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Particle Swarm Optimization based Multi-objective Optimization for Crop Planning: A Case Study of Bundelkhand

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SUMMARY

Indian agriculture and its allied sectors are undeniably the major livelihood source in India, especially in rural areas, and it heavily depends on natural resources, climatic condition *etc.* The continuous depletion of natural resources and unpredictable climatic condition can cause low productivity growth and food security issues. A modified cropping pattern can be helpful to improve the net profit by utilizing minimum resources. A crop planning model is proposed here for the optimal allocation of resources under a water-deficit region like Bundelkhand. This study presents a Multi-objective Particle Swarm Optimization using Crowding Distance (MOPSOCD) which is an evolutionary algorithm to solve the constrained bi-objective crop planning problem. The objective functions of the model are maximizing total net returns and minimize the net water requirements. Maximum and minimum available land area, cropping area for various crops were considered as constraints of the model. The optimized results obtained from the proposed model are compared with another well-known evolutionary algorithm i.e. non-dominated sorting genetic algorithm (NSGAII) and we got a better crop planning strategy using the presented method. Overall, multi-objective optimization technique using PSO with crowding distance effectively improve optimal area allocation for water deficit region Bundelkhand with high range of net return and utilizes low water.

Keywords: Crowding distance, Crop planning, Genetic algorithm, Multi-objective optimization, Particle swarm optimization.

1. INTRODUCTION

Agriculture heavily depends on natural resources like land, water, soil nutrients and climatic factors. The country needs to address the goals of sustainable agriculture to feed food for more than 135 crores of people with an annual growth rate of 1.13% (Chavan and Breyer, 2020). However continuous depletion of natural resources is causing the serious issues of low agricultural growth and food security. On one side we need to increase agricultural food production and on the other side, we need to preserve natural resources mainly water with the diminishing area under cultivation due to industrialization. Besides, farmers' income also needs to be improved with the reduced cost of cultivation. Thus there is a need for adopting an improved crop planning having the capability to improve the profit by utilizing minimum resources. There are several approaches available for crop planning, however, these are usually focusing on farm level planning which is normally ignoring the natural resources and considering the farm level availability of land, labour and capital (Maleka 1993, Uddin *et al.* 1994). Due to the lack of expertise in the development of crop plans, not many efforts are observed at the regional level. Jain *et al.* in 2018 provided a comprehensive review of various attempts at the national and international level in this direction. The study reported that most of the approaches are linear programming based and on a single objective function (Jain *et al.*, 2019 and Sethi *et al.,* 2006). With the emergence of open data policies, optimization software and new programming paradigms like R and Python, it is possible to develop optimal plans which are multi-objective and are at the regional level. In multi-objective crop plans, the solution

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is not as straightforward as it is for a conventional single-objective optimization problem (Márquez *et al.,* 2011). Therefore, different researchers have defined the various ways to solve a multi-objective optimization problem (Adeyemo and Otieno 2010, Gill *et al.* 2006 and Hosseini *et al.* 2016). The global criterion method has been used to transform plural problem optimization into a single problem optimization by minimizing the distance between multiple reference points and viable destination areas (Gunantara, 2018). In the weighted-sum method, all problems are combined into one problem using a weighted vector (Marler, 2010). The number of weights is usually normalized to one. Although the weighted-sum method is simple and easy to use, there are two inherent problems. Firstly, there is difficulty in choosing weights for problems that have different magnitudes. Therefore, there will be a bias in finding a trade-off solution. Secondly, a problem would appear if the plural problem that is optimized is not convex. This exclusion may skip over important representative candidate solutions that would be relevant to the end-user. To overcome difficulties in plural problems that are not convex, the ε-constraint method may be used but, the downside of this method is that there is no viable solution for certain vectors (Mavrotas, 2009).

Studies reported that multi-objective search and optimization might be a problem area in conventional methods but evolutionary algorithms may perform better than other blind search strategies (Zitzler and Thiele, 1998). Evolutionary algorithms include genetic algorithms, particle swarm optimization, Ant colony and many variants in such algorithms. However, due to the lack of expertise in agriculture, crop planning and evolutionary algorithms, not many attempts have been observed in literature in this direction.

In this paper, we propose a PSO based approach for crop planning in the Bundelkhand region of the country which is deficient in water availability, drought-prone and erratic rains. It contains 13 districts out of which almost all districts are under the aspirational category as per NITI Aayog. We use two objective functions and 3 relevant constraints for crop planning. We also compare the results with other similar approaches. The remaining part of this paper is organized as follows: Section 2 brings some previous related work done. Section 3 explains about used material and methods. The data description and complete explanation of the model formulation with experimental settings are described in section 4. Section 5 illustrate the experimental setting and discuss the results. Section 6 explains the conclusion.

2. LITERATURE SURVEY

Optimization techniques for crop planning have been used for a long time. Alam *et al.* in 2016 suggested the crop plan of Datia district in Bundelkhand, that shows sowing of kharif crops has to be done during the Standard Meteorological Week 27 for maximum utilization of rain water. Different optimization model based on the concept of linear programming for maintaining the resources efficiently and provide optimal crop plans like Regional Crop Planning model (Jain *et al.,* 2015) and Optimal crop planning and water resources allocation (Sethi *et al.,* 2006) has been developed. Whereas evolutionary algorithms have been successfully studied and applied extensively in the past few decades in agriculture, engineering and various other fields, and helped in solving complex problems and providingan optimum solution. Some work has been done by using an evolutionary algorithm likea GA based model (Kumar and Raju, 2006) for obtaining an optimal crop water allocation from an irrigation reservoir with objective to maximize the sum of the relative yields from all crops in the irrigated area and suggested an optimum crop planning for maximizing irrigation benefits for a typical irrigation system. Another crop planning model (Sarma *et al.,* 2006) based on GA in the non-linear problem and an optimal cropping pattern developed (Rath *et al.* 2017) using various swarm intelligence techniques, genetic algorithm (GA), cuckoo search (CS) and particle swarm optimization (PSO), are used to formulate an efficient cropping pattern with an objective net return maximization. Differential evolution algorithm (Adekanmbi *et al.* 2014) used to maximize total net benefit and production from farming.

Crop planning is a multidimensional problem, therefore better if it considers more than one objective function to solve the problem and to get more optimal results. Adeyemo and Otieno (2010) proposed a multi-objective optimization using differential evolution technique.

For optimum crop planning, we need to improve the solution so as to utilize the maximum available area. Pareto suggested ranking of the candidate solutions and keeping an archive of all the non-dominated solutions. Thus, it is possible to explore the entire Pareto front without any prior knowledge about the problem. It is the current state of the art in multi-objective optimization with PSO. Some studies have already used multi-objective PSO for parameter estimation in hydrology (Gill *et al.,* 2006) and, soil mechanical resistance (Hosseini *et al.*, 2016; Wang *et al.*, 2012) and similar improvement are required in crop planning also.

There are some regions where water has become the bottleneck for economic and social development. This paper presents a general idea of crop planning using evolutionary algorithms and solutions for multi-objective optimization.

3. MATERIAL AND METHODS

In this study, we are using the PSO algorithm for developing a new crop planning model with multi-objective functions, and the genetic algorithm used for result's comparison. PSO is a relatively recent metaheuristic algorithm that is based on the behaviour of swarming characteristics of living organisms.

3.1 Particle Swarm Optimization

Eberhart and Kennedy, (1995) developed an artificial intelligence-based evolutionary computation technique called Particle Swarm Optimization (PSO) which based on the social behaviour of bird flocking and fish schooling.

For describing in shortly, let's consider a swarm (population) containing p particles in a K–dimensional continuous solution space. The position of the i^{th} particle is denoted as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iK})$ and each i^{th} particle has its own position and velocity in K–dimensional vector. The best particle is denoted as *gbest* in the swarm. The best previous position of the i^{th} particle is recorded and represented as *pbest* $(p_i) = (p_{i1}, p_{i2}, \ldots, p_{iK})$, then the velocity can be manipulated as following the equations:

$$v_i^t = W \times v_i^{t-1} + c_1 r_1 \left(pbest_i^{t-1} - x_i^{t-1} \right) + c_2 r_2 \left(gbest^{t-1} - x_i^{t-1} \right) - (1)$$

$$x_i^t = x_i^{t-1} + v_i^t - (2)$$

Where 'W' is the inertia weight, c1 and c2 are acceleration coefficients, r1 and r2 are random numbers between 0 and 1. v is particle velocity, x is particle position, i is the i^{th} particle in a swarm, t is the t^{th} iteration number in the optimization process. Since

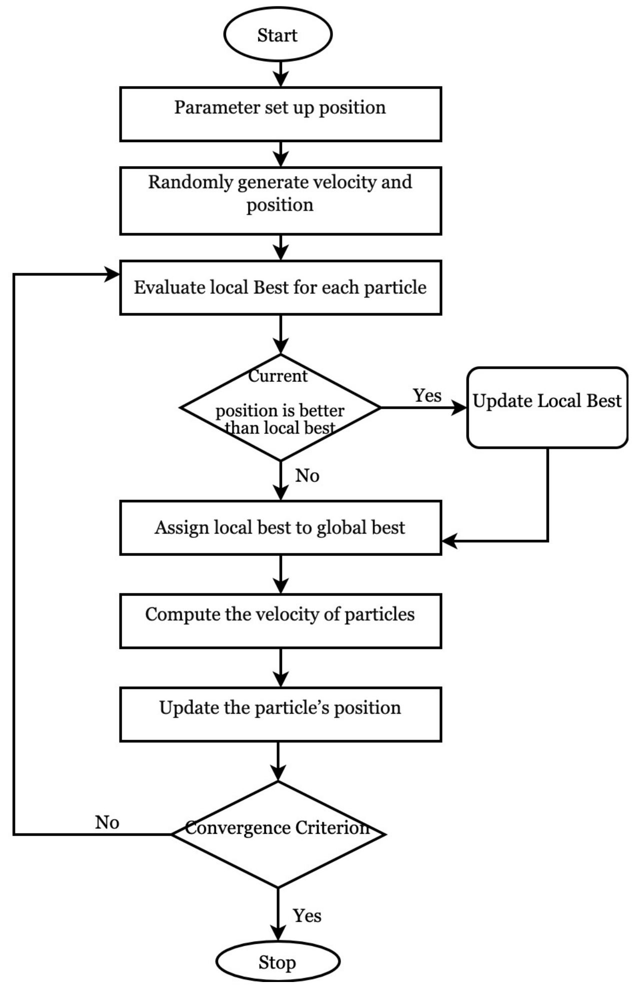


Fig. 1. Basic flowchart of Particle Swarm Optimization algorithm

each particle explores the possible solutions of space, therefore each of them represents a candidate solution to the problem. (Zhou *et al.,* 2003).

As described in Fig. 1, only p_{best} gives out the information to others. It is a one-way information-sharing mechanism. The evolution only looks for the best solution. The velocity and position of each particle are updated according to equation (1) and (2). Here all the particles tend to converge to the best solution. If the stopping criterion (maximum iterations or minimum error criteria) is met, its fitness value is returned.

A multi-objective PSO is an efficient algorithm but its major weakness is falling into a local optimum solution. To deal with such a problem, several sorts of techniques have been introduced to extend the PSO such as crowding distance, elitism, diversity operators, mutation operators and constraint handling. Coello in 2004 compared the performance of different evolutionary algorithms and conclude that the multi-objective PSO is the only algorithm that can cover the whole Pareto front. Then multi-objective PSO included a crowding distance mechanism for selection of leaders from an external archive to aid in the retention of the diversity of non-dominated solutions and multi-objective PSO extended to multi-objective PSO with crowding distance.

In the presented work a novel crop planning model developed using Multi-Objective Particle Swarm Optimization using Crowding Distance (MOPSOCD) approach with two objective functions. Here, the crowding distance of a particular solution provides an estimate of the density of solutions surrounding that solution and it's measured by taking the average distance of its two neighbouring solutions. Before calculating the crowding distance, sort all the solutions in ascending order according to their functional value.

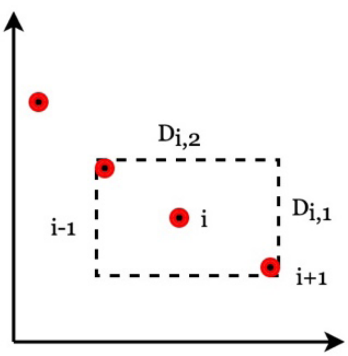


Fig. 2. Crowding distance of a solution (i)

In Fig. 2, with respect to particle i, the average distance of its two neighbouring particles in the Pareto front, namely particles i−1 and i+1, is defined as its crowding distance as follows in equation 3:

$$\boldsymbol{i} = \frac{\boldsymbol{d}_{i,1} + \boldsymbol{d}_{i,2}}{2}$$

The high crowding distance value indicates a lower density of the individual distribution and higher diversity of the solution and vice versa. (Raquel *et al.* 2005)

Here, Fig. 3 represents the MOPSOCD algorithm and this workflow define how it is different from a simple PSO algorithm. In this study, two objective functions including net return and water requirement are optimized for simultaneous maximization and minimization with constraints.

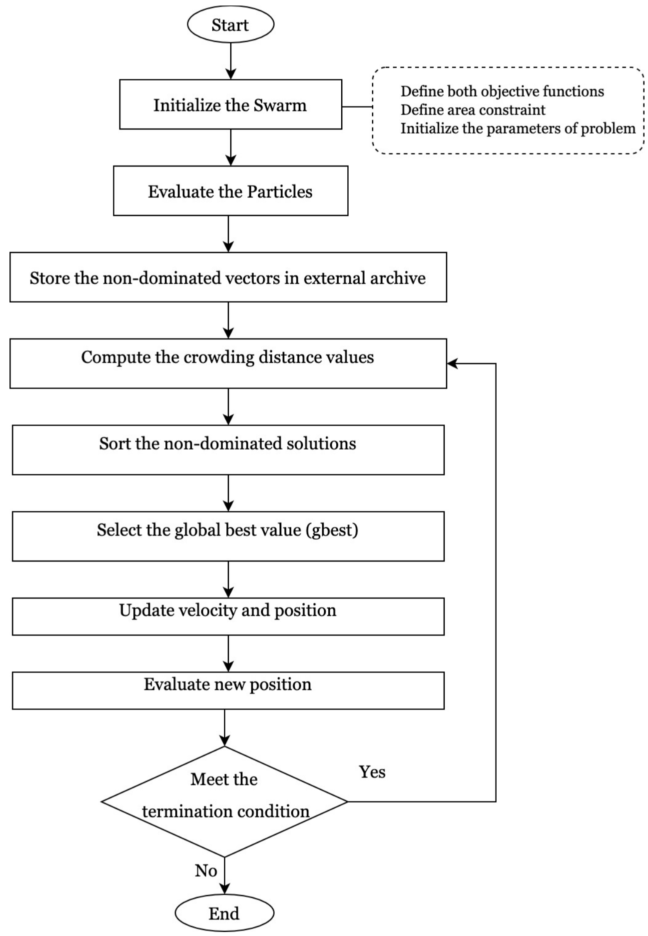


Fig. 3. Flowchart of MOPSOCD work

As viewed in the flowchart, the selection of pbest and gbest is one of the major actions in MOPSOCD and any non-dominated solution in the archive can be a gbest. Hence it is necessary to make sure the particles move to an unexplored site. The gbest value is chosen with the highest crowding distance value from non-dominant solutions. This enables the swarm to migrate to the least crowded area. Basically, it reduces the least important or similar results solutions and gives a more optimum solution finally.

3.2 Non-dominated Sorting Genetic Algorithm (NSGA II)

Genetic algorithms (Whitley, 1994) is a metaheuristic optimization technique based on the principles of Genetics and Natural Selection and it occurs under the evolutionary algorithm. In crop planning, a method required to find multiple Pareto-optimal solutions in one single run which is not possible through a simple genetic algorithm. The Non-dominated Sorting Genetic Algorithm (NSGA) proposed by Srinivas and Deb in 1995, was one of the first such evolutionary algorithms which concurrently optimizes all objectives. An improved form, NSGA II (Deb *et al.*, 2002) is a well-known, fast sorting and elite multi-objective genetic algorithm. As Fig. 4 explains that NSGA II algorithm contains three main parts for the selection of the new generation's members: a non-dominated sorting, density estimation, and a crowded comparison.

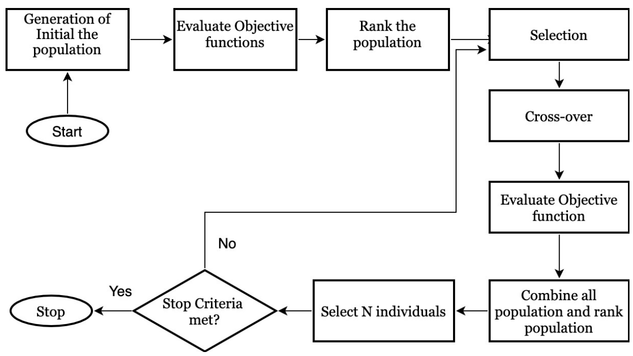


Fig. 4. Flowchart of NSGA II.

The density of each particular member is measured as the distance of the considered point and two members of its neighbour. In this paper, the NSGA II method used to determine the optimum solutions in the search space and for comparing the results with the proposed PSO based model.

3.3 PSO vs GA

The information-sharing mechanism in PSO is significantly different from GA. They don't have genetic operators like crossover and mutation, particles update themselves with the internal velocity and they also have memory which is important to the algorithm, *etc.* An important distinction is that GA is initially a discrete technique that is also suitable for combinatorial problems, and PSO is a continuous technique that is very poorly suited to combinatorial problems. To understand PSO's search space explorations, the particle movement in PSO can be seen as a form of path re-linking among pbest positions. In this sense, both PSO and GA can be seen as generating new solutions in the neighbourhood of two parents -- via crossover in GA and via attractions to two pbest positions in PSO.

To discuss the advantage of PSO over GA, PSO is really two populations -- pbests and current positions. This allows greater diversity and exploration over a single population (which with elitism would only be a population of pbests). Also, the momentum effects on particle movement can allow faster convergence (e.g. when a particle is moving in the direction of a gradient) and more variety/diversity in search trajectories.

When two nature-inspired methods are compared, we can never say that method A is better than method B. Method A may be good at exploration but bad at exploitation. So, there is some trade-off every time and that's why there are so many algorithms to tackle different aspects of the optimization problem. Similarly, PSO has expertise in some areas which are lacking in GA.

1. PSO has an inbuilt guidance strategy that lets the solutions in PSO obtain useful information from the better solutions and thereby helping them improve their own solutions. This results in faster convergence for the solutions in PSO. GA has no such guidance mechanism. Better solutions only pass the information when they participate in the crossover with some other chromosomes.
2. PSO uses memory to store the previous best solutions obtained by every candidate. This helps the candidates to recover their solutions when they get diverted in an unwanted direction. So, when the candidates start exploring an unwanted path and the quality of solutions starts degrading they can revert and get directed to the previous stage through the pBest (personal best) component in the velocity term. This makes the algorithm very robust and susceptible to degradation. On the other hand, GA does not use memory to keep track of the solutions throughout different generations.
3. Modern machines are really good with mathematical computations. PSO has an inherent tendency to exploit this advantage because all the computations and procedures in PSO are purely mathematical. But, GA has procedures like crossover, mutation which are not purely mathematical which makes GA more time-consuming than PSO.

To improve the capability of classical GA and PSO algorithms for crop optimization problems, we need to the compare non-dominant feasible solutions. For this purpose, more recent variants of GA and PSO were used in this paper. For understanding more merits of one over the other, readers are encouraged to refer the literature (Hassan *et al.,* 2005).

3.4 Implementation

Broad level steps required for optimum crop planning are presented in Fig. 5. The algorithms in section 3.1 and 3.2 are implemented using R software with Mopsocd, nsga2R, mco, ggplot2 and related packages. Readers can refer to https://CRAN.R-project.org for detailed instructions on downloading and using these packages. Specific details of each of these steps are explained with the help of a suitable example in Section 4.

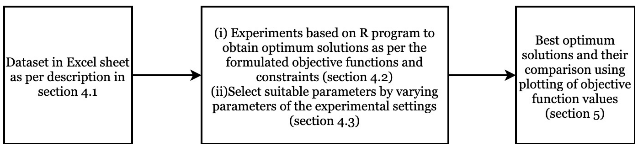


Fig. 5: Basic steps of optimum crop planning

4. MULTI-OBJECTIVE CROP PLANNING IN BUNDELKHAND REGION

4.1 About the data

The study is primarily based on the "Bundelkhand" region of India and concerned districts of it because their economy predominantly based on agriculture. But the infertility of the land, low productivity, improper land distribution in which a few medium and large farmers have a major share in landholdings, lack of irrigation facilities and unscientific cultivation in terms of non-use of modern methods in agriculture have kept the agriculture-based economy on the verge of subsistence only. The data collected 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. The other secondary data sources were used viz., Central Ground Water Board (CGWB), Ministry of Water Resources. Input and output coefficients and various return coefficients have been derived from the plot level data. Crop calendar year i.e. the growing period of crops has been taken as per the growing season. Table 1 shows a brief description about the variables of the raw data.

Collected data pre-processed by dealing with missing and noisy values for further use in the proposed model. Some special values are calculated using other relatable row values parameter which is used in model formulation. Such as net returns can be defined as the gross return (value of the main product and by-product) fever variable costs at the market price actually paid and received by the farmer.

Table 1: Attributes of raw data

Attributes	Description
Crops	27 crops which are grown in related districts of Buldelkhand Arhar, Barley, Chickpea, Rice, Wheat etc.
Yield	Yield of particular crop in quintal per hectare
Area	Maximum area and Minimum area allotted to particular crop
Water (cubic meter)	Required amount of water for individual crop
Crop calendar	A identity matrix to present the growing months of each of the 27 crops
Others	Human labour hours, NPK requirement, Working capital

$$NR = GR - VC \tag{4}$$

where, NR – Net return at market prices; GR – Gross Returns; and VC – Variable Cost.

An example given in table 2 explained the net returns calculations.

Table 2. Computation of NR for wheat in Buldelkhand, (Rs/ha)

Crop	Gross returns (a) ₹/ha	Variable cost (Cost A1 +imputed value of family labour) (b) ₹/ha	Net returns at Market prices (NRMP) (a-b) ₹/ha
wheat	40392	12827	27565

The Imputed Value of Family Labour (IVFL) has been calculated as:

IVFL= Working hours of family labour * Labour wage rate per hour

4.2 Model Formulation

In this study, a crop planning optimization problem with two objective functions and some set of constraints has been considered.

4.2.1 The objective function consists of:

a) Maximizing Net Returns

Jain *et al.* in 2015 developed a model on single objective regional crop planning using linear programming where an objective function was maximizing the net return. Here in this study, we have adopted the same objective function.

$$Max\,NR = \sum_{c=1}^{n}\left(Y_c P_c - C_c\right) A_c \tag{5}$$

Where Y_c denotes the yield of a crop c in one hectare of land, Pc is the received price from the output of crop c, Cc refers to the cost obtained to cultivate crop c in one hectare of area and Ac is the area under cultivation of crop c then the equation (5) represents sum of net return obtained from all the crops considered for the optimum crop model development. The objective is to maximize the net return (NR) based on the optimum crop plan.

b) *Minimizing water usage*

The second objective function in this study is minimizing the water requirement for crops. As we know water is a limited resource and especially in water deficit region like Bundelkhand in India, therefore it is important to get more profit with minimum use of water.

$$Min\,WR = \sum_{c=1}^{n} (W_c)\,A_c \tag{6}$$

where W_c denotes required water for a crop c in one hectare of land and Ac is the area under cultivation of crop c then the equation (6) represents sum of water requirement for all the crops considered for the optimum crop model development. The objective is to minimize the overall water requirement based on the optimum crop plan.

4.2.2 Restrictive Conditions

For getting the optimum results, there is some set of restrictive conditions that are required to be satisfied called Constraints. In this study 3 constraints have been used to get more optimize crop planning.

a) *Area Constraint*

Optimum use of the total net sown area for every month is necessary because of different crop grown during the different month according to the growing season. This can be achieved by having separate area constraint equations for a separate month. This helps to ensure that the total cultivated area under selected crops in each month should be less than the net sown area (NC_t).

$$\sum_{c=1}^{n} (\boldsymbol{a_{tc}})\,\boldsymbol{A_c} \le \boldsymbol{NC_t} \tag{7}$$

Thus, a_{tc} in equation (7) refers to the coefficient of crop calendar matrix for t^{th} month and c^{th} crop.

b) *Minimum and maximum constraints*

Some crops are necessary to grown for basic necessity or for some favourable reason. So, there should be some restriction on the minimum and maximum allotted area for individual crops.

$$\boldsymbol{A_c} > \boldsymbol{A_{MinC}} \tag{8}$$

The area for a particular crop should be in between the maximum area and minimum area specified by the experts according to need.

c) *Working Capital Constraints*

Farmers need some amount of money in initial time for a basic farming necessity like seed, fertilizer, machinery on rent *etc.* Working capital should be constraints to get maximum profit.

$$\sum_{c=1}^{n} (\boldsymbol{a_{tc}})\,\boldsymbol{w_c} \le \boldsymbol{wc_t} \tag{10}$$

Where w_c denotes working capital required for a crop c in one hectare of land and equation (10) represents the sum of all working capital requirement for all the crops considered for the optimum crop model development.

To avoid the overlapping of crop areas in any specific month /season, crop calendar is used. A crop calendar is a type of identity matrix that shows the months in which any particular crop is grown or not.

4.3 Experimental setting

While setting the experiment using evolutionary algorithm optimization techniques choice of parameters is very much important. The parameters should be fine-tuned so that the algorithms give the best result, this is done by the experimenting the parameter in ordered range. For the algorithms considered in the present study, the experiment was conducted with varied parameters and we selected the ones that gave the best result. The maximum number of generations set as 500, the same objective function and constraints used for both the algorithms. The finalized experimental settings which gave the best results in the present study are presented in Table 3.

Table 3. Experimental setting for MOPSOCD and NSGA II algorithms model

MOPSOCD settings		*NSGA II settings*	
Population size	500	Population size	500
Inertia weight (w)	0.7	Encoding	Real
Acceleration constants c_1 and c_2	2.0 and 0.90	Crossover rate	0.5
Objective function	2	Objective function	2
Variable number	27	Variable number	27

5. RESULTS AND DISCUSSION

Here in this work, we got a number of solutions using both the defined crop models (MOPSOCD and NSGA II),where each solution shows the area of all defined crops with maximized net return and less consumption of water.

5.1 Comparatives of objective functions in MOPSOCD and NSGA II

In MOPSOCD we found more solutions (options) as compared to NSGS II and these results are more tends to optimal results. Net returns obtained from both the crop models are shown below in the graph (a) and (b) of Fig. 6 as the one objective is to maximize the net return and the PSO method shows higher range net returns as compared to NSGA II. Here the range of net return is 134 billion in the case of the presented method and 120 billion rupees in NSGA II.

Fig. 7 presents the results secured by both the used algorithms for water requirement, and plots clearly show the lower water used requirements in MOPSOCD (9 billion cubicmeter) as compared to NSGA II (10.12 billion cubicmeter). Here it is clearly visible that the MOPSOCD method shows better results than a well-known evolutionary NSGA IIalgorithm.

As per the two contradictory objectives, MOPSOCD satisfies both the condition with se of constraints and gives better area allocation.

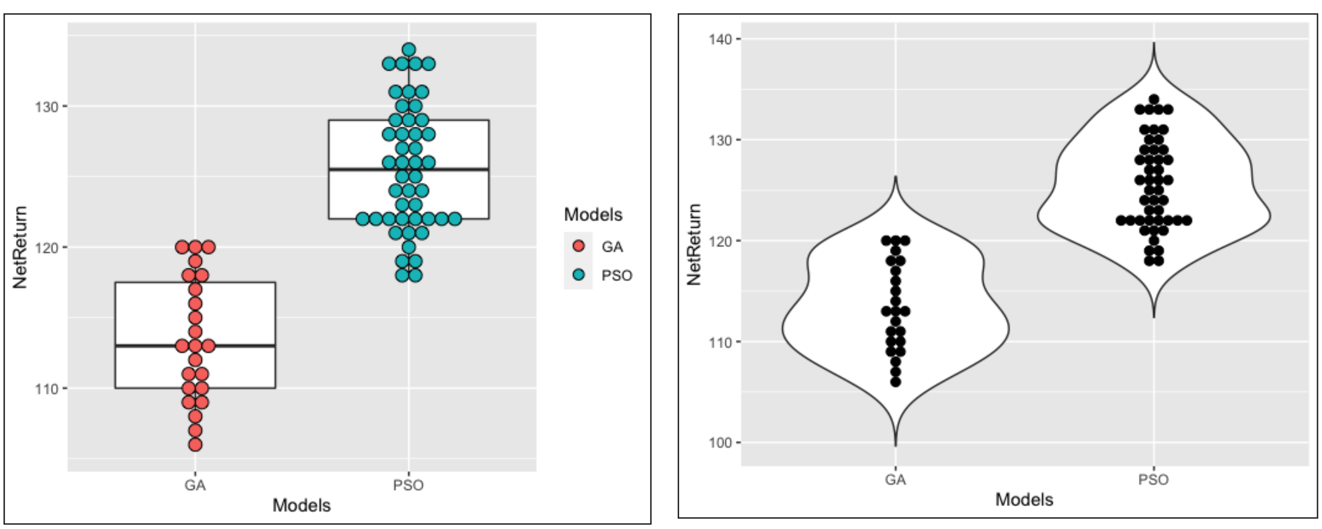
Fig. 8 below, shows the relationship between net return and water requirement of obtained solutions for the entire cropping area in the Bundelkhand region and the relationship is quite linear means as water requirement increases net return decreases and visa-versa. The two plots of MOPSOCD and NSGA II for feasible solutions and for all data, including infeasible too, show the exploration capability of these two algorithms.

5.2 Best optimum crop model in MOPSOCD and NSGA II

Not many studies are available on crop planning for Bundelkhand region. An attempt on Bundelkhand crop planning with rainfall data statistical modelling has been done by researchers but it estimates the week of sowing for better productivity (Alam *et al.,* 2016). The authors emphasized that SMW (Standard Meteorological Week) 27 is best for rainfed crops in Bundelkhand region. Alam *et al.* did not plan for optimum area allocations in the region. Due to absence of crop planning studies on Bundelkhand, we have compared the modelling results with the existing cropping pattern in the region.

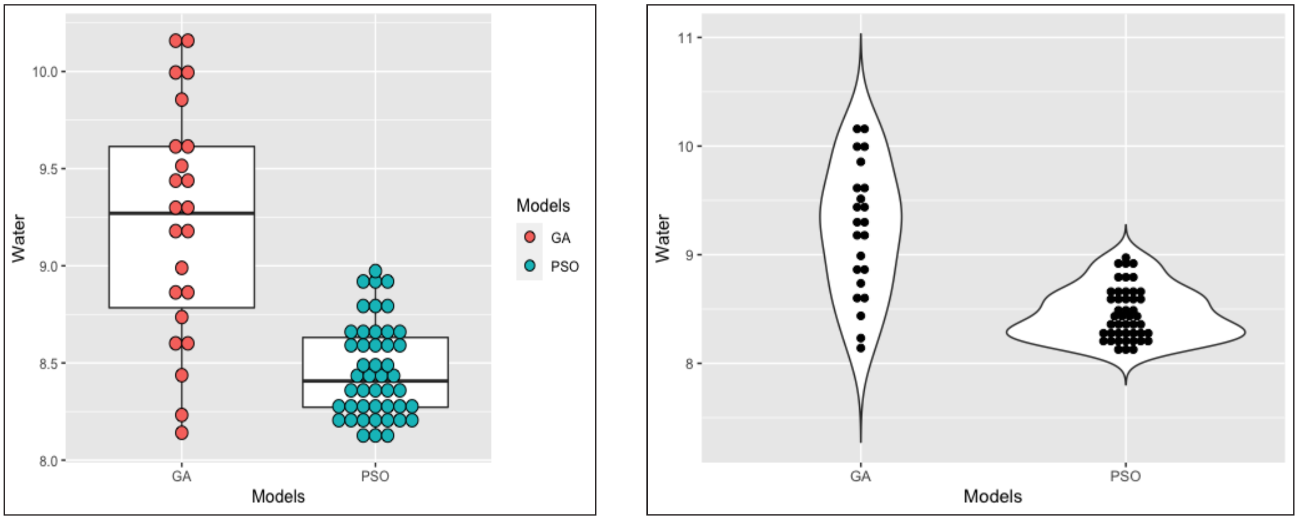
Table 4 represents the area allocated to specific crops by using both the algorithms MOPSOCD and NSGA II respectively. By using equation-11, percent of changes calculated with respect to existing cropping pattern area(CoC, 2015-16) to see the positive and negative changes observed in both the methods.

$$\text{\% Changes Observed} = \frac{AA - EA}{EA} \times 100 \qquad (11)$$



(a) (b)

Fig. 6. Net returns by MOPSOCD and NSGA II



(a) (b)

Fig. 7. Water requirement by MOPSOCD and NSGA II

Where AA- area allocated by either model (MOPSOCD or NSGA II); EA- Existing area allocated to crop in existing cropping pattern.

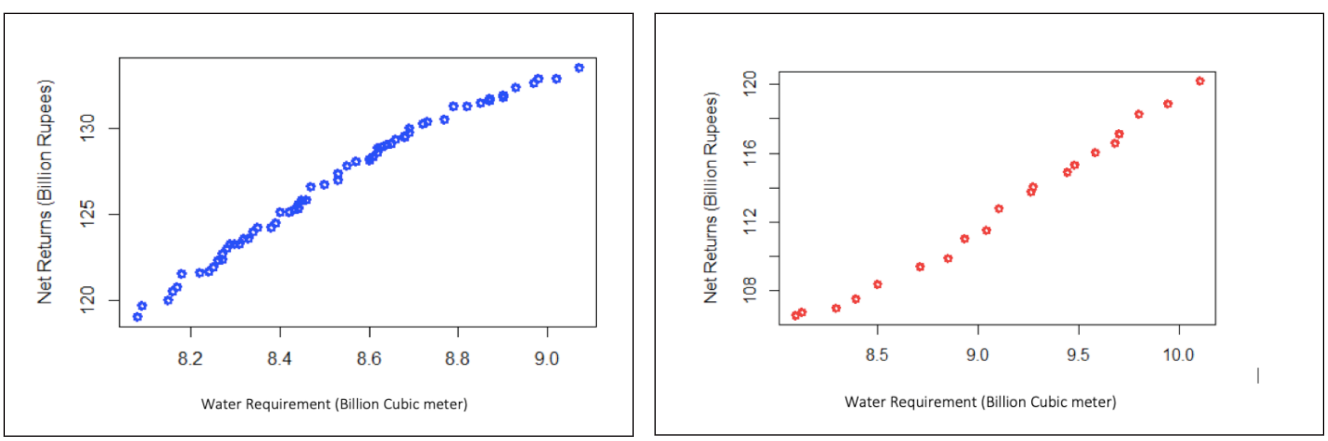
Here it is clearly visible that the total area allocation in MOPSOCD ismore efficientlyas compared to the existing pattern and NSGA II in a number of crops.

Results obtained from both the algorithm satisfies the area constraints (Max area and Min area), means each obtained crop area is less that the maximum specified and more than the minimum specified crop area.

In this research, here we got maximum net return by adopting the MOPSOCD is 134.274 billion rupees with 9.01 billion cubic meter water requirements, whereas 120.125 billion rupees net return and 10.12 billion cubic meter water requirements obtained with NSGA II evolutionary algorithm. Total cultivated area utilization and performance is better in MOPSOCD and it gives better values for both the objectives. It is quite apparent that MOPSOCD has explored a greater range of parameters than NSGA II.

5.3 Limitations of the study and future scope

Regional level, stakeholders are confronted with various limited resources and multiple options to achieve the desired benefits. The developed model is useful at the regional level based on regional level constraints. If the individual fam constraints and objective functions match the regional level constraints,



(a) (b)

Fig. 8. Relation between results (net return and water requirement by MOPSOCD (a)and NSGA II (b) respectively

Table 4. Area allocation by MOPSOCD and NSGA II crop models

Crops	Existing Area in '000' Ha	Allocated Area in '000' Ha		% of Changes	
		MOPSOCD	NSGA II	MOPSOCD	NSGA II
Arhar	105.61	128.55	106.13	21.71	0.48
Bajra	30.58	34.06	30.65	11.35	0.20
Barley	67.91	75.52	67.98	11.21	0.10
Berseem	2	3.53	3.37	76.52	68.64
Chillies	4.02	3.48	0.08	-13.54	-98.00
Chickpea	867.07	1184.87	867.80	36.65	0.08
Groundnut	83.20	96.97	83.52	16.54	0.38
Guar	0.34	0.56	0.58	64.10	68.51
Jowar	85.84	112.94	85.90	31.56	0.06
Khesari	5.14	6.86	5.17	33.55	0.68
Lentil	268.98	352.81	269.69	31.16	0.26
Linseed	22.92	25.02	23.52	9.16	2.61
Maize	53.94	61.52	54.21	14.03	0.49
Mentha	9.5	4.46	6.93	-53.06	-27.09
Mesta	0.1	0.11	0.20	14.73	97.00
Moong	48.42	64.12	48.52	32.41	0.19
Mustard	111.77	19.94	162.91	-82.16	45.74
Onion	8.83	6.88	4.10	-22.06	-53.63
Paddy	240	348.34	240.21	45.14	0.09
Pea	334.44	357.21	428.96	6.81	28.26
Sesamum	373.42	491.67	373.82	31.67	0.11
Soybean	593.01	926.72	593.80	56.27	0.13
Sugarcane	16.14	3.18	24.30	-80.31	50.52
Tomato	0.51	0.60	0.79	15.95	53.25
Urad	520.53	722.84	526.15	38.87	1.08
Wheat	1695.81	1707.21	2003.14	0.67	18.12
Total	**5550.11**	**6739.97**	**6012.40**	**348.94**	**258.27**

then the same model can be used. However, there will be some specific constraints like labour availability, soil suitability of farmer's land, credit availability to the farmer etc, which vary from farm to farm. Hence model will have to be adopted after consideration of more objectives and constraints. The authors encourage other researchers to build model scenarios for different category of farmers and use it for the development of recommender system for aspirational districts.

Authors believe that the reported optimum model is robust for the given constraints and objective function being based on crowding distance mechanism and parameter tuning. It is outside the scope of the present paper to analyze and describe the robustness of the developed model in detail. However, researchers are encouraged to consider it as interesting future research.

6. CONCLUSION

In the present work, a multi-objective, PSO-based crop planning optimization model is formulated using crowding distance for developing an optimal cropping pattern. The objectives are to maximize the net benefits and minimize the overall water requirements by taking care of constraints, the results obtained from MOPSOCD models are compared with the results obtained from another well-known NSGA II optimization model. The conclusions derived from the experimentations are: The maximum net return obtained by adopting the cropping pattern derived using MOPSOCD is 134.27 billion rupees with 9.01 billion cubic meter water requirements, whereas there are 120.12 billion rupees maximum net return and 10.12 billion cubic meter water requirements with NSGA II. The extra benefits will be amount of 14.15 billion rupees and 1.07 billion cubic meter water saving. Hence PSO is found to be an effective tool for optimal crop planning and can be used for other area. The findings of the research are significant and will be of great importance not only for the researchers but also will help the farmers to improve their standard of living. It is found that both the multi objective crop planning models generate a number of non-dominated solutions that can be used to solve crop planning problems and from where a farmer can select a solution that satisfies his specific condition. In further studies, we can consider more-objective functions which are equally important for getting improved crop planning as per the current situation of the locality.

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