimization models. Comparing NSGA-III to NSGA-II, the following conclusions can be drawn: (i) NSGA-III surpasses NSGA-II in producing nearly true Pareto optimal fronts for the considered crop planning problem, and (ii) it generates a well-distributed set of results for multi-objective optimal crop planning problems. Thus, NSGA-III emerges as a practical tool for aiding in the decision-making process of optimal crop planning. The findings also establish a direct correlation between groundwater usage and profit, implying that maximizing groundwater utilization leads to higher levels of net profit. Future research can explore alternative optimization techniques and compare them to NSGA-III to ascertain its superiority over various crop planning approaches.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the anonymous reviewers for providing suggestions and comments which led to the significant improvement in the manuscript.

REFERENCES

Abayomi, A.O. (2015). Differential evolution algorithm for optimal strategic decision making in crop farming system, Ph.D. thesis.

Adekanmbi, O.A., Olugbara, O.O., and Adeyemo, J. (2014). A comparative study of state-of-the-art evolutionary multi-objective algorithms for optimal crop-mix planning. International Journal of Agricultural Science and Technology, 2(1), 8-16.

Annepu Shi, Y., and Eberhart, R. (1998). A modified particle swarm optimizer. IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence.

Bao, C., Xu, L., Goodman, E.D., and Cao, L. (2017). A novel non-dominated sorting algorithm for evolutionary multi-objective optimization. Journal of Computational Science, 23, 31-43.

Coello, C.A.C., and Cortés, N.C. (2005). Solving multiobjective optimization problems using an artificial immune system. Genetic programming and evolvable machines, 6(2), 163-190.

Coello, C.A.C., Brambila, S.G., Gamboa, J.F., Tapia, M.G.C., and Gómez, R.H. (2020). Evolutionary multiobjective optimization: open research areas and some challenges lying ahead. Complex & Intelligent Systems, 6(2), 221-236.

Danapour, M., Fienen, M.N., Højberg, A.L., Jensen, K.H., &Stisen, S. (2021). Multi-constrained catchment scale optimization of groundwater abstraction using linear programming. Groundwater, 59(4), 503-516.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T.A.M.T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE transactions on evolutionary computation, 6(2), 182-197.

Deb, K., and Jain, H. (2013). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. IEEE transactions on evolutionary computation, 18(4), 577-601.

Dutta, S., Sahoo, B.C., Mishra, R., and Acharya, S. (2016). Fuzzy stochastic genetic algorithm for obtaining optimum crops pattern and water balance in a farm. Water Resources Management, 30(12), 4097-4123.

Fanuel, I.M., Mushi, A., and Kajunguri, D. (2018). Irrigation water allocation optimization using multi-objective evolutionary algorithm (MOEA)− a review. International Journal for Simulation and Multidisciplinary Design Optimization, 9, A3.

https://eands.dacnet.nic.in/Cost_of_Cultivation.htm

http://cgwb.gov.in/gw_profiles/st_Punjab.htm

https://www.esopb.gov.in/static/Publications.html

Jain, H., and Deb, K. (2013). An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: Handling constraints and extending to an adaptive approach. IEEE Transactions on evolutionary computation, 18(4), 602-622.

Jarin, S., Khatun, M.K., and Shafie, A.A. (2006). Multi-objective constrained algorithm (MCA) and non-dominated sorting genetic algorithm (NSGA-ii) for solving multi-objective crop planning problem. ARPN Journal of Engineering and Applied Sciences, 11, 4079-4086.

Kuo, S.F., Merkley, G.P., and Liu, C.W. (2000). Decision support for irrigation project planning using a genetic algorithm. Agricultural Water Management, 45(3), 243-266.

Lalehzari, R., Boroomand Nasab, S., Moazed, H., and Haghighi, A. (2016). Multiobjective management of water allocation to sustainable irrigation planning and optimal cropping pattern. Journal of Irrigation and Drainage Engineering, 142(1), 05015008.

Mansourifar, M., Almassi, M., Borghaee, A.M., and Moghadassi, R. (2013). Optimization crops pattern in variable field ownership. World Applied Sciences Journal, 21(4), 492-497.

Marko, O., Pavlović, D., Crnojević, V., and Deb, K. (2019). Optimisation of crop configuration using NSGA-III with categorical genetic operators. In Proceedings of the Genetic and Evolutionary Computation Conference Companion.

Márquez, A.L., Baños, R., Gil, C., Montoya, M.G., Manzano-Agugliaro, F., and Montoya, F.G. (2011). Multi-objective crop planning using pareto-based evolutionary algorithms. Agricultural Economics, 42(6), 649-656.

Mwiya, R.M., Zhang, Z., Zheng, C., and Wang, C. (2020). Comparison of Approaches for Irrigation Scheduling Using AquaCrop and NSGA-III Models under Climate Uncertainty. Sustainability, 12(18), 7694.

Nath, K., Jain, R., Marwaha, S., Roy, H.S. and Arora, A. (2020). Identification of optimal crop plan using nature inspired metaheuristic algorithms. Indian Journal of Agricultural Sciences, **90**(8), 1587-92.

Olakulehin, O.J., and Omidiora, E.O. (2014). A genetic algorithm approach to maximize crop yields and sustain soil fertility. Net Journal of Agricultural Science, 2(3), 94-103.

Oluwole, A.A., Oludayo, O.O., and Josiah, A. (2014). A comparative study of state-of-the-art evolutionary multi-objective algorithms for optimal crop-mix planning. International Journal of Agricultural Science and Technology, 2(1), 1-9.

Pal, B.B., Chakraborti, D., and Biswas, P. (2009). A genetic algorithm based hybrid goal programming approach to land allocation problem for optimal cropping plan in agricultural system. In International Conference on Industrial and Information Systems (ICIIS).

Raju, K.S., Vasan, A., Gupta, P., Ganesan, K., and Mathur, H. (2012). Multi-objective differential evolution application to irrigation planning. ISH Journal of Hydraulic engineering, 18(1), 54-64.

Sadati, S.K., Speelman, S., Sabouhi, M., Gitizadeh, M., and Ghahraman, B. (2014). Optimal irrigation water allocation using a genetic algorithm under various weather conditions. Water, 6(10), 3068-3084.

Srinivas, N., and Deb, K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. Evolutionary computation, 2(3), 221-248.

Sarker, R., and Ray, T. (2009). An improved evolutionary algorithm for solving multi-objective crop planning models. Computers and electronics in agriculture, 68(2), 191-199.

Sarma, A.K., Misra, R., and Chandramouli, V. (2006). Application of genetic algorithm to determine optimal cropping pattern. Opsearch, 43(3), 320-329.

Vafaeinejad, A. (2016). Cropping Pattern Optimization by Using of TOPSIS and Genetic Algorithm Based on the Capabilities of GIS. Iranian journal of Ecohydrology, 3(1), 69-82.

Van Veldhuizen, D.A., and Lamont, G.B. (2000). On measuring multiobjective evolutionary algorithm performance. In Proceedings of the 2000 Congress on Evolutionary Computation. CEC00, 1, 204-211, IEEE.

Wang, X.D., Hirsch, C., Kang, S., and Lacor, C. (2011). Multi-objective optimization of turbomachinery using improved NSGA-II and approximation model. Computer Methods in Applied Mechanics and Engineering, 200(9-12), 883-895.

Wei, W., Feng, Y., Tan, J., and Li, Z. (2009). Product platform two-stage quality optimization design based on multiobjective genetic algorithm. Computers & Mathematics with Applications, 57(11-12), 1929-1937.

Xevi, E., and Khan, S. (2005). A multi-objective optimisation approach to water management. Journal of environmental management, 77(4), 269-277.

Yusoff, Y., Ngadiman, M.S., and Zain, A.M. (2011). Overview of NSGA-II for optimizing machining process parameters. Procedia Engineering, 15, 3978-3983.

Yuan, Y., Xu, H., and Wang, B. (2014). An improved NSGA-III procedure for evolutionary many-objective optimization. In Proceedings of the 2014 annual conference on genetic and evolutionary computation.

Zeng, X., Kang, S., Li, F., Zhang, L., and Guo, P. (2010). Fuzzy multi-objective linear programming applying to crop area planning. Agricultural Water Management, 98(1), 134-142.

FUNDING STATEMENT:

The author(s) received no financial support for the research, authorship, and/or publication of this article.

AUTHOR'S CONTRIBUTION:

K.N., conceived the research K.N.and H.S.R. collected the data and designed the methodology. K.N., and H.S.R. supported the analysis. K.N. and H.S.R. and prepared the draft and edited the manuscript. H.S.R supervised all activities. All authors reviewed the manuscript. All authors have read and agreed to the published version of the manuscript.All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

AVAILABILITY OF DATA AND MATERIAL:

The study is mainly constructed on data composed from the "Comprehensive Scheme for Studying the Cost of Cultivation (CoC) of Principal Crops", Directorate of Economics and Statistics, Ministry of Agriculture, Government of India (https://eands.dacnet.nic.in/Cost_of_Cultivation.htm). Beneath this scheme, data were assembled from a sample of 300 farm households in 30 tehsils spread across three agro-climatic zones of Punjab. The other secondary data sources used in this study are- Central Ground Water Board (CGWB) (http://cgwb.gov.in/gw_profiles/st_Punjab.htm); Statistical abstracts of Punjab (https://www.esopb.gov.in/static/Publications.html), various issues.

CODE AVAILABILITY:

Code will be avaible on request to the coresponding author.

Ethics approval,Consent to participate,Consent for publication:

The manuscript does not report on or involve the use of any animal or human data and "Not applicable" in this section.

APPENDIX

1. NSGA-II implementation in Python:

```
import random
importnumpy as np
fromdeap import base, creator, tools, algorithms
# -------------------------------
# Problem dimensions
# -------------------------------
n = 14 # number of crops (11 for rabi, 14 for kharif)
Y =np.array([...]) # yield (kg/ha)
P =np.array([...]) # price (Rs/kg)
C =np.array([...]) # cost (Rs/ha)
Wr = np.array([...]) # water requirement (m3/ha)
Lb = np.array([...]) # lower bound of area (1000 ha)
Ub = np.array([...]) # upper bound of area (1000 ha)
Wt = 1.2e9 # total available groundwater (m3)
At = 250 # total cultivable area (1000 ha)
PENALTY = 1e8
# -------------------------------
# Objective function
# -------------------------------
def evaluate(A):
 A = np.array(A)
profit = np.sum((Y * P - C) * A)
water =np.sum(Wr * A)
penalty = 0.0
if water >Wt:
penalty += PENALTY * (water - Wt)
ifnp.sum(A) > At:
penalty += PENALTY * (np.sum(A) - At)
return -profit + penalty, water + penalty
# -------------------------------
# -------------------------------
creator.create("FitnessMin", base.Fitness, weights=(-1.0, -1.0))
creator.create("Individual", list, fitness=creator.FitnessMin)
toolbox = base.Toolbox()
fori in range(n):
toolbox.register(f"A{i}", random.uniform, Lb[i], Ub[i])
toolbox.register(
 "individual",
tools.initCycle,
creator.Individual,
  [toolbox.__getattribute__(f"A{i}") for i in range(n)],
 n=1
)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)
toolbox.register("evaluate", evaluate)
toolbox.register("mate", tools.cxSimulatedBinaryBounded,
low=Lb.tolist(), up=Ub.tolist(), eta=20)
toolbox.register("mutate", tools.mutPolynomialBounded,
```

```
low=Lb.tolist(), up=Ub.tolist(), eta=20, indpb=0.1)
toolbox.register("select", tools.selNSGA2)
# --------------------------------
# Optimization process
# --------------------------------
POP_SIZE = 200
NGEN = 400
population = toolbox.population(n=POP_SIZE)
algorithms.eaMuPlusLambda(
population,
toolbox,
mu=POP_SIZE,
 lambda_=POP_SIZE,
cxpb=0.9,
mutpb=0.1,
ngen=NGEN,
verbose=False
)
# --------------------------------
# Pareto-optimal solutions
# --------------------------------
pareto_front = tools.sortNondominated(
population, len(population), first_front_only=True
)[0]
```

2. NSGA-III implementation in Python:

```
import random
importnumpy as np
fromdeap import base, creator, tools, algorithms
fromdeap.tools import uniform_reference_points
# --------------------------------
# Problem dimensions
# --------------------------------
n = 14 # number of crops (11 for rabi, 14 for kharif)
N_OBJ = 2 # profit and groundwater use
Y =np.array([...]) # yield (kg/ha)
P =np.array([...]) # price (Rs/kg)
C =np.array([...]) # cost (Rs/ha)
Wr = np.array([...]) # water requirement (m3/ha)
Lb = np.array([...]) # lower bound of area (1000 ha)
Ub = np.array([...]) # upper bound of area (1000 ha)
Wt = 1.2e9 # total available groundwater (m3)
At = 250 # total cultivable area (1000 ha)
PENALTY = 1e8
# --------------------------------
# Objective function
# --------------------------------
def evaluate(A):
 A = np.array(A)
 # Objective 1: Maximize profit → minimize negative profit
profit = np.sum((Y * P - C) * A)
 # Objective 2: Minimize groundwater use
water = np.sum(Wr * A)
 # Constraint penalties
penalty = 0.0
if water >Wt:
penalty += PENALTY * (water - Wt)
ifnp.sum(A) > At:
penalty += PENALTY * (np.sum(A) - At)
return -profit + penalty, water + penalty
# --------------------------------
# NSGA-III
# --------------------------------
creator.create("FitnessMin", base.Fitness, weights=(-1.0,) * N_OBJ)
creator.create("Individual", list, fitness=creator.FitnessMin)
toolbox = base.Toolbox()
fori in range(n):
```

```
toolbox.register(f”A{i}”, random.uniform, Lb[i], Ub[i])
toolbox.register(
 “individual”,
tools.initCycle,
creator.Individual,
 [toolbox.__getattribute__(f”A{i}”) for i in range(n)],
 n=1
)
toolbox.register(“population”, tools.initRepeat, list, toolbox.individual)
toolbox.register(“evaluate”, evaluate)
toolbox.register(“mate”, tools.cxSimulatedBinaryBounded,
low=Lb.tolist(), up=Ub.tolist(), eta=20)
toolbox.register(“mutate”, tools.mutPolynomialBounded,
low=Lb.tolist(), up=Ub.tolist(), eta=20, indpb=0.1)
# -------------------------------
# Reference points (key difference)
# -------------------------------
ref_points = uniform_reference_points(nobj=N_OBJ, p=12)
toolbox.register(“select”, tools.selNSGA3, ref_points=ref_points)
# -------------------------------
# Optimization process
# -------------------------------
POP_SIZE = len(ref_points)
NGEN = 400
population = toolbox.population(n=POP_SIZE)
algorithms.eaMuPlusLambda(
population,
toolbox,
mu=POP_SIZE,
 lambda_=POP_SIZE,
cxpb=0.9,
mutpb=0.1,
ngen=NGEN,
verbose=False
)
# -------------------------------
# Pareto-optimal solutions
# -------------------------------
pareto_front = tools.sortNondominated(
population, len(population), first_front_only=True
)[0]
```