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Performance comparison of MOLA, IP, and GSA optimization algorithms in urban land use allocation based on landscape metrics

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Abstract

Sustainable land-use planning refers to the effort to establish a balance between economic growth, ecological structures, environmental protection, and social progress. Therefore, land-use suitability assessment and inclusion of land use compression are essential in this context. In recent years, the use of artificial intelligence (AI) tools significantly increased for land-use planning. In this study, the Multi-Objective Land Allocation (MOLA) algorithm, Gravitational Search Algorithm (GSA), and Image Processing (IP) technique have been applied to urban land use allocation of the Birjand watershed based on a comprehensive set of sustainable development goals. The objectives used include maximizing fitness functions (e.g., environmental and ecological suitability, compression functions, and landscape stability), minimizing land-use conversion, imposing limitations on flood-prone areas as protected sites with above 70% slope, the demand for urban areas, and consideration of only one land use per pixel. Visual assessment, statistical and landscape metrics analyses were employed to compare results from the selected algorithms. Results showed that MOLA (with an average suitability of around 215) had better allocation concerning land use suitability assessment for urban development. Also, MOLA and IP algorithms (with standard deviations of 41.037 and 41.729, respectively) were better than GSA. Additionally, based on landscape metrics analysis the studied algorithms behaved differently in terms of efficiency and superiority.

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Introduction

Land use planning and related changes influence the interaction between human activities and natural systems. On the other hand, optimizing land use allocation to provide ecosystem services and sustainable development is currently one of the influential challenges in urban management (Hasegawa et al., 2017). In general, issues related to land use allocation involve a set of spatial optimization models and the efficient distribution of suitable places to meet demands while maintaining physical, environmental, economic, and social constraints (García et al., 2017). Therefore, spatial optimization can be effectively used as a principled tool for land use spatial planning problems. It can be considered as the science of achieving optimal spatial arrangements, typically involving the identification of the best locations for activities and resources based on goals and limiting conditions (Yao et al., 2018). Spatial optimization in urban planning is grounded on the assumption that it encompasses multifaceted activities influencing land-use patterns through strategic spatial planning, land use planning, project planning, and others (Hersperger et al., 2018). Thus, spatial optimization is both complex and crucial. Optimization methods, in general, encompass powerful search techniques to attain optimal solutions within search spaces and among selected solutions (Nguyen et al., 2014).

Malczewski (2004) categorized land-use suitability analysis methods into three main groups: (a) computer-assisted mapping, (b) multi-criteria evaluation methods, and (c) artificial intelligence (soft computing-based procedures or geo-computation).

Civco (1993) pointed out that spatial data analysis in all methods, before the use of artificial intelligence, faced numerous problems such as inadequate accuracy, multiple-item measurement scales, interdependence of factors, improper standardization, unverifiable hypotheses, ambiguous inputs, independence assumptions, carelessness, inaccuracy, and linear relationships. In contrast, environmental issues often involve multiple goals that may not be linear or simple and can be contradictory and inconsistent with each other.

Classical methods are unable to provide logical solutions in this regard. Therefore, the third method (utilizing the capabilities of artificial intelligence) was proposed to optimize environmental issues and overcome problems in land-use suitability analysis (Wu & Silva, 2010). The latest evidence of working with AI indicates the implementation of advanced technologies and computational methods in land-use suitability analysis. Unlike conventional methods, these approaches share resistance to inaccuracy, ambiguity, and uncertainty, enabling them to provide accurate results quickly, covering all objectives. In essence, artificial intelligence algorithms represent another means of addressing complex decision problems that are extensive and challenging to comprehend. In situations involving spatial aspects, large research areas, multiple constraints, and ambiguous objectives, traditional methods fall short, while these algorithms prove cost-effective in terms of both time and resources (Meiring & Myburgh, 2015).

These emerging areas encompass evolutionary computation, genetic algorithms, evolution strategy, genetic programming (Lim et al., 2017), intelligent heuristic search for GIS databases (Openshaw, 1994), and new special-interaction models (Diplock & Openshaw, 1996). Some of these algorithms have been specifically employed to address land-use allocation problems. For instance, genetic algorithms, simulated annealing, ant colony optimization algorithms, and particle swarm optimization algorithms were respectively inspired by evolution / genetics, thermodynamic observations, the behavior of ants in finding the shortest path between home and food, and the social behavior of birds and fish (Liu et al., 2015; Chen et al., 2018; Wang et al., 2019; Zhu et al., 2021).

Today, innovative algorithms represent a new set of AI methods developed by Eastman et al. (1993). Innovative programming holds the potential to provide a robust and reliable technology for solving nonlinear land-use optimization problems. It has been suggested that innovative algorithms play a crucial role in addressing large decision-making problems related to land allocation. However, these algorithms do not guarantee an optimal solution but often offer a near-ideal solution. In this context, Cromle & Hanink (1999) reported that innovative algorithms can be helpful when providing near-optimal solutions. Therefore, artificial intelligence techniques, such as heuristic and meta-heuristic algorithms, can be considered as solutions to these challenges (Aerts, 2002).

Meta-heuristic methods encompass algorithms adapted from the physical and biological processes of nature, often operating based on population characteristics. Unlike classical methods, heuristic algorithms randomly explore the search space using a parallel processing approach. These methods rely solely on the fitness function to guide the search. Heuristic search methods involve iterative algorithms that apply different operators to various members of a population at each iteration. These operators are designed to foster self-adaptation, cooperation, and competition among population members (Sarker et al., 2002). Consequently, the population undergoes three targeted steps in each iteration, including adaptation to the environment, cooperation, and information exchange, and competition for survival using operators applied in these algorithms. In contrast, heuristic algorithms incorporate specialized techniques for executing each step, ultimately leading the population to the optimal solution (Rashedi et al., 2009). The Gravitational Search Algorithm (GSA) is one of the novel meta-heuristic algorithms.

The Multi-Criteria Decision Making (MCDM) method can also be employed to address issues related to land-use assessment and multi-objective land-use allocation, serving as a decision support tool in land-use suitability assessment (Zamarrón-Mieza et al., 2017). One of the multi-criteria decision-making methods capable of addressing the evaluation and allocation of multiple land-use objectives is the Multi-Objective Land Allocation (MOLA) method. However, MOLA primarily focuses on land suitability for land-use allocation and does not pay significant attention to the appearance and structure of land-use patches. MOLA is generally considered a selective heuristic approach based on proximity to the ideal point for resolving conflicts associated with incompatible land uses (Lahiji et al., 2020). This method is preferable when only the desirability of land-use assignments is considered. Nevertheless, it may not fully meet all requirements when other criteria, such as the spatial structure of land uses in the landscape, are taken into account (Kamyab et al., 2016).

Furthermore, image processing (IP) algorithms represent a novel approach to image optimization that can be integrated with GIS to facilitate land-use modeling (Rawat & Kumar, 2015). GIS can be paired with these algorithms through data exchange for spatial data processing and visualization. Additionally, some GIS functions can be utilized in the development of these intelligent algorithms (Liu et al., 2015). Consequently, as land-use planning involves allocating various land-use activities to specific spatial divisions, a GIS-based spatial optimization approach and mathematical models can increasingly support the evaluation of these activities (Ligmann-Zielinska, 2017).

The present study aimed to harness the capabilities of artificial intelligence in optimizing issues related to land-use suitability assessment in conjunction with GIS. Specifically, this study sought to develop various algorithms for solving multi-objective land-use allocation problems. In other words, the study aimed to assess the performance of meta-heuristic algorithms as secondary tools for land-use managers in creating land-use suitability assessment plans and achieving optimal outcomes for various objectives. In general, understanding problems through mathematical concepts and applying existing rules to problem-solving are critical components of working with algorithms. However, determining the most suitable locations for land uses is recognized as one of the most significant challenges in land-use planning. Therefore, it should be done based on desirability and considering their economic, social, and environmental consequences.

Consequently, different approaches have been classified for various uses in resolving these conflicts. In this study, three approaches, namely MOLA, GSA, and IP, each serving different purposes within MCDM, were compared for land-use assessment and land-use allocation, depending on different decision-making rules.

Materials and methods

Introducing the study area

Birjand Watershed, located in South Khorasan Province, Iran, was selected as the study area in this research. According to the latest available census in 2016, the population of Birjand was estimated to be 261324 people predicted to increase to around 308617 people in 2025. Therefore, urban planning for housing and developing the area in the coming years is one of the most critical challenges for urban planners. This area is located in the latitudes and longitudes of 32°44′ to 33°8′ N and 58°41′ to 59°44′ E, respectively (Figure 1). The total area of Birjand Watershed is about 3435 km^2 (980 km^2 as plains and the rest as highlands), in an arid region with average annual precipitation of 140 mm and average temperature of 16.5 °C. Plus, the maximum and minimum elevations above sea level of the Birjand watershed are estimated to be 2720 m (Koh Shah) and 1180 m (Fadeshk area), respectively.

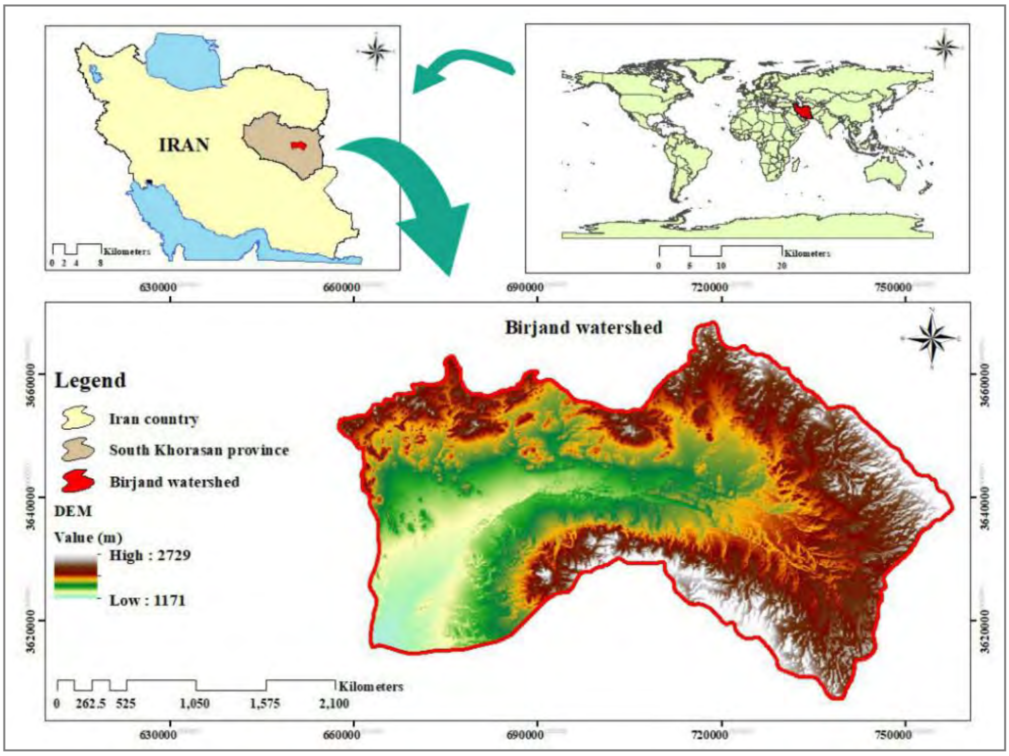

Figure 1. The geographical location of Birjand Watershed

Methodology

The history of modeling reveals that there are different tools to analyze the land, which are known as land-use simulation models. These models simplify reality, but the increase in computational power over the years has made it possible to combine more complexity in these models (Tolk and Glazner, 2019). In this study, three optimization algorithms of Multi-Objective Land Allocation (MOLA), Gravitational Search Algorithm (GSA), and Image Processing (IP) technique were employed to allocate urban land-use in the Birjand Watershed. First, the urban land use suitability layer was prepared using Fuzzy ANP, Boolean and WLC methods. As such, 13 criteria, including slope, aspect, height, soil texture, soil depth, soil drainage, land cover, and distance from town, road, power lines, faults, rivers, and water resources were selected as effective layers (benchmark maps) for land-use suitability assessment in urban development. Furthermore, to prepare the constraint map, parameters such as areas with slopes greater than 70%, protected areas of the Environmental Protection Organization, flood-prone areas, and protected land use were considered. After collating these layers in a spatial database, they were fuzzyfied. The weights of the factors were then calculated using the Analytical Network Process technique. Then, by considering the weight of each criterion derived from the ANP and using the weighted linear combination (WLC) method, the environmental suitability maps were prepared. Eventually, constraint maps for the study area were prepared using the Boolean method. In this step, due to the unequal weight of the raster layers, the maps were standardized by fuzzification in the range 0 to 255. The resulting layer was considered as the environmental suitability map.

Since IP and GSA algorithms require powerful programming software, the MATLAB software was used for this purpose. In general, the study consisted of two parts including preparing/producing maps and spatial data (using GIS) and programming to optimize objectives (using MATLAB). It should be noted that the MOLA algorithm was also implemented in IDRISI software. Also, as MOLA and IP algorithms can only make single-purpose decisions, the environmental suitability index was considered for both methods in this research. In contrast, given that GSA meta-heuristic algorithm can make multi-objective decisions, the fitting functions and objectives were evaluated using meta-heuristic algorithms to create optimal outcomes. In general, different steps involved in this research are summarized in Figure 2.

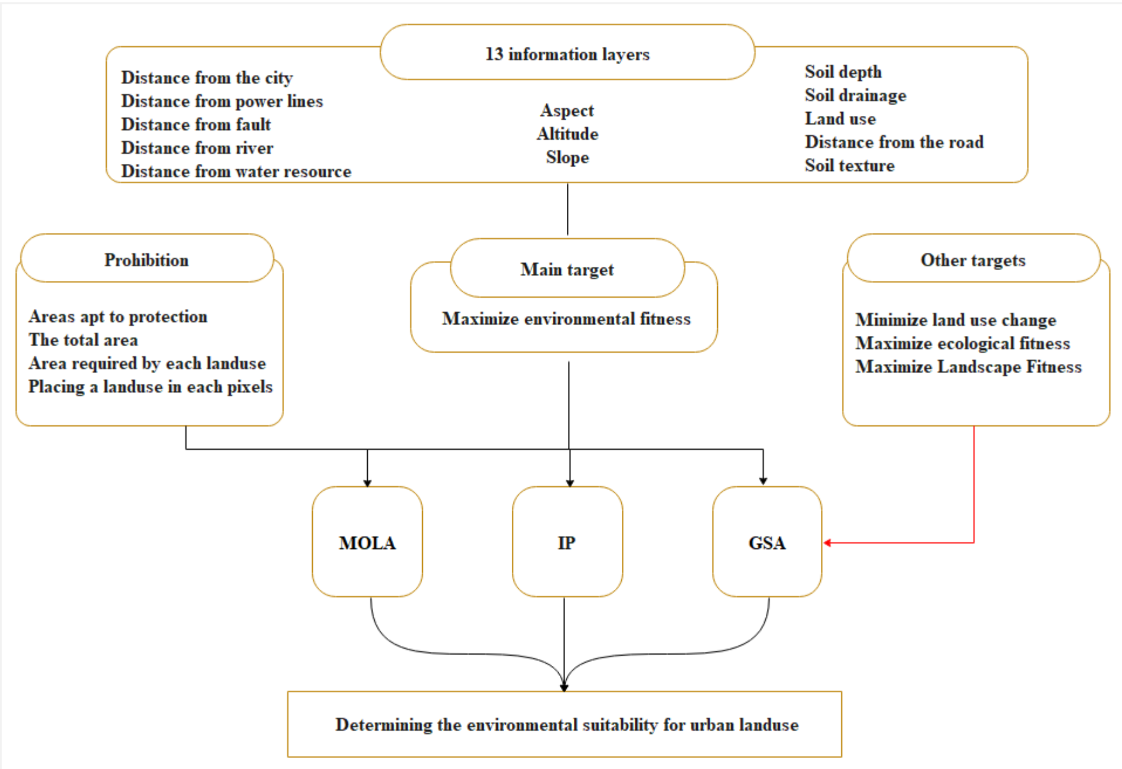

Figure 2. Steps of the present study under the application of MOLA, IP, and GSA optimization algorithms

GSA algorithm

GSA is a type of swarm intelligence optimization algorithm, where individuals are influenced by Newton's law of gravity and the laws of motion (Sun et al., 2018). This algorithm explores a multidimensional search space to identify the maximum value of the objective function. Essentially, each entity in this algorithm possesses knowledge of the positions and locations of other entities, forming an artificial system through the exchange of information (Han et al., 2017).

In this study, the suitability of urban land use was initially assessed based on various objectives and criteria. Subsequently, multiple fitness functions, such as spatial and ecological considerations, environmental suitability, minimal alterations, landscape criteria, and other objectives aimed at achieving an optimal outcome, were computed using meta-heuristic algorithms. Ultimately, these objectives were formulated to address land-use allocation issues and create an optimal model. Unlike the other two algorithms, which only focused on maximizing environmental suitability, this study simultaneously applied multiple objectives, a unique advantage of these algorithms.

Here, the objectives are defined within the framework of sustainable development principles and characteristics related to spatial optimization for land-use allocation problems using the GSA algorithm as follows:

Maximizing environmental suitability

Land-use allocation is performed based on physical, environmental, and infrastructural factors toward maximizing environmental suitability, which requires determining maps related to the effective factors and combining them. In this study, these maps were weighted and integrated based on Fuzzy ANP and WLC methods, respectively.

Maximizing ecological suitability

This item reduces the cost of social capital and increases the economic benefits to societies.

Minimizing land-use conversion Maximizing

Ecological assessment in any region, with regard to land-use planning, has unique advantages toward achieving sustainable development (Yong et al., 2010). Ecological benefits of land-use management can be assessed using Ecosystem Service Valuation (ESV), in which different areas with different ESVs are assessed (Kong et al., 2009).

Landscape sustainability

In landscaping concepts, compact and circular forms have more stability than fragmented forms, which is achieved by applying the maximization of compression function.

Maximizing compactness

For this, numerous concepts were considered including optimizing a more productive and profitable spatial model, reducing the pressure of town development, facilitating management, increasing landscape diversity through green infrastructure, efficient use of resources and energy, increasing access to facilities, reducing traffic, less need to services/infrastructure, and developing social equality.

Limitations

In this research, flood-prone areas with more than 70% slope, the required areas for urbanization, inclusion of only one land use per pixel, and the total area were considered as limitations.

IP Algorithm

Image processing involves the application of various algorithms to extract essential information from existing images (Lillo-Castellano et al., 2015). One branch of image processing focuses on image enhancement, which includes techniques like applying fading filters and increasing contrast to improve the visual quality of images and ensure their accurate display (Joshi, 2018). There are numerous image processing algorithms, some of which are employed to correct or remove salt-and-pepper noise and enhance edges (Wang et al., 2016).

The method employed here involves sorting all pixels based on their values. The required number of pixels for urban use is then selected in ascending order of their values, with the value of the last selected pixel serving as the threshold. Subsequently, all pixels with values exceeding this threshold are chosen, and area maps are defined. Following this, a two-dimensional filter is applied to eliminate noise, resulting in a compressed and consolidated map.

MOLA algorithm

Eastman (1993) suggested an ideal point-based heuristic approach to optimize land use planning which is called MOLA. The MOLA method is a multi-criteria decision-making method to create optimal solutions in spatial allocation for multiple and incompatible land uses (Riveria & Maseda, 2006). The multi-objective land allocation method solves land-use conflicts for a land unit (cell) based on proximity to the ideal point and ultimately assigns the cell to uses with the highest grade (Olmedo, 2018). The goal of this algorithm is to find an optimal solution based on iterative processes, in which land-use suitability for all uses is measured based on their ranks and grades (Irina et al., 2019). There are many examples of using MOLA method for land use planning (Fataei and Mohammadian 2015; Mehri et al. 2018; Sitko and Scheer 2019) which mainly focus on the natural environment or protected areas and do not consider the mixture of environmental condition with peri-urban and urban areas.

The MOLA method uses the following formula:

1) $$S_k = \left(\sum_i X_i \times W_i \prod_j r_j \right)_k$$

2) $$S = \sum (S_k \times W_k)$$

where S_k defines the suitability of land under objective k, $(X_i)_K$ is the standardized value of criterion i under objective k, $(W_i)_K$ is the assigned weight of criterion i under objective k, $(r_j)_K$is the constraint score of j under objective k which takes either 0 or 1 value. Also, S denotes the multi-objective suitability and W is the weight assigned to the objective k (Nourqolipour et al., 2015).

By integrating MCE with GIS and MOLA, routine map overlap procedures can be significantly improved (Zhang et al., 2013). MCE and MOLA, while providing a framework for solving multi-objective land allocation problems in objectively inconsistent cases, allow the individual to assess the relative priorities of an area based on the criteria and indicators of that area (Hajehforooshnia et al., 2011).

In this study, land use maps were used to choose appropriate urban land use in Birjand Watershed through MOLA method. Then, to resolve the conflicts between competing land-uses, a weight was assigned to each of the land uses based on expert judgment and by applying the desired area for each land-use. Then, optimizing land-use allocation of the Birjand Watershed was performed using the MOLA method based on land use suitability maps. It should be noted that expert judgments were made based on the opinions of a panel of environmental experts with a view to their expertise, experience, and knowledge of macro decision making and environmental assessment and planning. MOLA input data includes land suitability maps ranked in descending order for each objective. In other words, the best rank and the highest value are assigned the value 1. In other words, the descending map indicates the best grades for the intended objective, and the ascending map shows the worst ranks for other objectives (Honarbakhsh et al. 2017). Finally, in the MOLA method, a repetitive operation is performed to combine the ranked maps based on their weights. In our urban land use allocation with the MOLA algorithm, 50 cells were considered as the area threshold. As before, the area required for each land-use in the process of implementing the algorithm was determined with expert opinion.

Validity and Reliability of the Research Instrument

The obtained results of MOLA, IP, and GSA algorithms were compared to determine their validity in shaping the future urban land use of the Birjand Watershed. In order to have equal conditions for comparison of the algorithms, the number of cells needed in the urban land-use was estimated to be around 6000. Finally, the following methods were used to compare and evaluate the efficiency of the studied algorithms.

1. Visual assessment and consideration of coherence of allocated urban land patches.
2. Using the statistical parameters (such as mean and standard deviation) of urban

land use suitability in the allocated patches.

3. Landscape metrics analysis, including the number of patches (NP), patch density (PD), patch shape index (SHAPE_MN), perimeter-area ratiometric (PARA_MN), proximity index (PROX_MN), and patch cohesion index (COHESION) in FRAGSTATS software.

Results

Optimization objectives

Maximizing land-use suitability

Here, suit $_{ijk}$, which determines the suitability of cell (i,j) for the kth land use, was calculated using equation 3-5. In other words, this equation confers the potential or suitability of a cell to create urban land-use based on physical, environmental, and infrastructural factors.

1) $$F(x) = Max \sum_{K=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} Suit_{ijk}\, X_{ijk}$$

2) $$S_j c_i = W_1.a + W_2.b + W_3.c + W_4.d + \dots\dots\dots\dots\dots\dots + W_{13}.k$$

3) $$\sum_{i=1}^{13} wi = 1$$

Figure 3 shows the urban land-use suitability of fuzzy ANP and WLC techniques. The blue points inserted in the center of the mentioned map are the most suitable points for urban land-use, which are located around Birjand town and the Birjand plain.

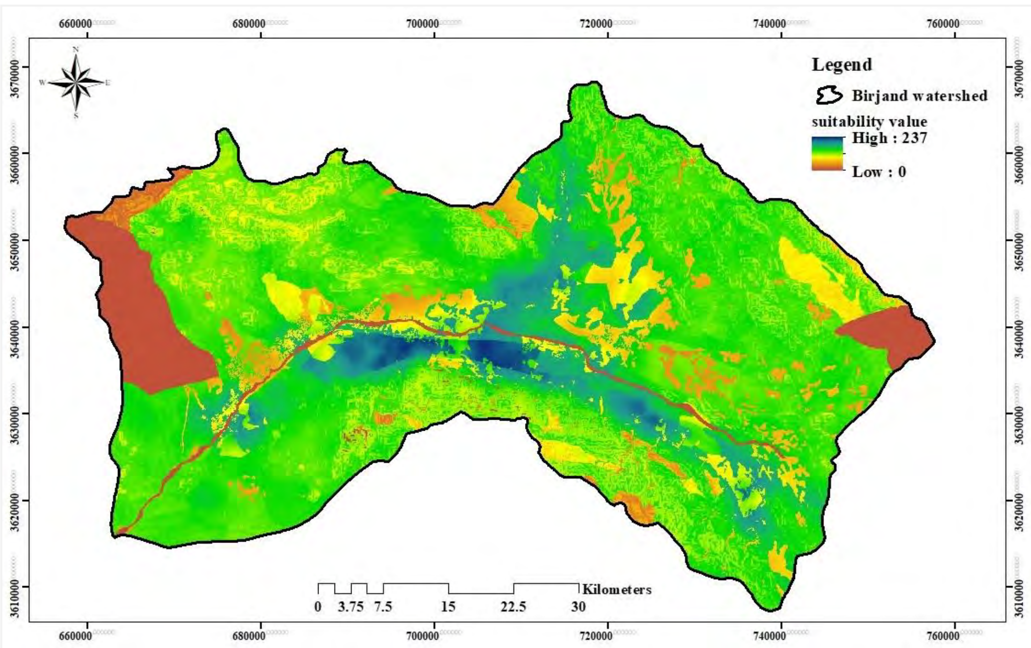

Figure 3. Urban land-use suitability map using fuzzy ANP and WLC techniques

Minimizing land-use conversion

The minimum conversion function is calculated by Equation 6, which indicates the ease of land-use change from u to m. In general, land-use conversion bans in the study area, such as rocky outcrops, clay playa, irrigation farming, riverbed, planted forests, woodland, and shrub-land are introduced in Table 1. The ability of land cover change alters in descending order from low-dense areas (poor rangelands), semi-dense rangelands, dense rangelands, and rain-fed agriculture, respectively. The range assigned to facilitate land-cover change to urban land-use is variable between zero and one, in which a lower score represents a greater constraint. Figure 4 displays the ease of conversion of land-cover to urban land-use based on Equation 6 and Table 1.

Equation 6: $F(x) = \min(1\text{-conv}_{um})$

Table 1. Land-use change constraints in the present research

Land cover	Residential coverage
Clay playa/Rocky outcrops	0
Irrigation farming	0
Planted forests	0
Riverbed/River Basin	0
Woodland/Shrub-lands	0
Rain-fed agriculture	0.25
Dense rangelands	0.25
Semi-dense rangelands	0.5
Low-dense rangelands	0.75
Residential areas	1

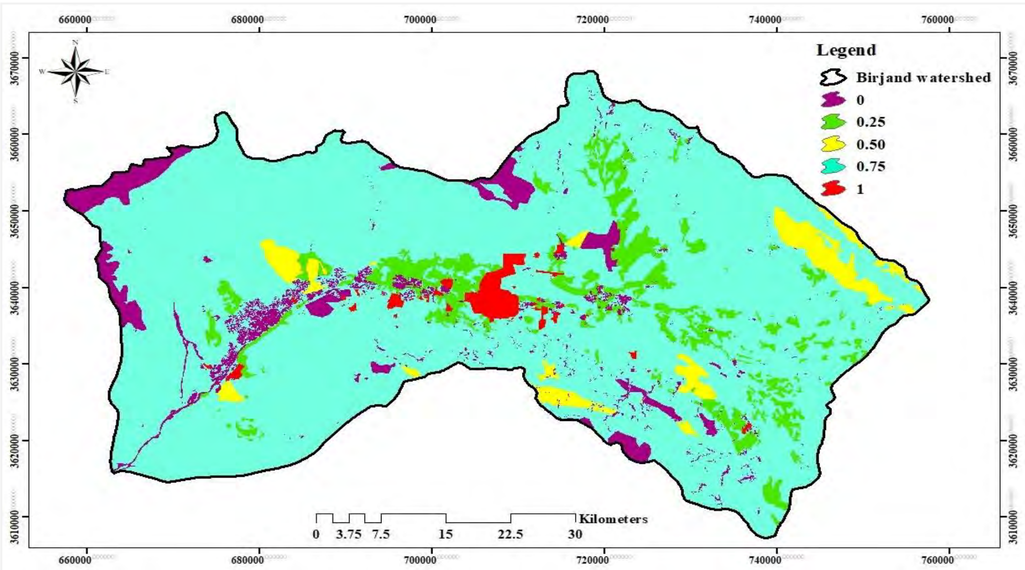

Figure 4. The map of conversion of land use/cover to urban land use

Maximizing ecological suitability

The preservation of natural features and environmental structure to maximize the green areas can be achieved using the value of ecosystem services (ESV). The process is achieved using Equation 7, which represents maximizing current ESV and future ESV.

Equation 7: $F(x) = \text{Max}(ESV_{future} - ESV_{current})$

The ecological values of land use and ESV differences between urban land-use and current land uses are listed in Table 2 for each 50 by 50 m pixel (adapted from the study performed by Costanza et al., 1997). As can be seen, the most valuable land uses of the studied area were respectively determined for planted forests, woodland, shrub-lands, dense rangelands, semi-dense rangelands, irrigation farming, and rain-fed agriculture. It should be noted that the most damage to the ecosystem caused by land-use change is determined based on the value of the mentioned uses. Differences between ESV resulting from urban land-use and current land uses of the studied area are shown in Figure 5.

Table 2. The value of ecological land use and the difference of ecosystem service values between future land use and current land use per pixel

Land-Use type	Ecosystem service value (Toman.ha^{-1})	Ecosystem service value per unit of land use (Toman.2500 m^{-2})	Urban land value minus Ecosystem service value (43592-EVS)
Clay playa/Rocky outcrops	371	43592	0
Rain-fed agriculture	6114	718395	-674803
Irrigation farming	6114	718395	-674803
Planted forests	18201	2138617	-2095025
Low-dense rangelands	371	43592	0
Semi-dense rangelands	6405	752587	-708995
Dense rangelands	6405	752587	-708995
Riverbed/River Basin	371	43592	0
Woodland/Shrub-lands	12157	1428447	-1384855
Residential areas	371	43592	0

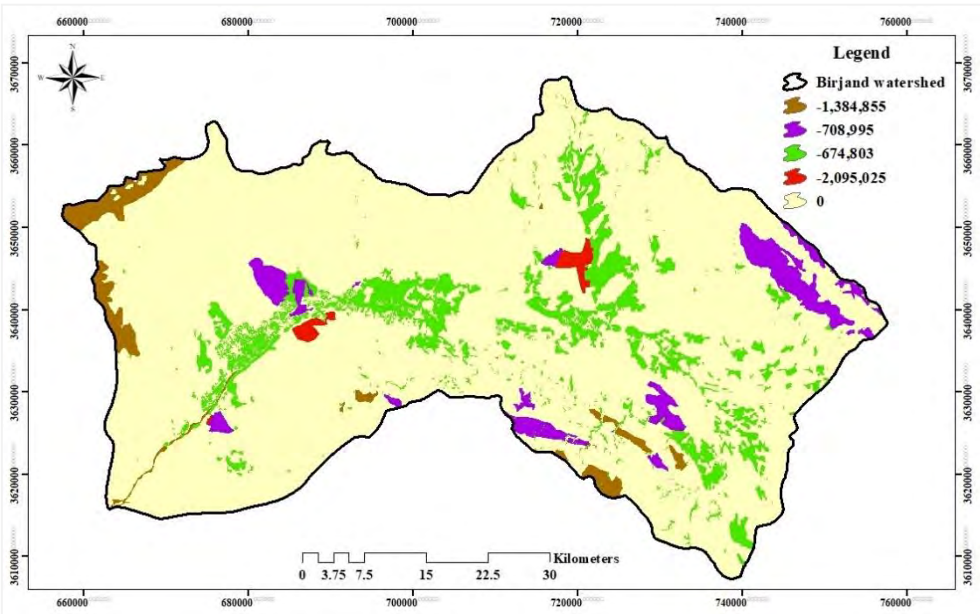

Figure 5. Difference between the EVS resulting from urban land-uses and current land-uses

Maximizing compactness function

To achieve this objective, 15 zones were designated for urban use, and the algorithm was tasked with selecting 15 urban center points within these zones. These points were chosen based on their highest density, which relied on the fitness level of each cell in conjunction with its neighboring cells for each land-use type. This fitness measure was derived from the summation of three factors: maximum environmental suitability, ease of land use change, and the value of ecosystem services, collectively forming what is referred to as the fitness map. Subsequently, the urban center points, also known as map gravity points, were determined through 50 iterations of the algorithm (refer to Figure 6). Figure 7 illustrates the spatial displacement changes per pixel (mass) during different iterations, showcasing a reduction in the center of gravity's displacement with increasing iterations, ultimately converging toward optimal points.

The oscillating pattern observed in the diagram is a result of the mass's movement towards the center of gravity. In certain instances, the mass passes through the center of gravity, causing this motion to exhibit a spring-like behavior. As the mass progresses toward the optimal solution, this vibrational movement gradually diminishes, signifying that it has a shorter distance to travel to reach the highest density.

Subsequently, circular regions with a diameter of 2500 square meters (equivalent to a radius of 50 cells) were defined around each center point. The choice of a circular shape was driven by its compact and geometric characteristics. Following this, certain existing urban land-use areas, referred to as mask regions, were isolated and assigned a value of zero. In the subsequent step, the necessary area for urban land use was selected from the remaining regions based on their values. Finally, the results pertaining to urban land-use optimization were obtained after thirteen minutes of algorithmic processing (see Figure 8).

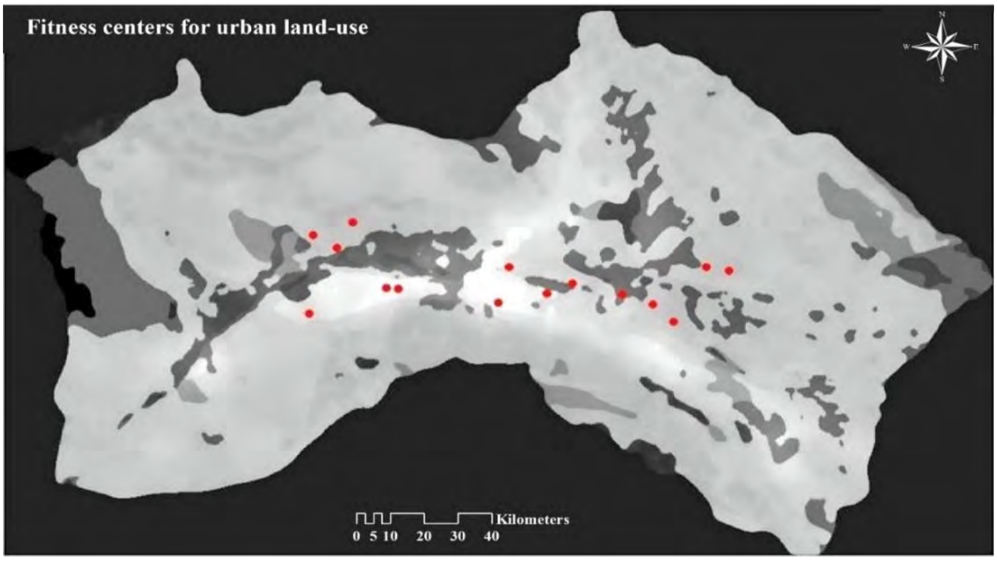

Figure 6. Centers with the highest fitness for urban land-use

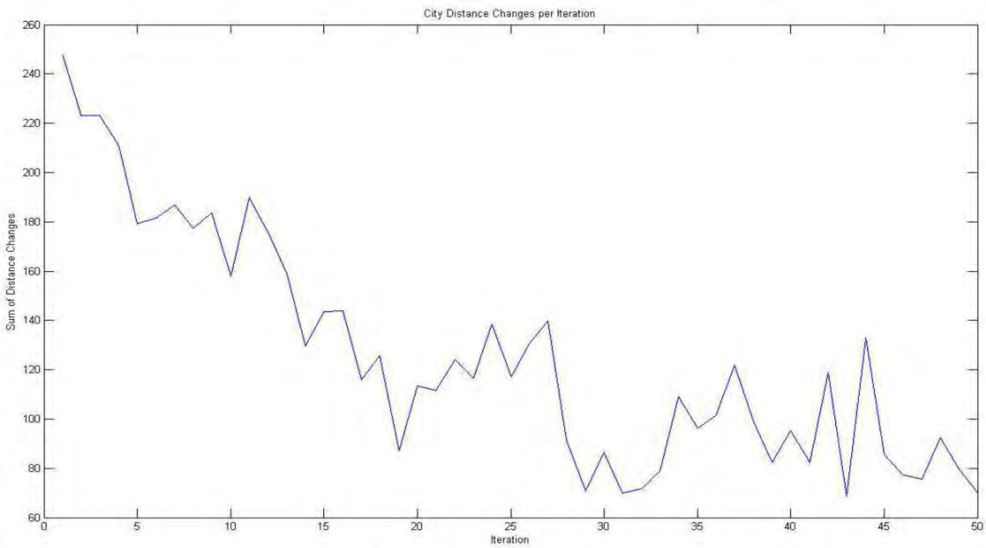

Figure 7. Spatial displacement changes of urban zone centers with increasing repetitions

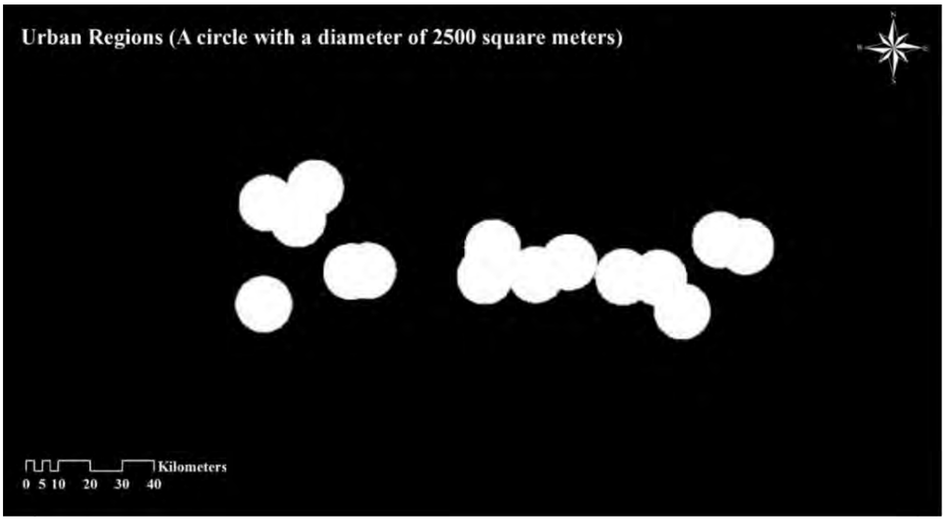

Figure 8. Areas with an average radius of 50 cells around the center of gravity (areas with the highest density)

Maximizing landscape metrics

This function is obtained by maximizing the compression function. In landscape metrics, compact and circular shapes are more stable than other shapes, and as such this concept was included in the compression objective function.

Constraints

Prohibition of land-use change in the protected areas

This prohibition included protected areas, steep slopes, and erodible/earthquake-prone areas, identified during preparation of suitability maps.

Limitation of the total/land area

The sum of all land uses should equal the total area of the watershed, namely around 3430.691 ha (Equation 8).

Equation 8: $\sum_{k=1}^{3} x_k = 3430.691(\text{km}^2)$

Land-use demand restrictions

The projected area in the 20-year vision of Iran (2024) was calculated using the Markov chain model and cellular automata by Yousefi and Jahanishakib (2019) and was equivalent to 18.9 km^2 of urban land use (18900000m^2). Therefore, the required urban land use was estimated to be around 7560 cells of 50 by 50 m.

Spatial restrictions

For this section, we ensured that only one land use is allocated to each cell.

Implementation of MOLA, IP, and GSA optimization algorithms

GSA algorithm

In this algorithm, the selection of the most suitable locations was guided by objective fitness functions. These functions encompassed objectives such as maximizing environmental and ecological suitability, achieving compactness, adhering to land-use planning principles, and minimizing land-use changes, while considering criteria such as spatial development constraints and demand. Furthermore, the centers of gravity, along with their surrounding areas exhibiting the highest density of urban land-use suitability, were identified by optimizing all the specified objectives and constraints through the GSA algorithm. Essentially, the potential solutions relevant to object placement within this algorithm were inherent to the problem, and objectives were established based on the fitness function. Ultimately, urban land-use allocation was modeled using the GSA algorithm, as illustrated in Figure 9.

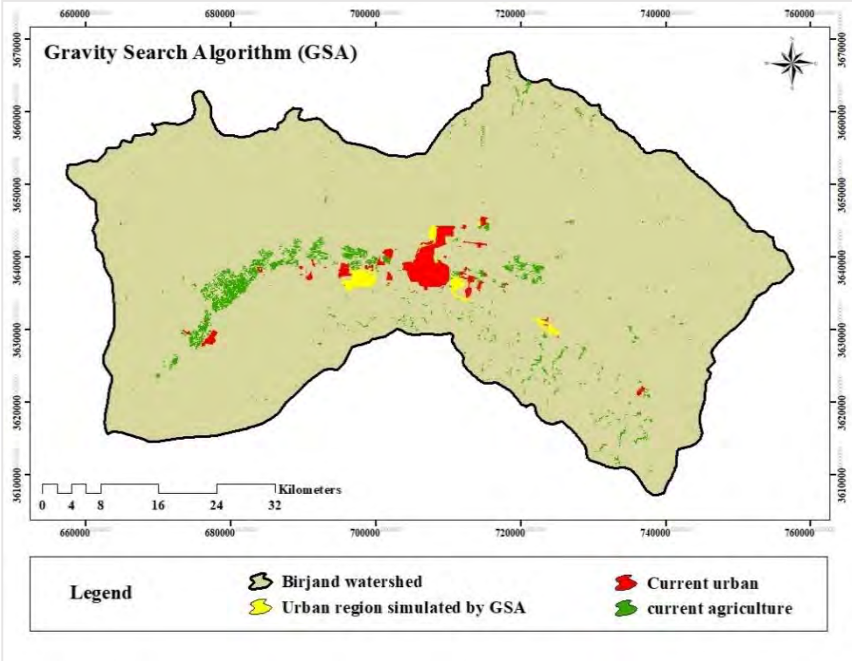

Figure 9. Urban land-use allocation using the GSA algorithm

IP algorithm

In this approach, pixels were organized according to their pixel values. Subsequently, a specified number of cells were selected to address objectives related to urban land use. Typically, the value of the last cell selected served as the threshold value. Following this step, blur filters and image contrast enhancement techniques were applied to eliminate noise, enhance image quality, and ensure accurate image presentation in digital monitoring environments. Figure 10 illustrates the allocation of urban land use using the IP algorithm.

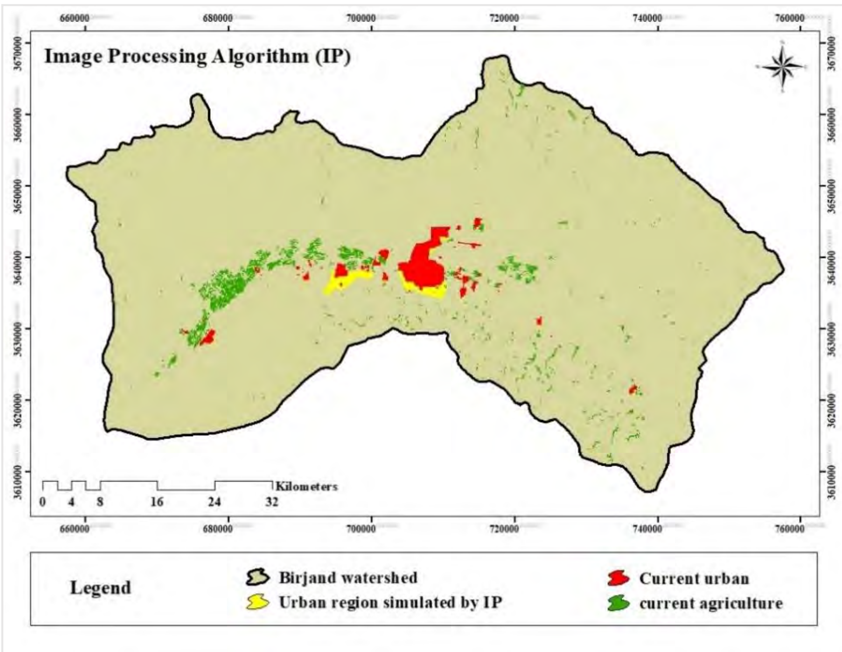

Figure 10. Urban land-use allocation using the IP algorithm

MOLA algorithm

The result from MOLA application is shown in Figure 11. In this process, the multi-objective allocation algorithm was applied based on the maximum land-use suitability, consideration of weights (the maximum allocation), and the required area. The result of this algorithm was confined to the areas around the current city.

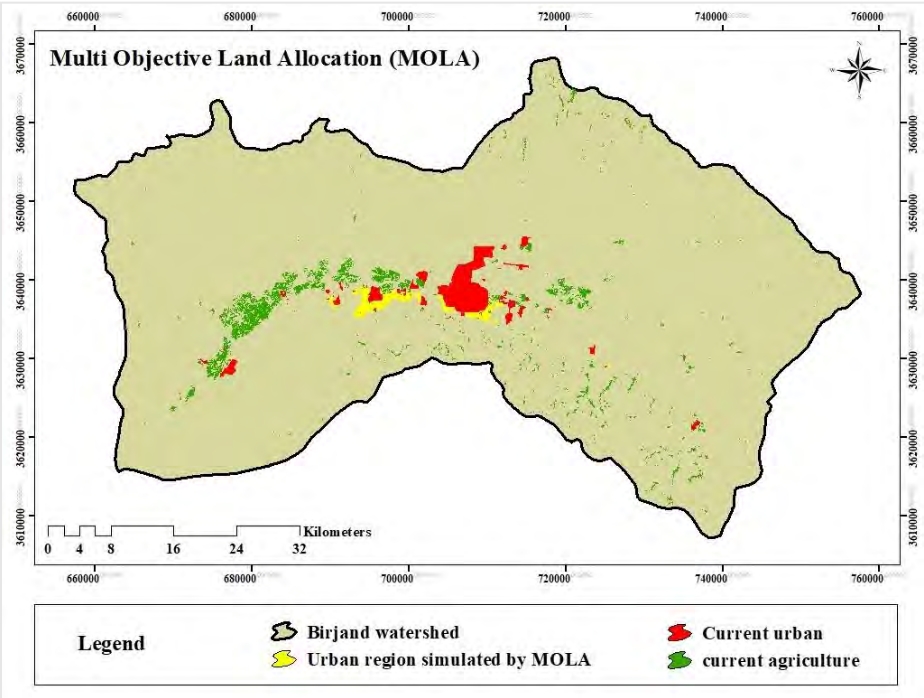

Figure 11. Urban land-use allocation through the MOLA algorithm

Validation based on visual, statistical, and landscape metrics

Visual assessment

Results of Figures 9, 10, and 11 confirm that all three algorithms used in the present study have relatively good performance concerning urban land-use suitability in the allocated patches. The GSA algorithm presented different urban patches and two other algorithms displayed almost identical locations for urban planning.

Statistical parameters

The statistical parameters (such as mean, standard deviation, and coefficient of variation) for urban land-use suitability in the allocated patches are shown in Figure 12. Results of the mean statistical parameter illustrated that the MOLA algorithm with a value of 215.136 had better efficiency for urban land-use suitability than IP (211.364) and GSA (210.710). Results of the standard deviation also showed that the MOLA (41.037) and IP (41,729) algorithms were better than the GSA algorithm (42.699). On the other hand, the GSA algorithm had the lowest coefficient of variation (4.864) compared to IP (5.065) and MOLA (5.243) algorithms.

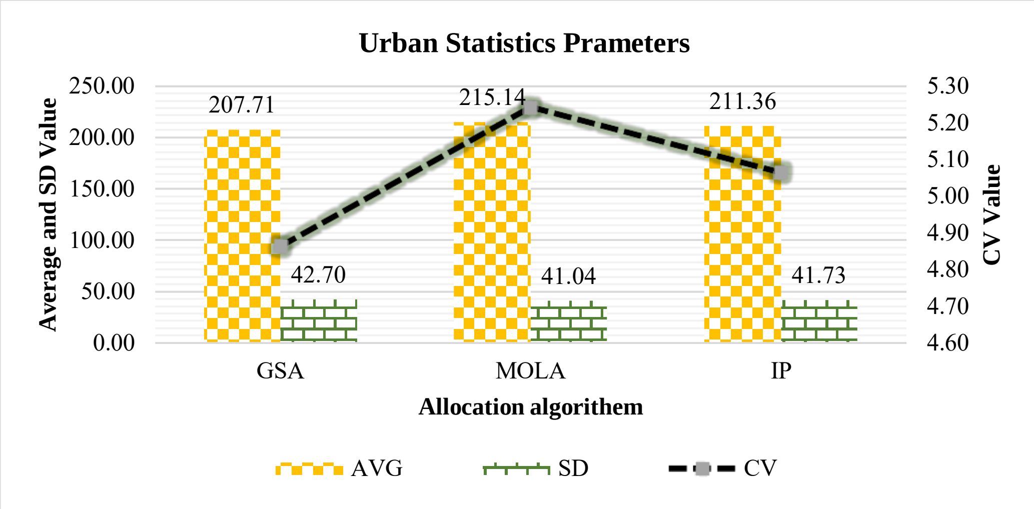

Figure 12. Statistical comparison of the efficiency of GSA, IP, and MOLA algorithms in urban land-use allocation

Landscape metrics

The efficiency of algorithms in urban land-use allocation using analytical approaches of landscape metrics, e.g., the number of patches (NP), patch density (PD), perimeter-area ratiometric (PARA_MN), proximity index (PROX_MN), and patch cohesion index (COHESION), were compared in the Birjand watershed (Table 3). The values in Table (3) indicate the relative efficiency and superiority of different algorithms in different landscape metrics. Overall, it can be seen that each algorithm had advantages in at least two landscape metrics (highlighted points). The highest values in indices of PD and SHAPE_MN with values of 0.020 and 1.261 were recorded for the GSA algorithm. In contrast, the lowest values of NP and PARA_MN (equivalent to 150 and 531.617, respectively) were obtained for the IP algorithm, which indicates the relative superiority of this algorithm over others. In addition, the MOLA algorithm had the highest values (relative superiority) for landscape metrics PROX_MN and COHESION (equivalent to 240.002 and 98.380, respectively) than the GSA and IP algorithms.

Table 3. Comparison of landscape metrics in optimizing land-use allocation

Result of urban land use allocation / Comparison criteria	Landscape metrics					
	Number of patches (NP)	Patch density (PD)	Average shape index (SHAPE_MN)	Average perimeter per spot area (PARA_MN)	Proximity index (PROX_MN)	Patch cohesion index
GSA	123	0.020	1.261	544.134	50.313	98.127
IP algorithm	105	0.017	1.249	531.617	39.479	98.190
MOLA	119	0.019	1.256	558.818	240.002	98.380

Discussion

The effective utilization of theories and models necessitates an understanding of the underlying assumptions, the identification of possibilities and limitations, and the application of these theories in alignment with their intended purposes. Conversely, as the complexity of a theory or model increases, users are required to possess a higher level of practical proficiency. In current conditions, decision support systems have streamlined this process (Briasolis, 1388). To develop algorithms for land use suitability assessment, the pivotal step involves identifying stable features and translating them into quantitative functions and concepts. In this study, we have undertaken this task, striving to incorporate the most critical indicators of sustainable land use suitability assessment, backed by robust scientific support.

In the realm of Geographic Information Systems (GIS), the criteria utilized are often characterized by inaccuracies and ambiguities. Consequently, alternative methods must be embraced to mitigate these issues. The employment of multi-criteria decision-making methods stands as a reliable approach to address the aforementioned challenges. In this study, we have employed fuzzy and Analytic Network Process (ANP) methodologies to enhance accuracy, optimize parameters, and bring our findings closer to reality. This approach enables the refinement of weights and input parameters while concurrently addressing uncertainties associated with assessed parameters, thus promoting a comprehensive standardization in research (Chamanehpour et al., 2020). Furthermore, since multiple factors influence the land-use suitability assessment process, potentially with opposing or synergistic effects (Pourebrahim et al., 2011), we have applied the ANP method to resolve issues related to factor independence, feedback loops, and interactive factors influencing evaluations.

Within this study, we have selected 13 environmental and infrastructure factors for urban land-use assessment. Our approach considered various aspects, including the selection of comprehensive criteria for accurate assessments, the incorporation of uncertainties, the standardization of diverse factors to enhance evaluation precision, and the application of the Analytic Network Process to address false assumptions, feedback loops, and interacting factors influencing evaluations.

This study also involved a comparison of three methods: MOLA, IP, and GSA. While the GSA algorithm defined multiple objectives for urban land-use allocation, the MOLA and IP algorithms optimized only for land suitability. Nevertheless, the results pertaining to ecological parameters and landscape metrics indicated no significant differences in algorithm outputs within the study area. Nonetheless, since these algorithms may exhibit varying performances under different conditions (utilizing distinct performance measurement criteria), it is conceivable that the most suitable algorithm may vary depending on the specific context. Notably, the image processing algorithm and MOLA yielded similar outputs, while the GSA algorithm exhibited slight differences, potentially attributed to a more comprehensive consideration of objective functions and constraints.

In summary, the application of metrics used in this research, such as patch integrity, coherence, and shape, is commonplace in land-use planning. Management requirements may vary based on their relative importance in urban planning processes. Additionally, the accuracy of land-use change simulation models is influenced by numerous factors, including the precision of input data, map classification, factor selection for land use determination, and simulation methods (Pahlavani et al., 2017). Given the multi-objective and nonlinear nature of environmental challenges, achieving precise solutions in large environments with multiple objectives using conventional methods can be exceedingly challenging and may yield conflicting or contradictory outcomes. Therefore, this research introduces one of the most powerful algorithms in the field of artificial intelligence, the GSA algorithm, as an auxiliary tool for land-use managers in developing land-use suitability assessment plans. This process evaluates land-use suitability through mathematical and spatial optimization, providing a combined method for multi-objective optimization in urban land-use allocation planning. The positive attributes of the GSA algorithm, such as rapid convergence, avoidance of local optimizations, reduced computational complexity compared to evolutionary algorithms, and minimal memory usage compared to collective intelligence algorithms, open up new avenues for research. This study represents the first application of this algorithm to land allocation issues. Additionally, the MOLA algorithm, another powerful tool employed in this research, has demonstrated its capacity to address complex factors, limitations, and multidimensional environmental effects (Masoudi et al., 2021).

Mwasi (2001) advocated that all objectives should be simultaneously addressed in land-use allocation decisions. To achieve this, objectives should be prioritized, ranked, assigned, and resolved. Thus, precise tools are indispensable for resolving conflicts. MOLA offers a framework to tackle such conflicts and manage the allocation of limited land resources to meet limitless demands. Yang et al. (2018) further affirmed that optimal solutions in MOLA tend to align more closely with reality, a result attributed to ongoing enhancements in mutation and crossover strategies during algorithm execution. Furthermore, selecting the appropriate number of iterations in this algorithm can yield optimal solutions within a reasonable time frame.

Current optimization methods fall under the category of multi-objective approaches, enabling the simultaneous evaluation of various objectives, such as suitability rates and landscape metrics, in land-use management. It is crucial to note that while multiple objectives can be considered, these methods explore numerous potential solutions to determine the best approach in each context, taking into account various factors, including time constraints. Given that the MOLA method can generate suitable solutions in terms of land-use suitability, it is suggested that MOLA be combined with one of the optimization methods to address conflicts and incorporate multiple objectives. In this context, Kamyab et al. (2016) utilized genetic algorithms to enhance the MOLA method. Ligmann- Zielinska et al. (2008) improved the MOLA model by eliminating one of its constraints, namely, scattered and disjoint patterns. As a result, they found that applying a density-based design constraint could enhance the efficiency of the model by promoting infill development or redevelopment, thus optimizing the utilization of urban spaces.

In conclusion, our research indicates that by defining a broader array of objective functions and constraints, results become more realistic, and the need for intervention by decision-makers is minimized. While the outcomes generated by the GSA algorithm may not always be the most precise, they maximize the overall fitness in situations involving limited land parcels. These parcels depend on both demand levels and required consolidation, making this approach more realistically advantageous.

Conclusions

This study investigated the effectiveness of MOLA, IP, and GSA algorithms as a decision support tool for land use planning.

Different algorithms solve the land use allocation problem in different ways. The MOLA algorithm is based on a computer decision matrix and provides an opportunity to resolve conflicts and overlaps between regions based on the optimal fit of each pixel. In the IP method, the basis of the work is based on the sum of the pixels' highest value (fit or suitability) and the amount of area required for urban land use. The GSA algorithm calculates all target functions for all pixels using gravitational search rules and determines the gravity areas of the image based on the force exerted from each pixel on the other pixels. Areas with the highest density are the best development centers for urban land use. In this algorithm, the desired answers are the position of objects in the problem space and the number of objects is determined according to the fitting function.

In this study, we presented an integrated land use management strategy using GIS-based land cover analysis to determine the optimal sites that meets all criteria for our goal. This study also shows that the algorithms used, as an automated GIS-based evaluation method, help to minimize land use planning workload. In determining land use arrangement based on quantitative and qualitative parameters, the overall suitability of each land unit was achieved based on the criteria of environmental suitability (maximizing suitability), compactness (maximizing compactness), ease of land use change (minimizing land use change), ecological suitability (maximizing the ecological fit (landscape) and restrictions such as the amount of land required for different land use, the total area, the allocation of only one land use per pixel. Then, the results were evaluated through land use metrics. Based on the results, in terms of the average urban land use suitability, the MOLA algorithm has better performance, followed by the IP and GSA algorithms, respectively. In terms of standard deviation, MOLA and IP algorithms are better than GSA. Also, the landscape metrics analysis showed that different algorithms have different efficiency and superiority in different metrics. For example, the MOLA algorithm performed better for patch cohesion indices and the neighborhood index.

The meta-heuristic algorithms are very helpful in solving complex and diverse problems of land use allocation with large dimensions, numerous goals with high accuracy and speed, providing near-optimal responses. Therefore, we suggest that such algorithms be used in solving other problems of land use allocation with large and complex space and other related research such as impact assessment projects.

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Data Availability
Data will be available upon request to the corresponding author.

Conflict of interest
The authors declare no conflict of interest.

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