

Introducing a Heuristic-Based Model for Optimizing Multi-Objective Land Use Change: a Case Study for Grap Sub-Basin of Taleghan Township, Iran

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Keywords: Heuristic, Land Use Change, Multi-Objectives Optimization, NSGA-II, Optimization

Abstract

One of the most significant challenges in land use planning and management is how to optimize the use of available arable lands based on their limitations for natural resource conservation. In this regard and due to the interaction of numerous conflicting objectives, multi-objective meta-heuristic algorithms are introduced for solving such types of issues. This research aims to analyze the sensitivity of NSGA-II parameters and introduces a model for land use change optimization considering some constraints. Three objective functions were established as economic benefits (F1), adaptability of land use (F2), and land conversion difficulty (F3) towards maximization of economic benefits and the adaptability of land use with its neighbors while minimizing land conversion difficulty (LCD). To prepare the land use map, Landsat8(OLI) images were classified using maximum likelihood classification (MLC) algorithm with an accuracy of about 93 percent. To generate a scheme and pairwise comparison for each objective function, AHP multi-criteria decision-making method was used. Then, the coefficient of NSGA-II operators was evaluated by trial and error approach to reach and select their optimal values. The gained optimal values for the objective functions result in an optimal plan for land use change. The evaluation of the convergence and stability of the algorithm proves the acceptability of achieved results. Based on different scenarios, increase the economic benefits are up to 99, 69, and 63 percent. Consequently, the introduced approach may be applicable for official managers to overcome multi-objective problems toward a sustainable development policy for environmental conservation on local and national scales.

1. Introduction

Nowadays, land use change is one of the influential factors in natural ecosystem dynamics (Schaffer, 1985; Yang et al, 2008). Planning and decision-making for optimized utilization and conservation of the natural environment is complicated due to the acts of different and conflicting objectives such as soil erosion and loss, increasing compatibility of land operations with local situations while maximizing economic benefits. (Datta et al, 2007; Matkan et al ,2016; Schlager, 1965). Hence, land use change assessment as a sophisticated process uses various influential factors on land use changes to magnify the complexity of this issue(Villalta, 2009). On the other hand, land use optimal allocation is undertaken based on a vast domain of criteria and information that may not be provided by traditional methods (Alaiimoghadam et al, 2016; Stewart et al, 2004; Sadidi et al ,2017; Nasiri, 2010). In terms of the mentioned issues, utilizing a powerful system like Geospatial Information Systems (GIS) would be useful to solve such types of problems (Malczewski, 1999; Matthews et al, 1999; Matkan et al ,2016). Also, due to a large number of objective function calculations, meta-heuristic genetic algorithms (GA) may help overcome these problems (Dias & Vasconcelos, 2002; Murata & Ishibuchi, 1995; Matthews, 2001).

Multi-objective optimization is referred to as finding one or more optimized solutions when more than one objective function exists (Dias & Vasconcelos, 2002). To solve a multi-objective optimization problem, a set of decision variables are

distinguished and then, the objective functions are optimized in terms of the constraints of the problem. Hence, the term “optimization” states to find a set of solutions that are adopted by all values of objective functions (Coello et al, 2007).

In comparing two solutions, if none of them is better for all objectives, it is said that the two solutions are non-dominated. If the importance of the objectives are identical together, it is impossible to define which one of the two solutions is better for all objectives, such sets of solutions are called Pareto optimal solutions (Deb, 2001) and its related objective vectors indicate Pareto optimal frontier (14).

Evolutionary NSGA-II (Non-dominated Sorting Genetic Algorithm) as a genetic and optimization algorithm (Goldberg, 2007; Goldberg, 1989), is one of the well-known, and widely used algorithms for searching as well as optimization of multi-objective problems in the real world (Deb et al, 2002; Debet al., 2000; Goldberg, 1989). The algorithm was first introduced by Deb and his colleagues in 2002 (Horn et al, 1999). NSGA-II exploits the elitism approach and can search in a vast domain of decision variables and objectives (Maringanti , 2009). In the algorithm, the initial population is randomly selected, and then, the population is divided by n Pareto fronts based on objective functions by the use of a non-dominated sorting operator. based on the dominance, each Pareto front is distinctly ranked and an identical ranking value is assigned to inter-front members. For the members who are on the same front level, a number is assigned by the crowding distance method that implies the

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distance rate. In the following, the parent population is selected according to less dominance and more distance rate. Then, the resulting population is formed using the classic genetic operators. Finally, the parent and child populations are crossed over together and consequently, the next generation is created comprising the elite population. This process is repeated in the following generations until the termination condition is reached.

Numerous researches have been conducted on land use change and other issues with different objectives using meta-heuristic NSGA- II (Shaygan et al, 2013; Ligmann-Zielinska et al, 2008; Matthews et al, 1999; Villalta, 2009; Goldberg, 2007; Shaygan et al, 2013; Datta & Deb, 2005; Datta et al, 2007; Cao et al, 2011; Masomi et al ,2011; Matkan et al ,2016; Aerts et al, 2003 ; Schlager, 1965) that imply the efficiency of such algorithms in land use change planning.

To discern which parameters have the most significant impact on model performance and to identify what are the most appropriate parameter values, there is a need to find a way to screen out sensitive parameters and quantitatively evaluate the influence of each parameter on model performance (Yanjun et al, 2014), this is generally called sensitivity analysis (SA). They categorized SA into two: local SA and global SA. The local SA explores the changes in model response by varying one parameter while keeping other parameters constant. The simplest and most common approach is differential SA (DSA), which uses partial derivatives or finite differences of parameters at a fixed parameter location as the measure of parametric sensitivity. Though simple and intuitive, DSA measures only local sensitivity whose value is location-dependent. On the other hand, the global SA examines the changes in model response by varying all parameters at the same time. The generalized SA (GSA) method is one of the global SA methods that are designed to overcome the limitations of local SA methods (Yanjun et al, 2014).

Hence, the current research aims to change a specific land use unit, subjected to maximization of economic benefits and adaptability and minimization of land conversion difficulty functions. To implement the idea, first of all, the ecologic sources and expert perspectives have been studied, and the coefficients of the economic benefits, adaptability, and land conversion difficulty have been defined via AHP (Analytical Hierarchy Process) method. AHP method was initially introduced by Prof. Thomas L. Saaty in 1990 and is a part of the multi-criteria decision-making method that rests on paired comparisons to derive ratio scales to derive ratio scales from the principal Eigenvectors and some small inconsistency in human judgment from the principal Eigenvalue (provide references). Different values for defined operators in the meta-heuristic NSGA- II algorithm (including the initial population, mutation population, crossover population, crossing-over method, and termination condition) were evaluated and the optimal values for each operator were determined and selected. The innovation of this study is defining different scenarios for a goal-oriented plan that enables the managers to prepare an optimal land use change plan following sustainable development and environmental justification.

2. Main body

2.1 Data

Taleghan area is located inside an east-west oriented big valley in the Alborz mountain range, 120 kilometers far from Tehran capital of Iran. Grap is one of the sub-basins of Taleghan as a study area (figure 1). The data used here are described as follows:

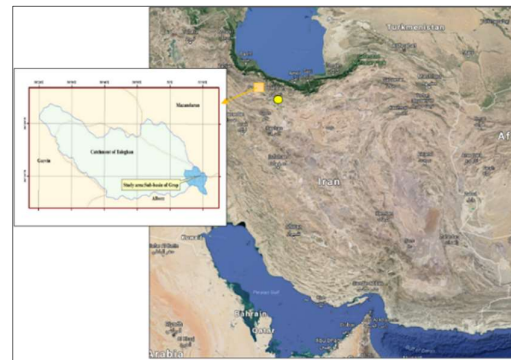


Figure 1. Geographic location of the study area (adopted from Google Maps)

2.2 Land Use Map Preparation

A land use map of the study area has been prepared using two Landsat 8 satellite images with 15 meters of spatial resolution in panchromatic and 30 meters in bands 5, 4, and 3 which are used in this research. The maximum Likelihood Classification (MLC) method has been used to produce the land use map shown in (figure 9-a). The accuracy of the classification is about 93 percent. The land use map was utilized as the base for the research. Notably, the smallest land-use area is about 2 hectares. Hence, the defined pixel size for the land use grid is 150 meters (2.25 hectares), and the study area is covered by 2714 land use pixels. Defining smaller pixels than 150 meters will result in more calculations and subsequently take more execution time with no further accuracy. The resulting land use grid is used to form the initial population (initial chromosomes).

The land use map preparation is followed by neighborhood mapping. The neighborhood map (polygon neighbors) is created based on polygon contiguity (overlaps, coincident edges, or nodes), so that, the number of or length of coincident edges with other land uses polygons is considered. For each of the scenarios, the neighborhood map facilitates allocating the land use segments to have more adjacent borders with a specific land use. The neighborhood map is used as one of the inputs of the model.

The information needed for calculating the optimization functions (economic benefits, adaptability, and land conversion difficulty) has been determined for each pixel by AHP multi-criteria decision making method.

2.3 Methods

The input data set comprises of land use map, neighborhood map and coefficient of factors of the optimization functions derived from different steps of AHP introduced by Saaty 1990 (these steps are: pair-wise comparison, making comparison Matrix, computing Eigen Value and Eigenvector, Consistency Index and Consistency Ratio calculation, and compute in a full hierarchy).

furthermore, Based on the Pareto front derivation and analysis explained earlier in the introduction section, the initial population is randomly selected, then, the population is divided by n Pareto fronts based on objective functions by the use of non-dominated sorting operator. based on the dominance, each Pareto front is distinctly ranked and an identical ranking value is assigned to inter-front members. For the members who are on the same front level, a number is assigned by the crowding distance method that implies the distance rate. Then, the parent population

is selected according to less dominance and more distance rate. The resulting population is formed using the classic genetic operators. Finally, the parent and child populations are crossed over together and consequently, the next generation is created comprising the elite population. This process is repeated for the following generations until the termination condition is reached. Inputs for all NSGA-II operators (including the number of initial population, the number of mutations and crossover population, crossover method, and termination condition of the algorithm) were evaluated by trial and error approach to reach the optimal values.

The evaluation was performed in conjunction with optimizing the three defined scenarios for maximization of economic benefit and adaptability functions as well as minimizing the land conversion difficulty function. It is worth mentioning that these three scenarios are performed all together and simultaneously. Figure 2 illustrates the research flow chart in more detail.

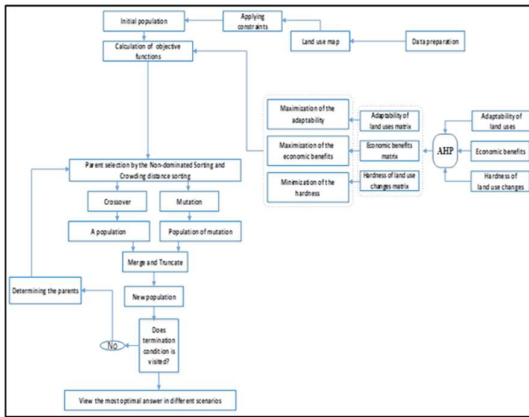


Figure 2. Flow chart of this research work in details.

2.3.1 Modelling of The Land Use Change Problem in The Algorithm

At this stage, the land use change problem is modeled in the meta-heuristic NSGA-II algorithm through the following steps:

Defining a solution in the optimization space

As mentioned before, in Graf sub-basin the minimum size of parcels cultivated by land owners is 2 hectares, which is why a 2.25 hectares grid has been selected. To define a solution, an index is assigned to each 2.25 hectares as a pixel area. The initial land use map is outputted by overlaying a 150 by 150 meters grid on the current land use map. It is important to note that, the land use would be assigned to a grid that is covered by more than 60 percent of the given land use.

A possible solution (figure 3) is composed of n land use units (here 2714 grids). The solution in Figure 3 can be thought of a chromosome in which L is optimized land use per grid on the condition that the problem constraints are considered and the optimization function is minimized or maximized. Also, another index is dedicated to each land use type. Here, 8 types of land uses exist.

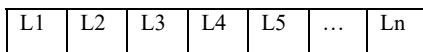


Figure 3: The definition of a solution (a chromosome)

2.3.2 Defining The Optimization Functions and Problem Constraints

In the current research, to define the land use change patterns, three objective functions have been introduced: economic benefits (F1), adaptability of land use (F2), and land conversion difficulty (F3).

This function attempts to maximize the economic benefits. The economic benefits matrix has not just been designed based on marketing economy but follows sustainable development policies such as minimizing soil erosion, and maximizing virtual water and oxygen production.

To apply the function, firstly, the economic benefits matrix has been formed by expert perspectives. Then, the matrix has been weighted using AHP multi-criteria decision-making method. Equation1 calculates the economic benefits of changing the current land use to the optimized suggested land use.

$$F1 = \sum_i^n \sum_j^n Pij \quad (\text{equation1})$$

Where, $P_{i,j}$ is the economic benefit value of changing to the suggested land use for pixel (i,j).

Adaptability of Land Uses

Increasing the adaptability between land uses in the model output patterns is the reason behind the use of this function. The function tends to minimize the peripheral impacts caused by neighborhood spatial relations. The function is calculated based on the adaptability of each spatial land use unit (2.25 hectares) with its neighbors. The function exploits a matrix in which different levels of adaptability between land uses are defined based on expert views using AHP method and equation2 and equation3 are used to calculate the adaptability of each pixel with its neighbors.

$$F2 = \sum_i^n \sum_j^n Cij \quad (\text{equation2})$$

$$C_{i,j} = \frac{\sum_{h=1}^n C_{i,j,h}}{n} \quad (\text{equation3})$$

Where: $C_{i,j}$ is the mean adaptability of pixel(i,j) with its neighbors, $C_{i,j,h}$ is the adaptability of pixel(i,j) with its hth neighbor, n is number of neighbors of pixel(i,j) and i,j are row and column numbers respectively.

Land conversion difficulty

One of the objectives of the current research is to minimize the Land Conversion Difficulty (LCD) in the model output patterns. To calculate the land conversion difficulty, the LCD matrix has been formed through AHP method. The matrix is filled by different levels of land use change LCD that have been weighted by expert perspectives. Consequently, the change in LCD from the current land use to the suggested one has been calculated for each pixel using Equation 4.

$$F3 = \sum_i^n \sum_j^n Dij \quad (\text{equation4})$$

Where: $D_{i,j}$ is the LCD of land use change pixel(i,j) from the current land use(i) toward the suggested land use(j).

Constraints of the problem

Constraints are set based on current rules and regulations of state governments. The proposed optimization has a number of constraints denoted in a matrix (table1), where, number 1 means that a land use pair may not be changed to each other. For example, the meadow-range land is not allowed to be changed to human-made structures. Also, zero means that a land use pair may get changed to each other. And -1000 implies that a specific

land use doesn't exist in the study area but has been considered as a possible land use by the meta-heuristic optimization method.

	Meadow-range lands	Agriculture-orchards	Agricultural lands	Orchards	Low density (poor) forest	Rangelands grade 3	Human-made structure	Dense forest plantation
Meadow-range lands	0	0	0	0	0	0	1	1
Agriculture-Orchards	0	0	0	0	1	0	1	1
Agriculture	0	0	0	0	0	0	1	1
Orchards	0	0	1	0	0	0	1	1
Low density (poor) forest	0	1	1	0	0	0	1	0
Rangelands grade 3	0	1	1	0	0	0	1	1
Man-made structure	1	1	1	1	1	1	0	1
Dense forest plantation	-1000	-1000	-1000	-1000	-1000	-1000	-1000	-1000

Table 1. Matrix of constraints

Generating the initial population

To initiate the process, several solutions (chromosomes) are randomly generated. Each land use is allocated to a pixel so that the problem constraints are met, otherwise, this solution is waived and a new solution is suggested. To generate the initial population, random solutions should be similarly created for as many as the generation members.

Selection of parents

The tournament method in NSGA-II algorithm has been used for parent selection. Firstly, probable parents are ranked in terms of fitness value and the highest score holders are selected as parents.

Crossover operator

One-point and two-point methods have been used for the mating of chromosomes. In the one-point method, since the crossover gene (location) is determined, each chromosome is divided into two parts and forms a half chromosome for the new generation. Figure 5 illustrates the one-point crossing over in land use change. It is worth mentioning that the constraints have to be regarded through each crossing-over because the constraints are already met for forming the initial population.

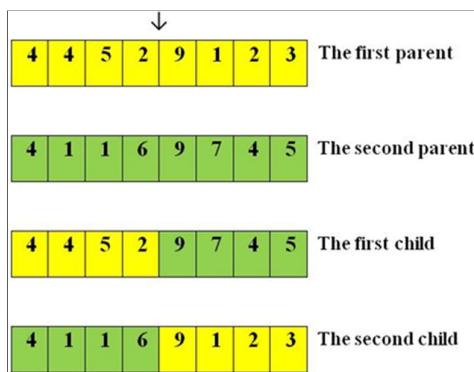


Figure 4. Single-point method to form the children

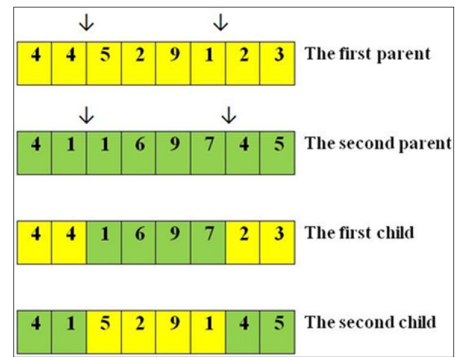


Figure 5. Two-point method to form the children

Mutation operator

The mutation is preceded by the crossover operator. To initiate the process, a mutation rate is determined. Then, a value between 0 and 1 is randomly selected. If the value is less than the mutation rate, a mutation operator will be performed. For mutation, two genes are randomly selected, then, the land use of the gene is randomly changed regarding the predefined constraints, otherwise, the gene should be stochastically allocated to another land use. The mentioned process is repeated n times to select the appropriate optimized land use. Figure 6 illustrates an instance of the mutation.

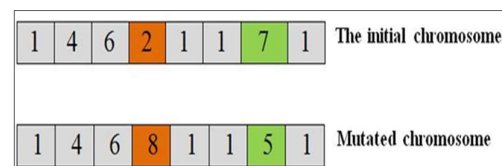


Figure 6. An example of a mutation in Land use change

New population generation

The new population is generated by integrating the mutation and crossover population.

Termination condition

Once an optimal solution is achieved, the termination condition is checked. If the defined criteria are met, the running process of the algorithm will be terminated, otherwise, the process is repeated again. The termination criteria may be a predetermined accuracy, a specific number of repetitions, a particular iteration, or a combination of all, for simplification here, a specific number of repetitions (3000 times) has been considered

2.3.3 Sensitivity Analysis of Meta-Heuristic NSGA-II Algorithm by Trial and Error

Due to the importance of parameters like the number of iterations, initial population, rate of mutation, crossing over point, executing time length, and optimization functions in performing such an algorithm, the Sensitivity analysis process has been implemented by changing the value of the iteration, initial population operators, mutation rate, crossing over point, executing time length and optimization function during the implementation of meta-heuristic NSGA-II algorithm. The results are as follows:

Repetition

In this research, repetition of 100-3500 has been evaluated. The optimal repetition value resulted from trial and error is 3000 during the used scenarios.

Number of initial population

A population of 100-600 members has been tested by trial and error. The result shows that the 500 is the optimized value for the number of initial population for the defined scenarios. It is notable that that values has not been tested one by one but was evaluated as a range of ten by ten for each run.

Mutation population

The population of mutation is one of the influential parameters in a meta-heuristic genetic algorithm. Here, the population has been varied from 10 to 300 during the running scenarios. In the most optimized scenario, the value of 200 was selected as the mutation population.

Crossover population

The crossover population is another effective parameter in NSGA-II. Here, the parameter has been changed between 10 to 350—consequently, the value of 300 visits is the most optimized case through the defined scenarios.

Crossover points

One point, as well as two points crossover methods, has been investigated in this research. The result shows that a two-point crossover is more efficient rather than a one-point method during the scenarios.

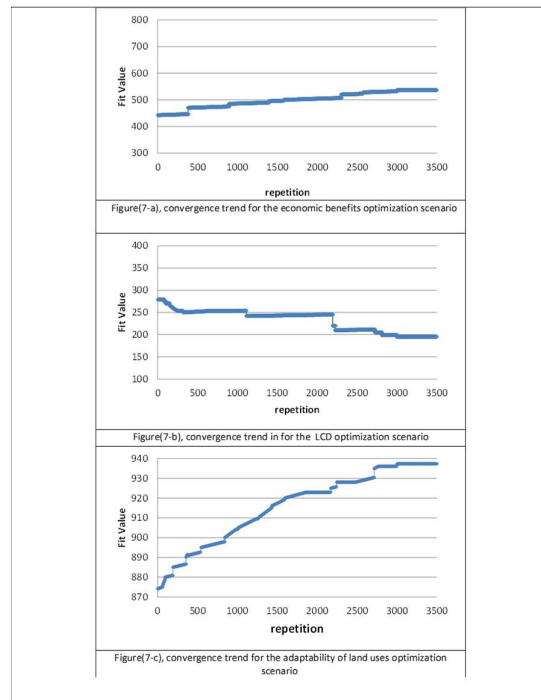
2.3.4 Evaluation of NSGA-II Algorithm

Convergence and stability parameters have been utilized to evaluate the efficiency of NSGA-II algorithm.

As an algorithm reaches faster convergence, the algorithm is more efficient. During the current research, a repetition of 1 to 3500 times has been assessed. Figure 7a- c) illustrates the convergence trend in NSGA-II. As it is clear from the graphs, the convergence values have not been changed after the repetition of 3000 in all three scenarios. This indicates that the algorithm has reached the local optimum. This is why the repetition number 3000 has been selected to recognize the best optimal solution.

evaluated operators	Domain of changes	The most optimal mode
Initial population	100-600	500
Crossover population	10-350	300
Mutation population	10-300	200
Crossing over method	One point- two point	Two point
Termination condition	100-3500	3000

Table 2. The evaluated parameters of NSGA-II



Stability of the algorithm

An algorithm has stability if similar results are achieved after during the consecutive running of that algorithm. To survey the stability, the variance of the final solutions for 10 iterations of the running algorithm was calculated (see Figure). For clarity, the variance of the normalized data is used. Due to the normalization, the variance is varied between 0 to 1. The algorithm stability increased when the variance was getting closer to zero.

3. Conclusion

As mentioned before, the current research aims to define a model to change the land use in the study area that enables the landowners to get the most economic benefits regarding the stability and LCD constraints as well as sustainable development goals. For sensitivity analysis of NSGA- II parameters and to define the optimized value for each parameter, the different iterations of the algorithm have been conducted in two specific stages. In stage one, the value of an operator is changed and the others are considered as constant. Subsequently, the most optimized value for each operator has been obtained. At the next stage (stage 2), the most optimal selected value for each operator is considered and other operators are changed so that the final optimal situation has been selected. The optimized values obtained in numerous repetitions for NSGA-II algorithm are represented in Table 2.

As depicted in Figure, in the early repetitions, the convergence speed is very fast. Gradually, the convergence steep is going to be slower and finally, is converged. Figure 7 illustrates that the optimization function behaves with diverse convergences on each part so that the graph is divided into distinct steps. The convergence acceleration from the initialization to iteration 280 is higher than the other parts of the graph. From repetition 280 to around 500, the convergence change is being slowed down. Then, a gradual trend is observed from repetition 500 to 800 and an incremental trend toward iteration 2470. Finally, after the repetition 2470, the algorithm is almost converged and thereafter, the trend is stable. Accordingly, in the early

repetitions, the convergence is faster, and in the following later repetitions, a gradual and incremental conversion exists.

Figure 8 shows the stability of variance in 10 iterations of the algorithm. Notably, the 3000 repetitions are independently implemented 10 times. In the performed iterations, the variance is equal to 0.112 proving the relative stability of the algorithm and the need doesn't arise to perform more than 10 iterations because the variance value is reasonable. It should be mentioned that the reasonable value for variance is 0.1-0.2.

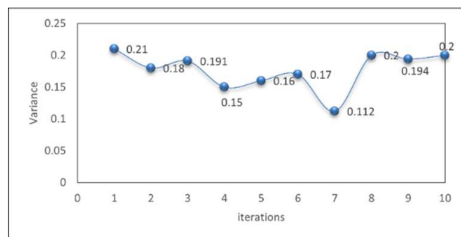


Figure 8. The trend of variance in different iterations

The main part of the study area is covered by rangeland grade 3 and subsequently, due to land use changing by NSGA-II algorithm, the LCD function tends to be increased. In contrast, the adaptability would be decreased. Through the implementation of the model, if no land use is changed, the economic benefits, adaptability, and LCD will be equal to 271.39, 1384.15, and zero respectively. However, in the best optimal situation based on the three designed scenarios the objective functions would be as follows:

- The first scenario is maximizing the economic benefits function. The outcome shows values of 536.80, 870.6943 and 276.767 for the economic benefits, adaptability and LCD functions respectively.
- The second scenario is performed for maximization of the adaptability function. The achieved outcome shows values of 458.013, 937.3937 and 204.555 for the economic benefits, adaptability and LCD functions respectively.
- The third scenario is targeted to minimize the LCD. In this scenario, the economic benefit is equal to 442.56, adaptability is 919.5107 and the LCD function value is 195.536.

Type of land uses	Area of land uses (in Hectares) in the area before and after the implementation of meta-heuristic NSGA-II algorithm in different scenarios			
	Optimal LCD	Optimal adaptability	Optimal economic benefit	Primary use
meadow-rangeland	715.9	754.6	736.6	830
Agriculture-orchards	82,282	31,04	63,9	36,1
Agricultural lands	34,6	57,1	49,8	72,4
Orchards	1401,7	1314,9	1357,4	36,5
Low density (poor) forest	1293	1367,6	1338,5	2153,1
Grade 3 rangeland	1552,7	1578,5	1565,5	3380,3
Human-made structures	24,9	24,9	24,9	24,9
Dense forest plantation	647,5	593,9	618,9	0

Table 3. The changed area of land uses by the sensitivity analysis of NSGA-II algorithm in different scenarios.

As shown in Table 3, according to the three defined scenarios, the area of dense forest, orchards, and agriculture-orchards land uses have been increased. In contrast, rangeland grade 3, meadow-rangeland, agriculture, and low-density (poor) forest land use areas have been decreased. Notably, human-made features have not been changed because it is one of the predefined

constraints. Figure 9 illustrates the current land use map of the study area (figure 9-a) versus the optimized changes resulting from this study in figures 9-b to 9d. Figure 9b shows the land use map when the maximum economic benefit is attended. Figure 9c shows the land use change plan when the minimum land conversion difficulty is targeted and finally, figure 9-d is achieved when the maximization of the adaptability between land uses is expected.

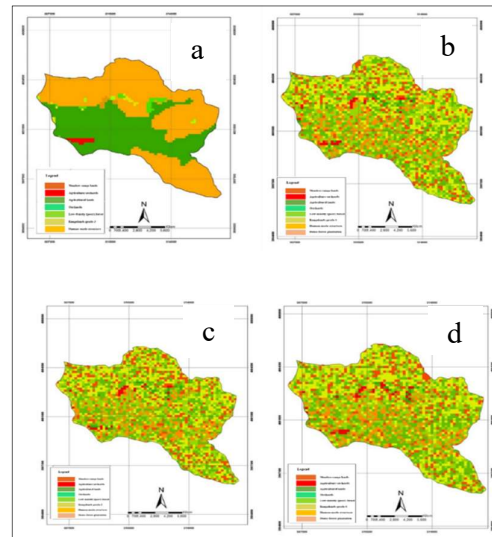


Figure 9-a. The current land use, b, the resulted land use for the economic benefit scenario, d, the resulted land use for the least land conversion difficulty scenario, c, the resulted land use for the most adaptability scenario

Due to the complexity and extend of the solution space to define the suitable and optimized land use as well as considered constraints in the land use change plan, a model has been designed to enable the algorithm to increase the economic benefits up to 99, 69 and 63 percent in the said scenario one, two and three respectively. The results show that the introduced model may play an efficient role in land use change plans and similar topics. Also, the significant influence of problem-algorithm-oriented operators on the search trend for the optimized solution can be viewed as another result of the current research. Finally, the research achievements augment the local as well as national scale managers to use the relative scenario based on predefined objectives.

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