



Research Article

Meta Mola: Metaheuristic Algorithms for Multi-Objective Land AllocationKamran Nasirahmadi^{a,b*} , Abdolrasoul Salmanmahiny^c, Seyyed Hamed Mirkarimi^c^a Department of Civil Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran^b UNESCO Chair on Coastal Geo-Hazard Analysis, Tehran, Iran^c Department of Fisheries and Environmental Sciences, Gorgan University of Agricultural Science & Natural Resource**ARTICLE INFO****Article history:**

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ABSTRACT

In some areas of land planning, such as forest management, construction and development of cities, and choosing the right place to establish factories and industrial units, allocating land individually and in a scattered manner can cause problems. The approach can lead to inefficiencies and challenges in coordinating land use effectively. These problems increase the importance of the current research because the research aimed to provide a method to solve the problems. In this research, Meta Mola software has been introduced, which used metaheuristic algorithms to optimize land allocation in Gorgan Township in multi-objective problems. The main goal of this study was to provide an efficient method for contiguity and compactness land allocation using particle swarm (PSO) and firefly (FA) algorithms. By integrating metaheuristic algorithms and compactness and contiguity optimization capabilities, the software effectively modified the scattered patterns of the land and provided a more optimal allocation. One of the outstanding features of Meta Mola is the ability to use the Emgu graphical interface to identify key points and create reallocations that allow connection to GIS software. The results showed that this software, especially with an emphasis on contiguity and compactness, acts as a useful tool for land use planning with optimal performance in complex land allocation issues. The results can significantly help to reduce negative environmental effects and improve productivity in land planning. It also provides the basis for the development of sustainable development patterns.

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1. Introduction

Land use optimization is a method for allocating resources in which a particular usage is assigned to a specific land unit. Such problems usually require simultaneous attention to multiple and conflicting goals, such as environmental and economic objectives [1, 2, 3]. The goal is to achieve sustainable land use allocation for new economic growth through an optimal land use structure. The spatial nature indicates that additional objectives (spatial components) and complexity should be taken into consideration [4]. A compact and continuous spatial structure is one of the main aims of optimizing the allocation of land use in different planning areas, including the management of forests and the design of reserves. In this way, addressing compactness and fragmentation are among the common objectives of

Sustainable planning of land use has become a very important topic of interest nowadays [5, 6]. Today, there is an increasing need for tools that can support the process of planning, particularly the allocation of land. allocating the best use for each piece of land is known as the most complex task of this process, ultimately resulting in an optimal map of different areas with specific uses. This final map is known as a land use zoning map [7]. It is worth noting that recently, there has been a gap between the growing need for allocation of land-use and the development of practical and software packages for executing the process [8]. One of the most recognized attempts to integrate multi-objective allocation of land-use with GIS refers to a module in IDRISI, MOLA, which was generated by Eastman et al. [9]. However, this method has a potential

*** Corresponding author.**E-mail address: dr.nasirahmadi@mazust.ac.ir, nasirahmadi.k@gmail.com**Cite this article as:**

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weakness in producing sporadic patterns [10], due to the limitations mentioned in the Brookes 1997, Herwijnen and Rietveld 1999 studies. Regarding that, a patch (optimum area) has cells with the maximum levels of fitness, as well as Optimal spatial attributes like orientation, shape, compression, and overlap [11]. There is a good range of meta-heuristics available for tackling multi objective optimization problems [12]. Particle swarm and optimization algorithms have been applied to resolve complex spatial problems with multiple objectives [13, 14]. In the present article, the application of the algorithms for optimized allocation of land use has been examined as a technique of modeling, by integrating the dot net library of Microsoft using c# programming language based on parameters such as land suitability and area demand as a new software called Meta Mola. To achieve more optimized allocation, we present a new compactness and contiguity module in Meta Mola software to identify disjoint and scattered spots and then use a shape index to reallocate them. All of the executable functions required to run the intended algorithm codes under Meta Mola software have been developed using the .NET Framework of Open CV-library and implemented in the Visual Studio "Integrated Development environment" Software. As mentioned, using the top-down approach to identify major spots by the Emgu graphical interface in the .NET Framework is one of the important capabilities of this software in re-allocating dispersed patterns. Finally, we demonstrate a real-world application of the model to land use planning in Gorgan Township, Golestan Province, Iran. The research question of the present study:

- Does Meta Mola provide significant and reliable results in real case studies?
- How does the use of meta-heuristic algorithms such as particle swarming and Firefly in this software reduce the challenges related to land fragmentation?

2. Structure of Particle Swarm and Firefly Algorithm

2.1 Firefly Algorithm

FA, which stands for the firefly algorithm, is known as one of the swarm intelligence methods originated by Yang in 2008. The algorithm is stochastic, meta-heuristic, nature-inspired and can be used for solving the very hard optimization problems (generally NP-hard problems) [15]. This algorithm is based on a physical formula of light intensity. In this formula, the intensity of light is inversely related to the square of the distance from the light source (r^2). Increasing the distance from the light source leads to the attenuation of the light through spreading out over more space and absorption by the environment. Such physical phenomena are introduced as mathematical parameters into the objective function to simulate natural behavior. The base FA used in this study can be illustrated in Figure 1 [15]. The Figure shows the key steps of the algorithm. The algorithm consists of an initial population

of fireflies and then searches for the optimal solution using an objective function. The population of fireflies gradually improves its position to move towards the best possible solution.

2.2 Particle Swarm Algorithm

PSO, which stands for Particle Swarm Optimization, was initially developed by James Kennedy and Russell Eberhart in 1995 as an optimization technique globally [16]. One of the characteristics of this algorithm is population-based optimization. The start of the algorithm is with an initial population of generated particles in a random way. Each particle remembers and stores the position of the best place it has previously found. Meanwhile, each particle is influenced by and attracted to both its own best experience and the best experience of the particles around it (best-found position by the neighbors) as follows [18]:

$$\bar{V}_i(t) = w \cdot \bar{V}_i(t-1) + (p_1 r_1 (\bar{p}_i - \bar{x}_i(t-1)) + \varphi_2 \cdot r_2 (\bar{p}_g - \bar{x}_i(t-1))) \quad (1)$$

$$\bar{X}_i(t) = \bar{X}_i(t-1) + \bar{V}_i(t) \quad (2)$$

In the formula above, vi(t) refers to the velocity of the ith particle, xi(t) stands for the position of the ith particle, pi refers to the best previous position for the ith particle, and pi stands for the global best particle found by all particles thus far. w refers to the weight value applied to balance the local and global search abilities of a particle. φ_1 and φ_2 refer to two learning factors, which are acceleration coefficients, and r1 and r2 refer to two uniformly distributed random variables in the range (0, 1). The base PSO used in this study can be formulated as illustrated in Figure 2 [17].

1	Initialize: gen.counter, best solution, attractiveness
	• $t = 0;$ • $x^* = \emptyset;$ • $\gamma = 1.0;$
2	Initialize a population
	• $P^{(0)} = \text{InitializeFA}(\dots);$
3	Start the search operation
	• while ($t < \text{MAX_FES}$) do
4	Determine a new value of α
	• $\alpha^{(t)} = \text{AlphaNew}(\dots);$
5	Evaluate x according to $f(x)$;
	• $\text{EvaluateFA}(P^{(t)}, f(x));$
6	Sort x according to $f(x)$;
	• $\text{OrderFA}(P^{(t)}, f(x));$
7	Determine the best solution
	• $x^* = \text{FineTheBestFA}(P^{(t)}, f(x));$
8	Vary the attractiveness accordingly
	• $P^{(t+1)} = \text{MoveFA}(P^{(t)});$
9	
	• $t = t + 1;$
10	
	• End while

Fig. 1. Pseudo code of the base Firefly algorithm.

3. Materials and methods

3.1 The zone of study

The location of the investigation was in Gorgan, a city located in the northeastern part of Iran near the Caspian Sea, Iran (Figure 3). The city is the capital of the Golestan Province. The city has geographical coordinates between 54° 10'-54° 45' E and 36° 44'- 36° 58' N, and the area of it is approximately 1316 KM2. In Gorgan town, there are different land uses including agriculture, forestry, and urban development, which provide a suitable field for testing optimal land allocation algorithms and especially the use of algorithms based on artificial intelligence [18].

3.2 Meta Mola Software Structure

The Meta Mola software was developed in C# in the Visual Studio environment, based on the .NET framework. The particle swarm and firefly algorithms were implemented by incorporating the intended target functions in the base code of these algorithms. Finally, to enhance user-friendly, the .NET Framework executive functions in the OpenCV library were used to change the Meta Mola code. One of the unique capabilities of this software to achieve optimal land use allocation is the use of the Emgu Graphical Interface capacity to identify the main patches for the reallocation of scattered patterns. This software is a specialized tool for land use planning and optimization that works in a standard ASCII format and is compatible with most GIS software. Its initial version is designed to find the best way to divide land based on important criteria such as suitability of the land for each use, area required, contiguity indices, and compactness. The main stages of this software work in four key steps, which are explained below (Figure 4).

3.3 Input Data

Two categories of inputs are used: a land-use suitability map and constraint maps. Looking at the input section, one will notice another input called Mola. The output map generated by the MOLA multi-objective land-use allocation procedure can be loaded here, which in this study, is the result of MOLA in Idrisi software.

It is worth noting that the suitability and constraints maps used in this study have been produced using a multi-criteria evaluation procedure in the land use planning project of Golestan Province [19]. Seven maps consisting of four suitability maps, two constraint maps, and a Mola map of the Idrisi were used in this study which are shown in Figure 5.

3.4 Firefly and PSO Algorithms

At this stage, the performance of each algorithm can be tested in a single-objective approach and for each land use. It is worth noting that the parameters for each algorithm should also be set correctly. Live results of the algorithm execution

can be seen pixel by pixel in the display window until the desired area is accomplished. In this step, we can test the output of the algorithms in combination mode by taking into account the multi-objective land use map of other software such as Idrisi. To do this, we could just tick the check box called Mola acts.

```

For each particle i
  For each dimension j
    Initialize position  $x_{ij}$  randomly with permissible rang
    Initialize velocity  $v_{ij}$  randomly with permissible rang
  End for
End for
Iteration k=1
Do
  For each particle i
    Calculate fitness value
    If the fitness value is better than  $Pbest_{ij}$  in history
      Set current fitness value as the  $Pbest_{ij}$ 
    End if
  End For
  Chose the particle having best fitness value as the  $Gbest_{ij}$ 
  For each particle i
    For each dimension j
      Calculate velocity according to the equation
       $v_{ij}^{t+1} = \omega v_{ij}^t + \phi_{1j} (Pbest_{ij}^t - x_{ij}^t) + \phi_{2j} (Gbest_{ij}^t - x_{ij}^t)$ 
      Update particle position according to the equation
       $x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1}$ 
    End for
  End for
  K=k+1
While maximum iteration or minimum error criteria are not
  attained.
  
```

Fig. 2. Pseudo code for the base PSO algorithm.

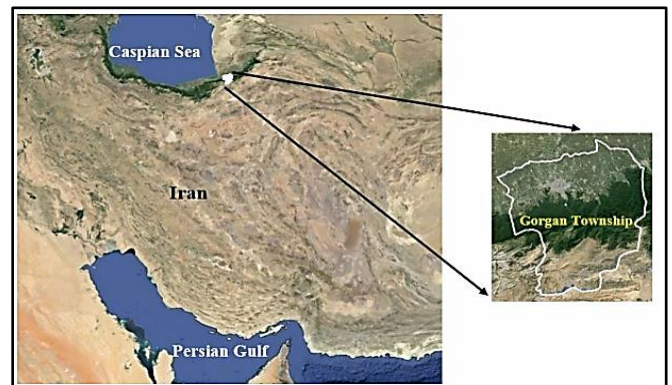


Fig. 3. Study area

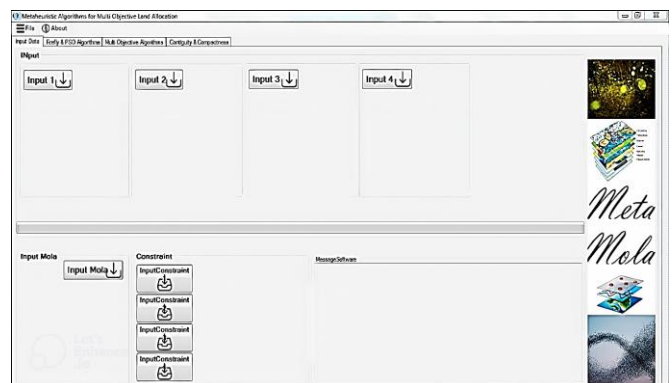


Fig. 4. Structure of Meta Mola Software

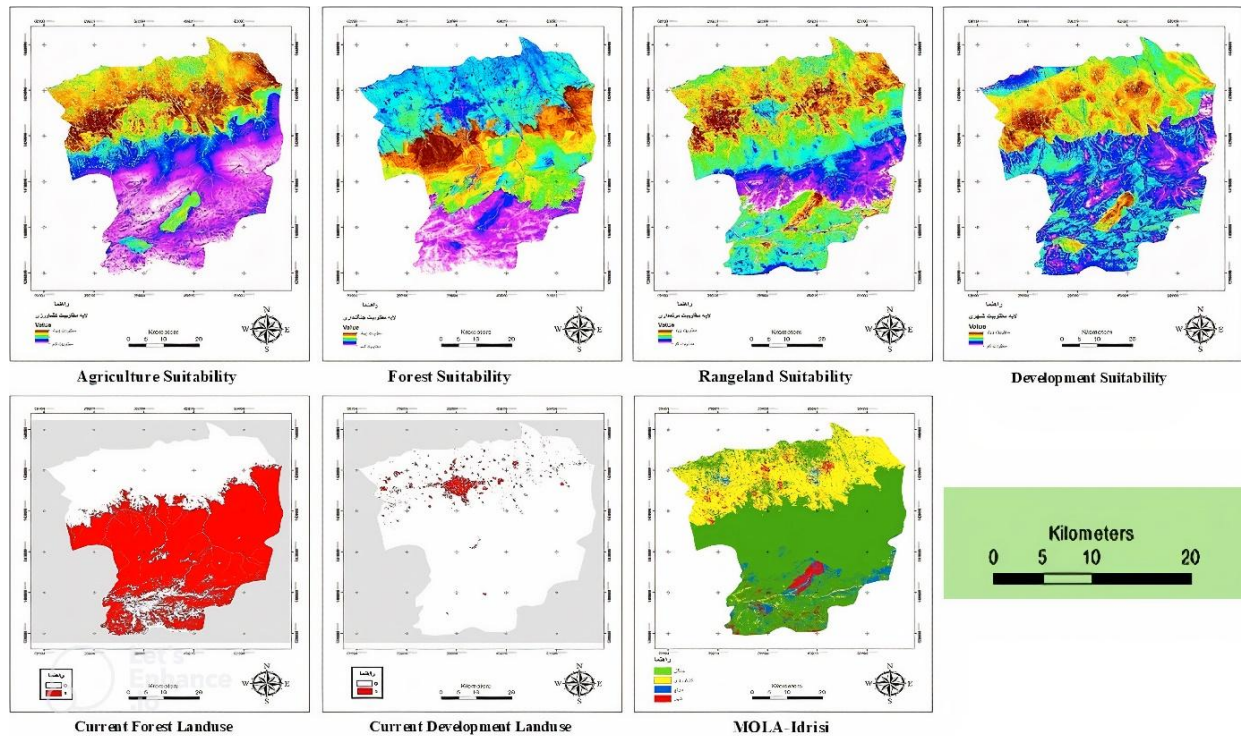


Fig. 5. Input maps

3.5 Multi-Objective Allocation

This section comprises four main sections, including intended area, weight, firefly algorithm parameters, and particle swarm algorithm parameters, which are described below in detail.

3.5.1 Area of each fitness

Most of the methods for land use allocation optimization require the calculation of land area as an input for each land use [20, 21]. In Gorgan Township, only about 99,000 hectares of land are available for land allocation. In other words, only 62% of the area can be used for new allocation or modification. Of this, about 35% of the changeable areas are located in forest areas, which should be treated with caution. In this study, the required area has been selected completely randomly. The aerial requirements to allocate each land use for Gorgan city have been revealed in Table 1.

3.5.2 Weight

The weight of every application was considered to be 0.25. However, for various purposes, weights are often changed.

3.5.3 Firefly Algorithm Parameter

The optimal setting of parameters in algorithms is said to matter, and typically, there's no notion of the simplest setting [14]. The quantity of every parameter during this study is predicated on the experiences of other researchers which are shown in Table 2.

3.5.4 Particle Swarm Algorithm Parameter

In general, the adjustable parameters of the particle swarm algorithm include factors like inertia weight w , and training factors c_1 & c_2 [22]. The worth of the parameters has additionally supported the experiences of other researchers [14]. within the present study, we set the parameters as shown in Table 3.

Table 1. Land area necessities (Hectares)

Use of land	The present zone	New zone in Meta Mola	Changing
Developing	4395/5	5278/2	+882/7
Forest	35259/3	103691/6	+48432/3
Rangeland	15297	7677/4	-7619/6
Agriculture	48656/6	45104/9	-3551/7
Water bodies	1036/2	**	**
Road	3278/9	**	**
Protected area	50059/5	**	**
Changeable	99212/9	**	**
Non-Changeable	58770/1	**	**

Table 2. Firefly Algorithm Parameter

Parameter	Value
npop	50
iteration	500
α	0.2
γ	1
β	1
Elitest	10

Table 3. PSO Algorithm Parameter

Parameter	Value
npop	50
iteration	500
w	0.7
C_1	1.4944
C_2	1.4944
Elitest	10

3.6 Compactness and Contiguity

3.6.1 Compactness

Compactness may be a relative term used to describe the ultimate sort of land use allocation (Chen et al., 2023).

Generally, compactness occurs when cells belonging to an equivalent type are combined, and when these cells are combined with adjacent differing types of land use, the method may cause scattered spots [23].

3.6.2 Contiguity

In general, the contiguity means all cells related to a land-use type are connected [24].

3.6.3 Contiguity and Compactness Implementation Procedure

At this stage, discrete and scattered pixels were identified using the neighborhood relationships shown in black in Figure 6, and then these black pixels were assigned thereto specific land use supported by the closest neighbor cells. Next, using the capabilities of the graphical interface of the Emgu within the Find Candidate module, most patches of the outputs related to the specified algorithms were identified (Figure 7) and then were reallocated supported by the specified target functions.

4. Results

Results of the implementation of firefly and particle swarm algorithms within the present study were compared in three general modes of the bottom (PSO & FA), combined (PSO-Combined & FA-Combined), and compact (PSO-Compact, PSO-Combined-Compact, FA-Compact, FA-Combined-Compact) with MOLA output in Idrisi. Nine indices consisting of patch number, largest patch index, patch area, perimeter-area ratio, shape index, fractal dimension, continuity, and patch cohesion in Fragstats software v.4.2.1 were used for comparison. The optimized land use map generated by each of the algorithms within the various states, plus the spatial output map in Idrisi, is shown in Figure 8. Results associated with the implementation of the algorithms are also shown in Table 4.

In general, FA-Compact and PSO-Compact perform better than other algorithms in most indices (such as largest patch,

area of patches, and patch cohesion). On the other hand, MOLA-Idrisi has the highest suitability value, which indicates the most appropriate allocation in terms of adapting to different needs. These results indicate that FA and PSO algorithms, especially in optimized versions (such as contiguity and compactness), have been able to provide better allocation.

5. Discussion

In this investigation, an approach to allocation of land use is presented according to metaheuristic algorithms that have a stronger structure than the MOLA in Idrisi. According to the results, the approach in the meta mola software has a relatively weaker performance in terms of suitability relative to the output of MOLA in Idrisi.

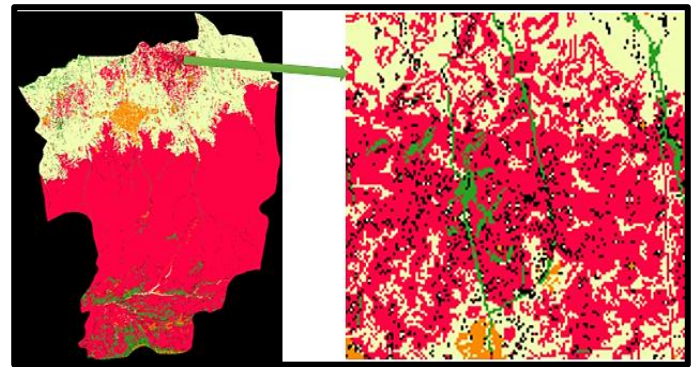


Fig. 6. Overview of disjoint and scattered spots

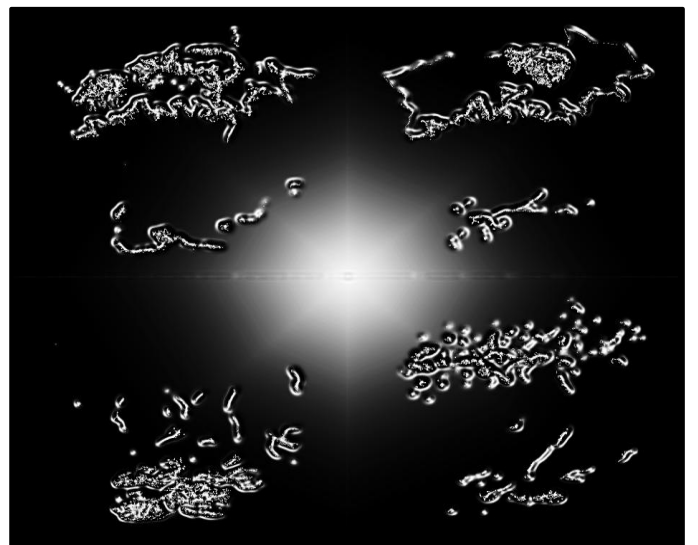


Fig. 7. Output of the find candidate module (source: The study findings)

Table 4. Result of algorithm implementation

Comparison index Algorithms	Suitability	Number of Patches	Largest Patch	Patch Area	Shape	Fractal Dimension	Contiguity	Patch Cohesion
FA	176	15213	9.536	8.83	1.28	1.0460	0.185	98.44
FA-Compact	176.25	6549	9.595	19.57	1.60	1.0715	0.308	98.96
FA-Combined	181.75	21111	9.395	9.35	1.26	1.0451	0.166	96.53
FA-combined-compact	181	6825	9.708	18.17	1.51	1.0673	0.281	98.31
PSO	175.5	18222	9.556	8.49	1.27	1.0452	0.170	97.84
PSO-Compact	176	7528	9.569	16.94	1.57	1.0696	0.280	98.79
PSO-Combined	181	23596	9.258	8.24	1.26	1.0450	0.160	96.26
PSO-Combined-Compact	176	7619	9.250	16.46	1.57	1.0705	0.292	98.30
MOLA-Idrisi	182	20933	9.408	9.41	1.26	1.0453	0.167	96.56

It is also indicated that MOLA has better performance for other indices such as contiguity and compactness. Regarding the assessing of the performance of the firefly along with particle swarm algorithms, it is worth noting that the particle swarm algorithm showed a weaker performance than the firefly algorithm. In this regard, other investigations are in line with the study findings (e.g. Aydilek [25]; Khan et al. [26]; Wang et al. [27]). Based on the study by Aydilek [25] and Khan et al. [26], which used a hybrid firefly along with a particle swarm optimization algorithm, revealed that the performance of the firefly is weaker than that of particle swarm algorithms. But solving the quality of the hybrid algorithm is better than when they are applied alone.

It has been pointed out that optimization methods, such as metaheuristic algorithms, used for the development of the Meta Mola software, are appropriate tools for solving land-use allocation problems, and their results are also satisfactory. A key point about the optimization process in this investigation is that the metaheuristic algorithms, even in their basic form, have produced a much more compact and contiguous pattern than the MOLA output in Idrisi. However, the separate module of the Meta Mola software, which can also use the output of other software to create a compact and continuous allocation, is one of the obvious potentials of this software. The software is free and allows users to apply that to other areas. Considering the many issues that occur in the land-use allocation process, such as the discrepancy in the allocation and the existence of scattered patterns, Meta Mola software can be a step forward

in solving this problem. In addition, in some way, by providing an integrated allocation pattern, it can help lower the negative environmental impacts of discrete patterns when applying land use allocation plans and ultimately approach sustainable conditions. Although the Meta Mola can use the output of other software as input, the lack of integration and complete compatibility with other common tools in the planning of land use presents one of the limitations of its more extensive usage.

One of the obvious limitations of Meta Mola software is its lack of full integration and compatibility with other common tools in land planning. This can prevent users from easily using and integrating outputs from other software into this software.

6. Conclusion

In the present study, Meta Mola integrated metaheuristic algorithms and compression and continuity optimization capabilities and modified the scattered patterns of the land allocation to a more optimal allocation. According to the results of this study, it is suggested for future research to integrate meta-heuristic algorithms with machine learning methods to improve fit accuracy. It is also suggested to assess the performance of the software in situations like crisis problems of water and land. The outcomes of this research will help policymakers to increase the participation of local stakeholders in the decision-making process by providing more optimal plans and finally lead to the realization of goals in comprehensive and sustainable planning.

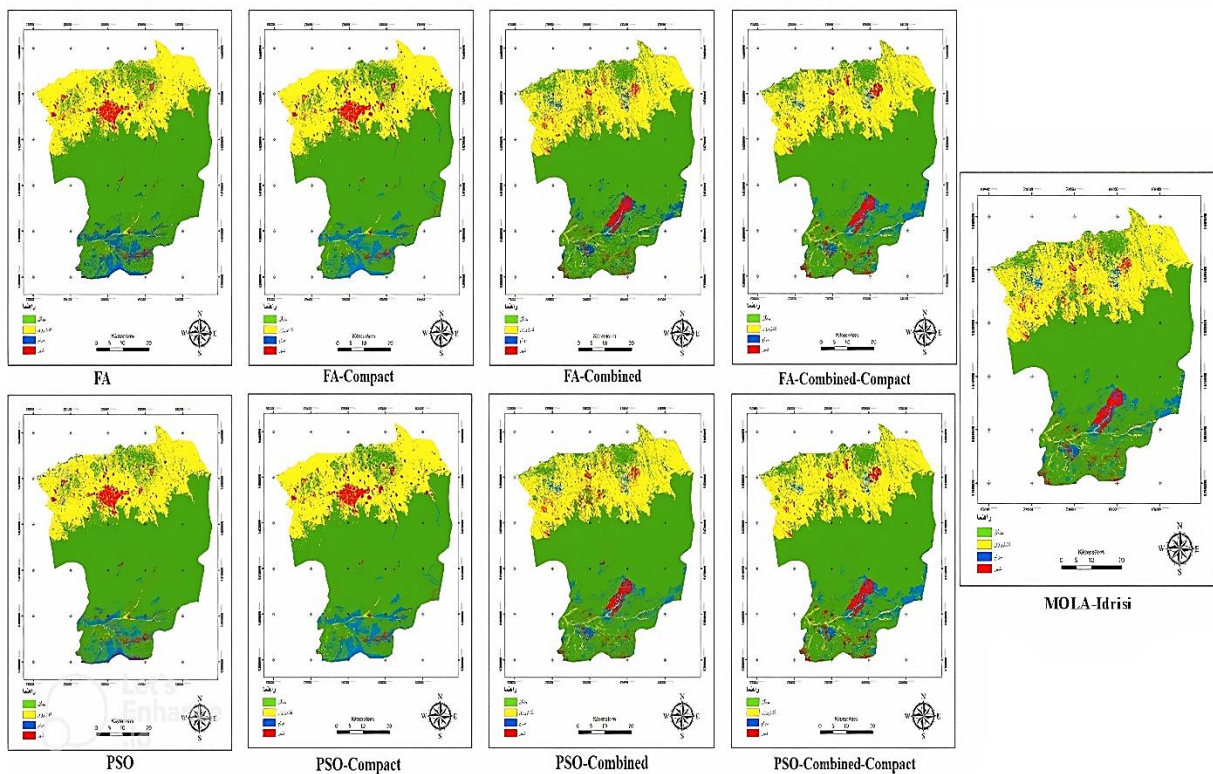


Fig. 8. The output of intended algorithms and MOLA in Idrisi

Nomenclature

$v_i(t)$	The i^{th} particle velocity
$x_i(t)$	The i^{th} particle position
P_i	The best-known position achieved by particle number i
p_i	The optimal solution collectively discovered by the entire swarm up to this point
W	The weight value applied to balance the global and local search abilities of a particle
ϕ_1, ϕ_2	Acceleration coefficient
r_1, r_2	Uniform distribution of random variables in the range (0, 1).

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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