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Evolutionary Computing for Optimum Crop Planning

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Abstract

Evolutionary computing (EC) is a soft computing technique inspired by the biological concept of natural selection or Darwin's theory in genetics. An EC algorithm starts with creating a population consisting of individuals that represent solutions to the problem. The first population of solution is created randomly and then refined by an EC algorithm. Thus, an EC algorithm does the job of environmental pressure which leads to the survival of the fittest and in turn the increase of the average fitness of the population. The final converged population is the optimum solution to a problem.

Crop planning is essential for agricultural systems management for increasing productivity and sustainability of the resources. The central objective of optimal crop planning is to search for an optimal combination of different resources and crops to maximize the overall contributions by concurrently satisfying a set of constraints *e.g.* availability of land, water, capital *etc.*

While optimizing crop planning with more than one objective function, there exist several Pareto optimal solutions. To solve such a problem is not as straightforward as it is for a conventional single-objective optimization problem. Evolutionary algorithms have helped in solving complex problems to provide an optimum solution. In this paper, Particle Swarm Optimization algorithms are adapted for optimal crop plans using a case study. We conclude that evolutionary computing is a viable and convenient alternative for crop planning at a regional level and should be explored further for crop planning at a farm and country level.

Key words: Crop planning; PSO; Bundelkhand; Multi-objective optimization.

1. Introduction

Crop planning is essential for agricultural production systems management and it can resolve how much resources are allocated to different cropped areas in obtaining certain goals such as the maximization of return from cultivated land under the limitation of resources (Jain *et al*., 2015). The central objective of crop planning is to search for an optimal combination of crops amongst those considered to maximize the overall contributions while concurrently satisfying a set of constraints such as land availability and capital. An important issue in those problems is the optimization objective(s). Optimization problems may be single or multi-objective based on the number of goals to be achieved. Maximization of net returns,

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maximization of gross margin, and minimization of water use are some of the goals that are desired.

Traditionally, linear programming based approaches have been used for crop planning similar to other domains like route optimization, resources optimization in the manufacturing industry *etc*. (Jain *et al*., 2017). With the advent of high speed and high memory-based computers, EC methods need to be explored for optimum crop planning because of the four reasons namely: (i) easier implementation, (ii) exploration of non-linear solutions, (iii) avoidance of local solutions, and (iv) easier implementation of multi-objective optimization.

2. Review of Literature

Optimization techniques for crop planning have been in use for a long time (Jain *et al.*, 2018b). Different optimization models based on the concept of linear programming for utilizing the resources efficiently and providing optimal crop plan like the Regional Crop Planning model (Jain *et al.*, 2015; Jain *et al.*, 2017) and allocating water resources optimally (Sethi *et al.*, 2006) have been developed. 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 to provide near to optimum solutions. Evolutionary algorithms like GA (Kumar *et al.*, 2006) have been used for allocating optimal crop water from an irrigation reservoir to maximize the sum of the relative yields from all crops in the irrigated area. The authors recommended optimum crop planning for maximizing irrigation benefits for a typical irrigation system. Other crop planning models based on GA, swarm intelligence, and differential evolution algorithms have been used to maximize total net benefit and production from farming (Sharma and Jana 2009; Nath *et al.*, 2020). Adeyemo and Otieno (2010) formulated a multi-objective optimal crop-mix problem and solved using the generalized differential evolution. Crop planning is a multi-dimensional problem, therefore it is desirable to have more than one objective function to solve the problem and to get more optimal results.

Pareto rank candidate solutions keep an archive of all non-dominated solutions in multi-objective optimization using EC (Coello *et al*., 2004). Some studies which already used multi-objective optimization using PSO are parameter estimation in hydrology (Gill *et al.* 2006), estimation of soil mechanical resistance parameter (Hosseini *et al*., 2016) and optimization of feeding composition for methane yield maximization (Wang *et al*., 2012). Jain *et al*. (2018b) presents a review of available crop planning techniques and concluded the need for exploring EC techniques for crop planning (Table 1). More on crop planning methodology, data preparation steps, case studies of optimum crop plans under different constraints are available in the literature (Jain *et al.*, 2019; Jain *et al.*, 2018a).

2.1. Evolutionary computing framework

The review reflects that evolutionary computing techniques have not been explored for crop planning. Evolutionary algorithms fall into the category of “generate and test” algorithms. They are stochastic, population-based algorithms. In genetic algorithms and evolutionary computation, crossover, also called recombination, is a genetic operator used to combine the genetic information of two parents to generate new offspring. The mutation is a genetic operator used to maintain genetic diversity from one generation of a population of genetic algorithm chromosomes to the next. The mutation alters one or more gene values in a chromosome from its initial state. In mutation, the solution may change entirely from the previous solution. Variation operators (recombination and mutation) create the necessary diversity to facilitate novelty. Selection reduces diversity and acts as a force pushing quality (Figure 1).

Table 1: Summary of past work related to optimization of crop plans

Studies	Scope	Approach	Objective(s)	Constraints
Maleka 1993	Farm (Gwembe Valley, Zambia)	Target MOTAD	Maximize net revenue	Land, labour, credit, moisture, cost of risk taking
Tajuddin *et al.* 1994	Farm (Bangladesh)	LP	Max net returns	Land, labour, cap min cereal requireme
Sarkar and Lingard 2002	Country(Bangladesh)	LP (QSOM)	Max over all contribution of agriculture sector	Land, capital, area import bound, minim food requirement
Sethi *et al.* 2002	Farm(Coastal river	DLP& CCLP (QSB)	Maximize net revenue	Land, water
Sharma *et al.* 2007	District(Ghaziabad, India)	FGP (Lingo)	Max crop production, net profit, labour, min water, machine	Land, capital, food
Mohaddes and Mohayidin 2008	Farm (Atrak Watershed, Iran)	FGP	Max profit, Max employment, min erosion	Land, water
Sharma *et al.* 2009	State (Himachal	DNLP (GAMS)	Max profit	Land, labour, capital
Sethi and Panda 2011	Farm (Costal River	LP based DSS (QSB+)	Max net returns	Land, water
Soltani *et al.* 2011	Local(Kerman province, Iran)	FGP & LP (QSB)	Max crop production & net returns, min labour employment, water &	Land, labour, wa machine
Rani *et al.* 2012	Farm(Mahabubnagar ,	LP	Max profit, input cost min & water usage min	Land, water, min-r yield requirement
Karunakaran *et al.* 2012	Regional (Bhavani	LP (GAMS)	Max net income	Land, water, soil
Mirkarimi *et al.* 2013	Farm (Amol,	FGP (Lingo)	Max profit,	Self sufficiency
Mortazavi *et al.* 2014	Country (Iran)	LP, GP,FP, FGP (MCDA/MCDM)	Max gross revenue, max employment, min water consumption,	Land, labour, water
Kaur *et al.* 2010; Kaur *et al.* 2015	State (Punjab)	LP	Max profit	Land, labour, wa capital , crop maxim minima
Martin *et al.* 2015	Country (Spanish	LP (GAMS)	Max net return	greening constra based on CAP of EU

Source: Jain et al., 2018*b*

3. Material and Methods

3.1. Study area and the dataset

The Bundelkhand is a semi-arid region of India that comprises seven districts (Jhansi, Jalaun, Lalitpur, Mahoba, Hamirpur, Banda and Chitrakoot) of Uttar Pradesh and six districts (Datia, Tikamgarh, Bhhatarpur, Panna, Damoh and Sagar) of Madhya Pradesh (https://bundelkhand.in/). Agriculture in Bundelkhand is rainfed, diverse, complex, under-invested, risky and vulnerable. In addition, droughts, short-term rain, intermittent dry spells, flooding in fields, and abrupt temperature change add to the uncertainties and seasonal migrations (Jain *et al.*, 2020). Major problems in Bundelkhand are water deficiency, infertility of the land, soil erosion, improper land distribution, depleting groundwater resources and unscientific cultivation in terms of non-use of modern methods in agriculture (GoI, 2015). The yields of cereals, pulses and oilseeds in kharif and rabi seasons are generally lower (Yadav *et al.*, 1996) and even below the parent state average for the majority of the crops (GoUP, 2018; GoMP, 2018). Therefore, considering water, land, capital and other constraints, Bundelkhand is a challenging region for optimum crop planning. The dataset and variables used for experimentation and optimum plan development are summarised in Table 2 and Table 3.

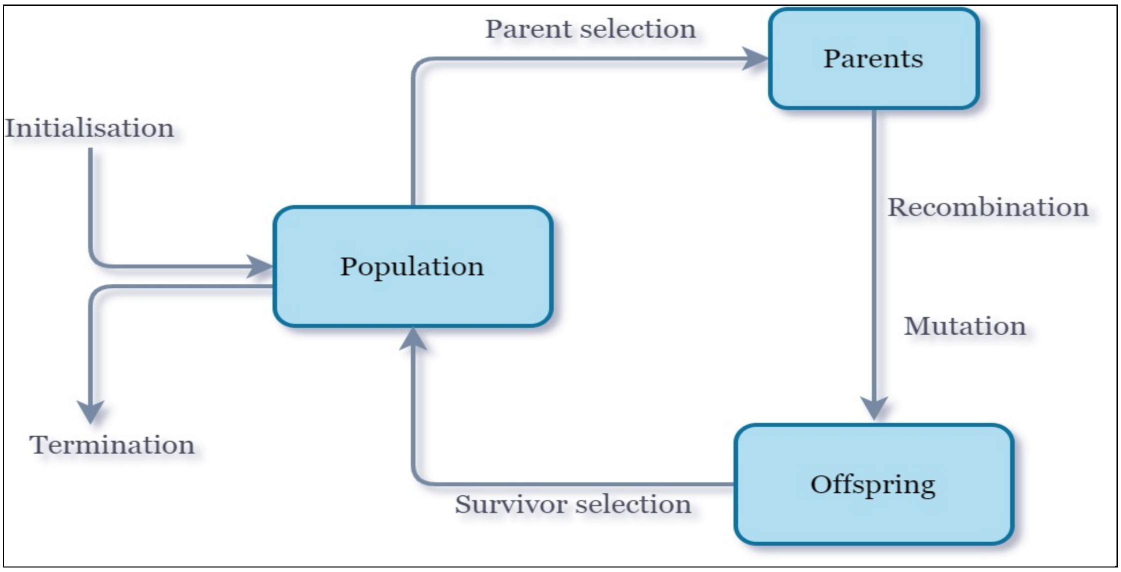


Figure 1: General scheme of evolutionary computing

The data values for the study are based on the unit level data available from the cost of cultivation scheme (https://eands.dacnet.nic.in/Cost_of_Cultivation.htm) for the study area for the year 2017-18 following the data extraction methodology developed by Jain *et al.* (2015). However, the data used for validation of model is interim and have not been generalized for a longer period. Methodology for estimating crop-wise water requirement is based on the literature (Chand *et al.*, 2020). The dataset was compiled as per Table 2 and Table 3. *MinArea* and *MaxArea* are estimated based on current areas, advice of the experts and food security considerations (Jain *et al.*, 2015). Table 4 illustrates a sample from such a dataset. The variables are self-explanatory.

Table 2: Description of the dataset

Item	Description
Location	Bundelkhand
Number of districts	13 *i.e.* Jhansi, Jalaun, Lalitpur, Mahoba, Hamirpur, Banda and Chitrakoot) of Uttar Pradesh and six districts (Datia, Tikamgarh, Bhhatarpur, Panna, Damoh and Sagar)
Number of variables	5 *i.e. MinArea*, *MaxArea*, *R* (Net Returns per ha), *M* (Working Capital per ha), *W* (Water Requirement per ha) for each crop
Number of crops	26 *i.e.* Arhar, Bajra, Barley, Berseem, Chillies, Chickpea, Groundnut, Guar, Jowar, Khesari, Lentil, Linseed, Maize, Mentha, Mesta, Moong, Mustard, Onion, Paddy, Pea, Sesamum, Soyabean, Sugarcane, Tomato, Urad, Wheat

Table 3: Description of the variables

Variable ID	Variable description	Datatype	Unit
Crop	Crops name	character	Identification variable
A	Area to be allocated for a crop	double	000' hectare (ha) per crop
NCA	Net cultivable area	double	000' ha for all crops in the region
MinArea	Minimum allocated area for the crop	double	000' ha per crop
MaxArea	Maximum allocated area for the crop	double	000' ha per crop
R	Net returns from a crop	double	rupees per ha
Z	Overall returns from the region	double	million rupees
M	Money (Working Capital) required for purchase of inputs and other basic things for a crop cultivation	integer	rupees per ha
C	Overall working capital available	double	rupees
W	Water requirement for a crop	double	m^3 per ha
V	Overall irrigated water available	double	billion cubic meters (BCM)

Table 4: Dataset illustration for selected sample crops

Crop	Minimum Area desired under a crop (*MinArea*) (ha)	Maximum Area desired under a crop (*MaxArea*) (ha)	Irrigated Water Requirement (*W*) (m^3/ha)	Net Returns (*R*) (`/ha)	Working Capital (*M*) (`/ha)
Chickpea	867074	1300611	1114	20734	10373
Groundnut	83205	124663	0	8933	12862
Guar	343	36000	0	18000	5938
Paddy	240000	360040	250	16721	16181
Wheat	1695819	2543729	3319	27565	9942

Table 5 presents the comprehensive list of crops, the existing cropping pattern and the crop calendar based on the environment and agricultural practices in the region. A value of '1' means the land may be cultivated by a crop in the specified calendar month.

3.2. Generalised mathematical model

Mathematical Programming can be used for developing and presenting the mathematical model of optimum crop plan (Jain *et al.*, 2019). It provides formulation to use limited resources and maximises the productivity with minimum working capital and/or minimum irrigation water use under many constraints like land availability *etc.* The mathematical formulation for the optimum crop model is characterised by a set of equations in Table 6. The presented formulation is based on two objective functions defined in Equation 1 and Equation 2. In this model, *net returns from a crop*(R) = (*total value of the main product and by-products*) – (*variable costs*). Here variable costs contain Cost $A1$ and imputed value of family labour at market prices paid and received by the farmer or imputed in some cases. The methodology for estimation of R is adopted from Jain *et al*. (2015). Maximization of Z (the sum total of returns from all the crops over the region) is the prime objective of the optimum crop model (Equation 1). Bundelkhand has limited irrigation water availability, hence it is necessary to use minimization of irrigation water *i.e.* V as another objective function (Equation 2). In the case of single objective-based implementation, irrigation water availability needs to be known and it can be used as a constraint. In this paper, we have implemented both (single as well as multi-objective) kinds of mathematical models.

Table 5: Crops and respective calendar for crops used in the model

Crops	Area (ha)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Arhar	105616	0	0	0	0	0	1	1	1	1	1	1	1
Bajra	30587	0	0	0	0	0	1	1	1	1	0	0	0
Barley	67912	1	1	0	0	0	0	0	0	0	0	1	1
Berseem	2000	1	1	1	1	0	0	0	0	0	1	1	1
Chillies	4020	0	0	0	0	0	0	0	1	1	1	1	0
Chick	867074	1	1	0	0	0	0	0	0	0	1	1	1
Gnut	83204	0	0	0	0	0	1	1	1	1	1	0	0
Guar	3430	0	0	0	0	0	1	1	1	1	1	1	0
Jowar	85845	0	0	0	0	0	1	1	1	1	0	0	0
Khesari	5140	1	0	0	0	0	0	0	0	0	1	1	1
Lentil	268984	1	1	0	0	0	0	0	0	0	1	1	1
Linseed	22924	1	1	0	0	0	0	0	0	0	1	1	1
Maize	53948	0	0	0	0	0	1	1	1	1	0	0	0
Mentha	9500	0	1	1	1	1	1	1	0	0	0	0	0
Mesta	100	0	0	0	0	0	1	1	1	1	1	1	0
Moong	48426	0	0	0	0	0	1	1	1	1	0	0	0
R&m	111777	1	1	1	0	0	0	0	0	0	1	1	1
Onion	8833	1	1	1	0	0	0	0	0	0	1	1	1
Paddy	240000	0	0	0	0	0	1	1	1	1	1	0	0
Pea	334440	1	1	1	0	0	0	0	0	0	1	1	1
Sesame	373423	0	0	0	0	0	1	1	1	1	1	0	0
Soya	593011	0	0	0	0	0	1	1	1	1	0	0	0
Scane	16141	1	1	1	1	1	1	1	1	1	1	1	1
Tomato	515	0	0	1	1	1	1	0	0	0	0	0	0
Urad	520532	0	0	0	0	0	1	1	1	1	0	0	0

Wheat	1695819	1	1	1	0	0	0	0	0	0	0	1	1

Note: Self-explanatory short names of crops are used due to space constraint *e.g.* gnut: groundnut

Table 6: Mathematical formulation of Optimum Crop Plan

Eq.	Equation Functions	Variable Description
1.	$Max\ Z = \sum_{c=1}^{n} R_c A_c = \sum_{c=1}^{n} (Y_c P_c - C_c) A_c$	Z: overall net returns from all crops in the cultivated area R_c: Net returns from crop *c* per ha Y_c: yield of crop *c* P_c: market price of crop *c* C_c: cultivation cost of crop *c* A_c: area allocation for crop *c* *n:* number of crops available for cultivation *i.e.* 26
2.	$Min\ V = \sum_{c=1}^{n} W_c A_c$	V: Overall irrigated water W_c: water required for crop *c* per ha A_c: area allocation for crop *c*
3.	$\sum_{c=1}^{n} A_c M_c \ \leq\ C$	M_c: working capital for crop *c*in `/ha C: total working capital available for the region (regional constant constraint)
4.	$\sum_{c=1}^{n} (a_{tc}) A_c \ \leq\ NCA_t$ for all *t* from1 ..12	a_{tc}: crop calendar coefficient for month *t* and crop *c*. Coefficient a_{tc} = 0 means cultivation of the crop *c* in month *t* does not happen. NCA_t:: net cultivable area in the region in a month(regional constant constraint). We have taken it the same for all months. Equation 4 represents 12 area constraints one for each month
5.	$A_c \geq MinArea_c$	$MinArea_c$: Minimum allowable area for crop *c*
6.	$A_c \leq MaxArea_c$	$MaxArea_c$: Maximum allowable area for crop *c*

3.3. Evolutionary computing based model

Particle Swarm Optimisation (PSO) was developed in 1995 by Kennedy and Eberhart, inspired by the behaviour of social organisms in groups, such as bird and fish schooling or ant colonies (Kennedy and Eberhart, 1995; Kennedy, 2010). The algorithm emulates the interaction between members to share information. PSO has been applied to numerous areas in optimisation and combination with other existing algorithms. This method performs the search of the optimal solution through agents, referred to as particles, whose trajectories are adjusted by a stochastic and a deterministic component. Each particle is influenced by its 'best' achieved position and the group 'best' position but tends to move randomly. One of the reasons for using the individual best is probably to increase the diversity in the quality solutions; however, this diversity can be simulated using some randomness. The individual best is useful when the optimization problem of interest is highly nonlinear and multimodal.

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 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.* Finally, the velocity can be computed by using Equation 7 to Equation 8.

$$x_i^t = x_i^{t-1} + v_i^t - \ (7)$$

$$v_i^t = inertia \times v_i^{t-1} + c_1 r_1 (pbest_i^{t-1} - x_i^{t-1}) + c_2 r_2 (gbest^{t-1} - x_i^{t-1}) (8)$$

where *inertia* is the inertia weight, c_1, c_2 are acceleration coefficients, r_1, r_2 are random numbers between 0 and 1,v is particle velocity, x is particle position, i is a particle identifier in a swarm and t is an iteration number in the optimization process. Since each particle explores the possible solutions of space, each of them represents a candidate solution to the problem. For example, one candidate solution for optimum crop plan (based on 26 crops) for a given region is shown in Figure 2.

x_{i1}	x_{i2}	…	x_{i25}	x_{i26}

Figure 2: Example of an i^{th} candidate solution for PSO based optimum crop plan

In Figure 2, x_{ik} represents area allocation for a crop k where k varies from 1 to 26 in i^{th} candidate solution of our case study. Each candidate solution is called a crop plan (a particle in PSO *i.e.* x_i in Equation 7). Figure 3 presents a self-explanatory basic flow chart for implementing the PSO. We observe that it is an iterative algorithm that works until the solution converges.

3.4. Software

PSO based OCP has been implemented in this work using the MOPSOCD package in R (Naval, 2013; Table 7). Multi-objective optimization involves maximizing or minimizing multiple interacting/conflicting objective functions subject to a set of constraints. MOPSOCD is a multi-objective optimization solver based on particle swarm optimization that uses crowding distance computation to ensure an even spread of non-dominated solutions. Crowding distance is calculated by first sorting the set of solutions in ascending order of objective function values. The crowding distance value of a particular solution is the average distance of its two neighbouring solutions. The crowding distance mechanism together with a mutation operator maintains the diversity of non-dominated solutions in the external archive. The approach is highly competitive in converging towards the Pareto front and generates a well-distributed set of non-dominated solutions. The details of the package are available at https://cran.r-project.org/web/packages/mopsocd/ mopsocd.pdf.

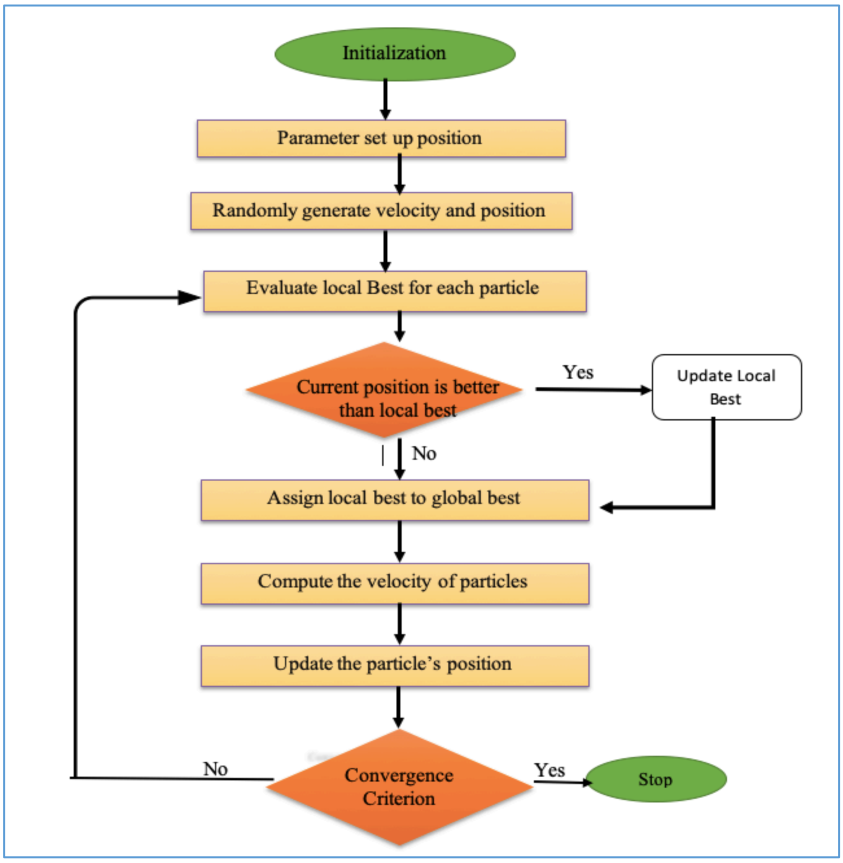


Figure 3:Basic flowchart of Particle Swarm Optimization algorithm

Table 7: Implementation details of using PSO for optimum crop planning in Bundelkhand

Algorithm and parameters	Implementing software	Package	Source
PSO N = 100 c_1 = 1.041 c_2 = 0.948 *inertia* = 0.629	R software	mopsocd	https://CRAN.R-project.org/package=mopsocd
		pso	https://CRAN.R-project.org/package=pso
		ggplot2	https://CRAN.R-project.org/package=ggplot2
		plot3D	https://CRAN.R-project.org/package=plot3D

Note: N is user-defined for the number of iterations;c_1, c_2 and inertia are defined in Equation 8 in Section 3.3.

4. Results and Discussion

Evolutionary computing approaches can be used for linear as well as non-linear optimization. Besides, they are convenient to use for single and multi-objective functions. We explored PSO for optimum crop plan development in Bundelkhand region for increasing farm income while utilizing the scarce resources efficiently. Presently, Bundelkhand has 5.3 million ha gross cropped area (GCA) with overall returns (Z) of `105.46 billion by using 18.6 BCM of water with an inefficiency of 52 per cent. Thus, the actual water requirement of crops that can be fulfilled is 9.12 BCM.

4.1. Single objective function

Firstly, we explain the results obtained from our experiments for single objective function optimization under various scenarios (Table 8-9). Later, we explain various scenarios under multi-objective function optimizations and the corresponding results. Table 8 presents the scenarios formulated depending on the availability of irrigation water in the region. Bundelkhand is a water-scarce region where irrigation facilities are available only in 50 per cent of the cultivable area. In the remaining area, rainfed crops are cultivated. Hence, there is a need to explore how the profitability changes under the variable availability of irrigation water.We explore a single objective function along with variable availability of irrigation water (Table 8) and variable availability of working capital (Table 9) and present the results in Table 10 and Table 11 respectively.

As water availability increases, net returns also increase. The maximum optimum profit under the current use of water is `159.41 billion which increases to `160.9 billion with an increase of water availability by 20 per cent. Under optimum plans, there is an increase in allocated area under crops that need less water. Allocation under berseem, guar, khesari, mesta and tomato increase substantially. Besides, allocation under chillies, mentha, rapeseed and mustard, onion and sugarcane decrease in most of the optimum plans. Further, we observe that area under all other crops shows an increase (Table 10). Bundelkhand has a scarcity of working capital due to the lack of formal credit infrastructure, hence it is important to develop optimum crop plans under variable constraints of working capital. With an increase in working capital by 10 per cent, we can increase net returns to `161.20 billion at the most. But, further increase in working capital will not increase the net returns due to limitations of other factors. In optimal plans, net returns increased by nearly 50-52 per cent (Table 10-11) and water use decreased up to 20 per cent. This has been made possible by the use of fallow land available in the state during rabi season. We observe that PSO using single-objective functions can achieve the optimum plans under various constraints. However, it requires estimation of the supply of resources which is not always feasible to estimate. For such scenarios, multi-objective optimization will be useful and the corresponding optimization results are explained further.

Table 8: List of scenarios and corresponding description for variable water constraints

SNo.	Short Name	Description	Water (*V*) Constraint (BCM)	Overall water used by crops (BCM)
1	W_NO	No water constraint in the model	-	12.16
2	W_Curr	Current use of water	18.65 **	9.10
3	W_Avail	Available irrigated water(after taking account of water efficiency in Bundelkhand) for model development	17.36	8.50
4	W_0.7	70% of the current water requirement	13.05	6.30
5	W_0.8	80% of the current water requirement	14.92	7.20
6	W_0.9	90% of the current water requirement	16.78	8.19
7	W_1.1	110% of the current water requirement	20.51	10.01
8	W_1.2Curr	120% of the water requirement	22.38	10.92

Notes: '*': Land and capital constraints were not changed; Model parameters land=4.2 million ha; working capital (C) =`53.15 billion
'**': Water use efficiency in Bundelkhand is 52.6%

Table 9: List of scenarios and description for variable working capital constraints

SNo.	Short name	Description	Working Capital (C) Constraint* (`billions)
1	C_NO	No working capital constraint in the model	NA
2	C_Curr	Current use of working capital is constrained	53.15
3	C_0.9Curr	90% of working capital is available	47.83
4	C_0.8Curr	80% of working capital is available	42.52
5	C_0.7Curr	70% of working capital is available	37.20
6	C_1.1Curr	110% of working capital is available	58.46
7	C_1.2Curr	120% of working capital is available	63.78

Note'*': Land and water constraints were not changed.
Model parameters are: Irrigated Water use= 18.65 BCM; land=4.2 million ha;

Table 10: Percent change in area allocations to different crops under different scenarios for the single objective function and variable irrigation water constraints

Crop	W_No	W_Curr	W_Avail	W_0.7	W_0.8	W_0.9	W_1.1	W_1.2
Arhar	10	32	34	33	23	28	45	44
Bajra	10	32	19	29	36	41	37	2
Barley	46	5	24	18	41	3	34	4
Berseem	184	630	393	1454	568	709	68	193
Chillies	–33	–5	–54	–12	17	19	1	–59
Chickpea	50	10	50	50	50	50	50	50
Gnut	47	34	21	24	29	50	34	38
Guar	399	764	865	949	735	–15	637	79
Jowar	35	48	25	29	20	48	13	38
Khesari	937	585	1032	590	635	986	299	626
Lentil	35	30	35	50	49	50	37	20
Linseed	22	23	24	44	29	18	22	9
Maize	13	17	26	10	23	5	24	14
Mentha	–47	–46	–28	–44	–39	–65	–52	–46
Mesta	2876	2931	3826	4366	820	5618	5098	4723
Moong	7	46	36	38	13	36	30	33
R&m	–34	–68	13	30	–31	50	16	–82
Onion	–17	–78	–63	–2	–60	15	–76	–53
Paddy	42	30	50	41	45	35	40	49
Pea	50	13	31	23	50	50	50	41
Sesame	47	47	47	36	41	46	44	47
Soybean	56	56	55	56	56	56	51	56
Scane	–1	–19	10	–28	28	53	–2	–17
Tomato	783	1362	1192	559	1289	1060	1135	392
Urad	49	49	48	49	49	48	49	49
Wheat	50	32	50	50	50	50	50	50
V in BCM	12.16	9.10	8.50	6.30	7.20	8.19	10.01	10.92
GCAin Mha	8.11	8.10	8.14	8.12	8.15	8.25	8.13	7.90
Z in ` 10^9	159.0	159.41	159.70	159.03	159.93	158.17	159.11	160.90
Change Z %	50.78	51.16	51.43	50.8	51.65	49.98	50.87	52.57

Note: Current GCA: 5.3Mha; current *Z*: `105.46 billion; Current *V* = 9.12 BCM

Table 11: Percentage change in area allocations to different crops under different scenarios for single objective function and variable working capital (C) constraints

Crop	Variable working capital (C) constraints						
	C_No	C_curr	C_0.7	C_0.8	C_0.9	C_1.1	C_1.2
Arhar	32	32	46	6	37	50	32
Bajra	32	32	12	11	32	16	32
Barley	5	5	47	20	21	17	5
Berseem	630	630	754	1630	958	1278	630
Chillies	–5	–5	–64	–35	–58	–37	–5
Chickpea	10	10	50	50	50	50	10
Gnut	34	34	38	50	43	50	34
Guar	764	764	586	945	675	851	764
Jowar	48	48	48	37	40	38	48
Khesari	585	585	366	388	1024	625	585
Lentil	30	30	43	35	50	50	30
Linseed	23	23	34	35	7	25	23
Maize	17	17	10	39	40	44	17
Mentha	–46	–46	–49	–26	–40	–64	–46
Mesta	2931	2931	1813	2479	3174	2962	2931
Moong	46	46	28	42	18	15	46
R&m	–68	–68	50	50	–66	50	–68
Onion	–78	–78	–69	–37	–13	–10	–78
Paddy	30	30	40	50	45	49	30
Pea	13	13	50	20	50	33	13
Sesame	47	47	46	29	47	40	47
Soybean	56	56	56	56	56	52	56
Scane	–19	–19	53	53	–45	–73	–19
Tomato	1362	1362	1867	1355	1001	1637	1362
Urad	49	49	49	31	19	49	49
Wheat	32	32	50	50	50	50	32
C in ` 10^9	75.43	53.15	37.20	42.52	47.83	58.46	63.78
GCA in Mha	7.96	8.10	8.01	8.00	8.02	8.20	8.22
*Z*in ` 10^9	156.70	159.41	157.60	158.60	158.40	161.20	160.80
% change *Z*	48.59	51.16	49.44	50.39	50.2	52.85	52.47

4.2. Multi-objective function

Evolutionary computing is also useful in developing optimal plans for multi-objective optimization (Table 12-13). Table 12 presents the various scenarios that were experimented with PSO. The list is only indicative to show the potential of evolutionary computing. The first two scenarios seek to optimize profit under minimum water and minimum working capital use respectively. The third scenario is just to explore the maximum capital requirement. Scenario 4 and scenario 5 make use of three objective optimizations. Table 13 shows only one such case for each scenario. However, the results of each of these optimizations are a Pareto-optimal curve showing multiple solutions for each scenario

(Figure 4-6). Thus, the evolutionary techniques can deliver the Pareto-optimal solutions as expected from multi-objective optimizations. We observe that net returns increase 15-30 per cent in different scenarios (Table 13).

The relationship of net returns (*Z*) with variable availability of water (*V*) or variable availability of working capital (*C*) is presented in Figure 4. These relationships are obtained based on the optimization of two objectives using evolutionary computing and the resulting Pareto optimal solutions are shown in Figure 5. We observe multiple solutions for three different models namely MaxP_MaxC, MaxP_MinC and MaxP_MinW (Table 12 for the description of scenarios). Profit maximization is the prime objective in each of these two objective-based optimizations. We observe the maximum profit in the case of MaxP_MaxC and the number of solutions is also limited with lesser variability. On the other hand, in the case of MaxP_MinC model, we get very high variability in solutions with *Z* ranging from 110-145 billion rupees with an average profit of 125 billion rupees in Bundelkhand. For the third MaxP_MinW model, we observe the intermediate variability of solutions with *Z* ranging from 122-140 billion rupees with an average profit of 132 billion rupees for the region. We observe that an increase in availability of both resources namely working capital (*C*) and water (*V*) increase net returns to the farmers. This emphasises the need to explore three objective optimizations. The number of solutions achieved for such scenarios is shown in Figure 6. Thus, a diverse set of solutions are available and any one can be chosen depending on the available resources. These models, if used at the farm level have the potential to recommend optimum plans to farmers based on the status of available inputs at farm level.

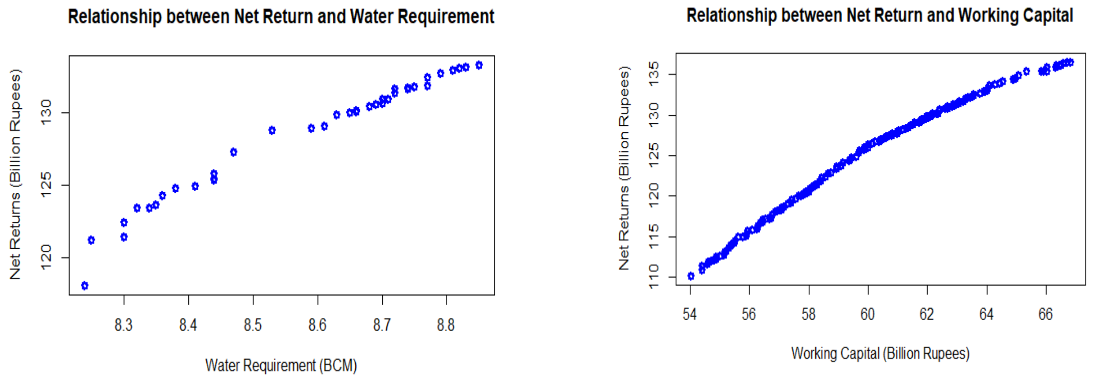
Table 12: List of multi-objective scenarios and the corresponding description

S.No*.	Short name	Description	Other parameters
1	MaxP_MinW	Maximise profit and Minimise water	*C* = `53.15 billion
2	MaxP_MinC	Maximise profit and Minimise Working capital	Water (*V*) = 9.10 BCM
3	MaxP_MaxC	Maximise profit and maximise working capital	Water(*V*) = 9.10 BCM
4	MaxP_MinW_MinC	Maximise profit, Min water, Min work capital	-
5	MaxP_MinW_MaxC	Maximise profit, Min water, Max work capital	-

Note '*': S.No.refers to scenario number

Table 13: Change in area allocations (%) to the crops under multi-objective scenarios

Crops	MaxP_MinW	MaxP_MinC	MaxP_MaxC	MaxP_MinW_MinC	MaxP_MinW_MaxC
Arhar	47	22	24	49	35
Bajra	9	13	6	21	31
Barley	15	31	22	5	29
Berseem	66	1221	65	511	155
Chillies	-51	-54	1	-35	-35
Chickpea	43	2	6	12	26
Gnut	32	26	47	28	28
Guar	682	284	632	579	372
Jowar	32	9	43	21	25
Khesari	761	377	267	567	856
Lentil	37	43	3	24	12
Linseed	22	17	16	33	34
Maize	10	16	42	34	32
Mentha	-61	-56	-35	-77	-59
Mesta	810	262	1900	3310	4859
Moong	44	28	22	39	13
R&m	-60	-57	-73	-64	-90
Onion	0	-65	26	-81	-87
Paddy	33	1	42	10	42
Pea	2	1	17	5	6
Sesame	38	17	46	13	40
Soybean	56	0	56	25	56
Scane	-6	-28	-11	-6	-94
Tomato	475	1781	1192	1043	1181
Urad	48	2	49	30	40
Wheat	0	21	29	13	0
C in ` 10^9	65.84	58.35	67.92	60.89	63.53
GCA in Mha	6.90	6.19	7.12	6.46	6.71
Z in ` 10^9	131.78	121.78	137.82	124.64	126.44
Z in % change	24.96	15.48	30.68	18.19	19.89



Max Net returns and Min Water **Max Net Returns and Min Working Capital**

Figure 4: Relationship (i) Net returns (*Z*) *vs.* water used (*V*) (ii) Net returns (*Z*) *vs.* working capital (*C*) using the single objective function

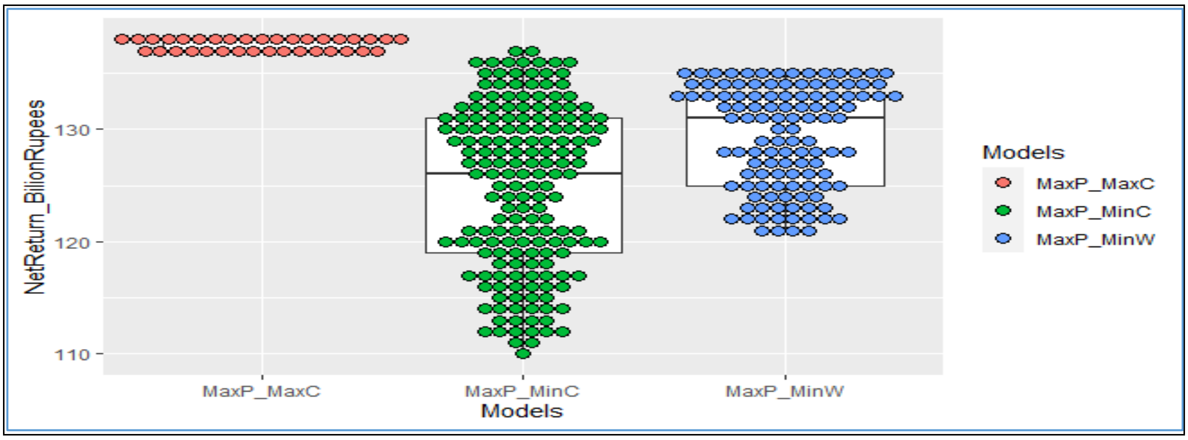


Figure 5: Number of solutions obtained from PSO based optimization for two objectives

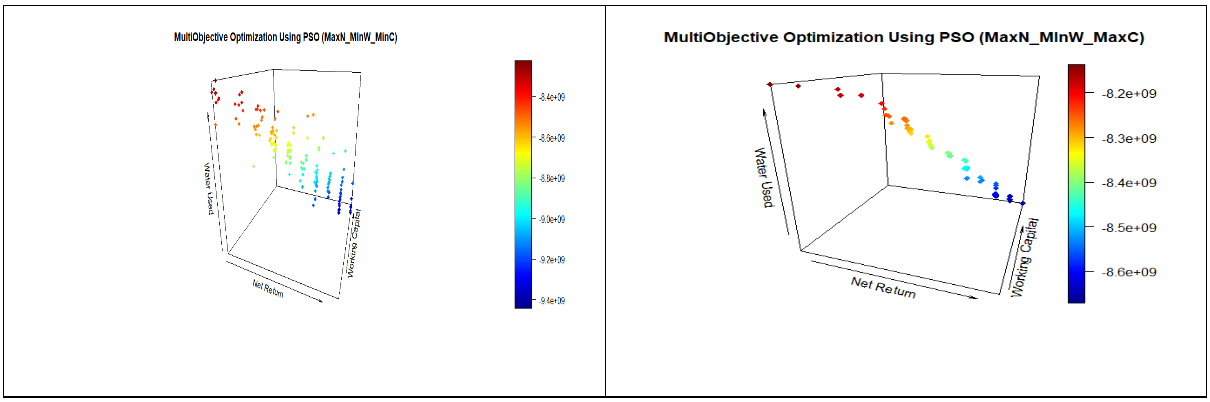


Figure 6: Number of solutions obtained from PSO based optimization for three objectives

5. Conclusions and Future Scope

Researchers have attempted various techniques for optimum cropping plans at various levels (farm, region, state, country) with various objectives and constraints depending on the resource availability and objectives of the farms or region. These models have been set up as a research tool or a teaching aid only as farmers and the end-users have directly used very few models. By using the versatile models presented in this paper, extension services can create awareness and give advisory services under expert guidance based on the available resources of individual farmers and the regions. This paper strengthens the opinion (Nath *et al.*, 2020) that the use of evolutionary computing for optimization in crop planning needs to be explored further and algorithms may be modified to suit the specific needs of crop planning.

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