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Monitoring and predicting land cover changes in the coastal areas for optimal land allocation (Case study: Chaf and Chamkhaleh, Guilan, Iran)

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Abstract

The main aim of the present study is to explain the trends of land cover change. For this purpose, the changes were estimated and then predicted using Markov chain and cellular automata. It was indicated by comparing the images of the three periods during a 26-year period that the changes in coverage were associated with the loss of agricultural lands, the loss of natural production and the destruction of the landscape. In addition, the output of the Markov cellular model suggests that with the continuation of the current trend, we will face to the loss of paddy field coverage, while the area of the urban cover will increase significantly in 2030.

Keywords: Land Allocation; Land Cover; Changes Prediction; Chaf and Chamkhaleh

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1. Introduction

The main issue of land allocation is to create a balance between urban cover and other land uses. So that social and economic needs of the community are met and the least environmental degradation occurs. Therefore, looking for the most optimal and sustainable pattern of land allocation is actually the search for the most suitable areas for assigning to urban land use.

Land use and land cover changes are nonlinear and depend on other changes in the bio-physical and social system (Meyfroidt and Lambin, 2010). In other words, the increasing pressure of the population growth and the need for housing and employment along with technological developments, land use policies, development plans, investments, creative innovations, land speculation and egotistically land exploitation, all brings the land to dramatic changes. Given that the changes vary spatially, temporally, and in terms of dominant viewpoints of processing (Serra et al., 2008; Krausmann et al., 2003), so, we will face to the micro and macro patchy dispersion and changes in all areas of the study region. So that it is not possible to encompass the process of transformation without the use of efficient tools. Today, with the help of the remote sensing tool, we can observe the balance of the cover classes, spatially and temporally. Because the discrete coverage classes are limited and specified and do not exceed seven or eight classes. Built-up, agricultural (crops and gardens), rangeland, wet, arid, facilities, access networks and forests make up macro land cover classes. The distribution, shape, and extent of each, are subject to changes over time and a new coverage composition is created. Often, the built-up cores are extended with population growth. Sometimes, the agricultural or coastal cover change with the economic function. Some products are sometimes depressed from the market. In which case, the land under their cultivation is abandoned. Industrial activities, tourism, drought, earthquake, flood, landside, cultivation alternation, construction of a road network, etc., can change the face of the land cover. Periodically monitoring of the cover change will help determine the process governing the changes and the rate of increase or decrease in the coverage classes' extent. Several factors simultaneously cause land cover changes that vary in severity. However, what important is identifying the key elements of change and finding solutions to control changes in coverage. Certainly, any factor that causes the loss of land, the loss of its productive properties, the degradation of the ecosystem and the environment, destruction of the landscape and the forest should be limited. The most important reason for the lack of optimal land allocation in the study area is the lack of accurate study. Hence, the first step to get rid of the existing conditions is to know the trends governing land use and land cover in this coastal area. It makes it possible to recognize the past and present spatial developments and to take the necessary measures for improving the future situation in the region.

1.1. Literature review

1.1.1. Literature review on monitoring and simulation of land cover changes

In a study in 2009, Kamusoko et al. found a relationship between the probability of change and the spatial pattern using cellular automata (Kamusoko et al., 2009). The results of a study by Suzanchi and Kaur (2011) showed that research must be carried out on land cover scale to obtain clear responses and avoid interventions on micro-scale land uses (Suzanchi and Kaur, 2011). Guan et al. (2011) utilized a Markov-cellular automata model to simulate the spatial distribution of land use and predict future changes in Japan. In this study, land cover species were evaluated in six levels of agricultural lands, forests, waterbodies, built areas, roads and other lands (wastelands and beaches) (Guan et al., 2011). Pandian et al. (2014) used satellite images and GIS to investigate land use changes over two periods. The results of their studies showed significant land use changes in the study area, so that agricultural lands were exposed to a decreasing trend and urbanization activities had an increasing growth (Pandian et al., 2014). In a study conducted in Australia, Bryan et al. (2016) reviewed the sustainable land use under the influence of global and local changes using the Land-Use Trade-Offs (LUTO) model and scenario analysis. Their findings indicated widespread land use changes in the studied areas, whose implications affected their sustainability (Bryan et al., 2016).

1.1.2. Literature review on foresight and scenario planning in spatial and physical planning

Ahmed et al. (2009) conducted a scenario planning study in Egypt to identify the main drivers using the MIC-MAC analysis and analyzed the key objectives and positions of stakeholders through the MACTOR method (Ahmed et al., 2009). In a study on rural development factors, Serrano et al. (2010) used MIC-MAC software for futuristic structural analysis and graphical representation of relationships between the influential and influenced factors (Serrano et al., 2010). Turoff and Banuls (2011) used the Delphi method and cross impact analysis for scenario planning (Turoff and Banuls, 2011). In a study in 2015, Fierro conducted internal and external analyses using the SWOT model and utilized the MICMAC and MACTOR model to analyze the strategic variables and identify the role of relevant stakeholders, respectively. He also applied the SMIC method to generate probable, possible and plausible scenarios (Fierro, 2015).

1.1.3. Literature review on land allocation

In 2012, Wu et al. conducted a study entitled “Development priority zoning (DPZ)-led scenario simulation for regional land-use change”(Wu et al.,2012). In an article, Veburg et al. (2013) assessed the uncertainty of changes in future spatial allocation of agricultural lands in Europe. The results of their study showed that some specific regions are faced with the trajectory of certain land changes more than other areas (Veburg et al., 2013). Chen and From (2013) conducted a study entitled “Dynamic simulation of urban land use change in Dalian, China”. In this study, they simulated three future spatial change scenarios in 2020 as three hypotheses (Chen and From, 2013). In a study entitled “Future land use change scenarios for the Black Sea basin”, Mancosu et al. (2013) utilized suitability and constraints maps and population trends to regulate the modeling process (Mancosu et al., 2013). Puerts et al. (2014) suggested a combined land use allocation model in their study, which included logistic regression, Markov chain and machine cells models (Puerts et al., 2014). Wang et al. (2015) used the DE-CA model in their study to simulate the optimal land allocation in China. The results of simulation showed that the output of model was properly compatible with the actual conditions and could be used as a basis for formulation of regional land use and optimal land use (Wang et al., 2015). The results of studies by Dyazedin et al. (2016) demonstrated that there was a competition between land uses because of their value fluctuations. Other economic factors, such as wages and interest rates, had no considerable effect on land allocation. In addition, the population also made a significant impact upon land use allocation; of course land allocation was also affected (Dyazedin et al., 2016).

2. Theoretical framework

Rapid urban growth in the 20th and 21st centuries and associated insufficiencies, which are predominantly occurring in developing countries, have led all communities to adapt to the sustainable development paradigm to achieve sustainability patterns in the city. In this regard, principled use of water and soil resources and the optimal allocation of land resources - also called "Sustainable Land Allocation" - have been taken into consideration by planners since 1990. The limited usable lands along with rapid changes in communities and development in land-uses highlight the importance of the correct planning of land and purposeful decision making for optimal land allocation. Land use allocation for sustainable strategy balances economics, efficiency, and ecological issues (Chang, 2013). Based on the characteristics and systemic principles of land, optimal allocation of land resources can be achieved using some scientific principles, technological methods and management tools (Wang et al., 2015). Considering different spatial development perspectives as well as geographic constraints, computational approaches can help to solve land use allocation problems and cope with the associated limitations by generating a set of possible solutions (Li and Parrott, 2016). In the field of land allocation, the focus is often on creating models with multiple goals and parameters. However, socio-economic development and ecological sustainability are always two main objectives of land use process (Zhang et al., 2014). One of the techniques that has been considered by urban planners over the past years is the use of Geographic Information System (GIS) to monitor land cover changes over different periods. Obviously, knowing the changes' trends in the land cover classes in different periods is of great importance as a pre-requisite for future study.

3. Methodology

This study is a descriptive – analytic investigation. In this regard, the data needed for this research was gathered through satellite imagery processing, field observations, interviews with experts in rural and urban planning, reliable books and papers, and interviews with residents of the region. Data analysis is done in several steps. So that, an estimation was conducted on land cover changes over three periods and in the form of a crossover table in order to classify the coverage of the study area. Finally, prediction of changes was analyzed using Markov chain and cellular automata and in the form of fuzzy logic. Chart 1 shows the operational process of the study.

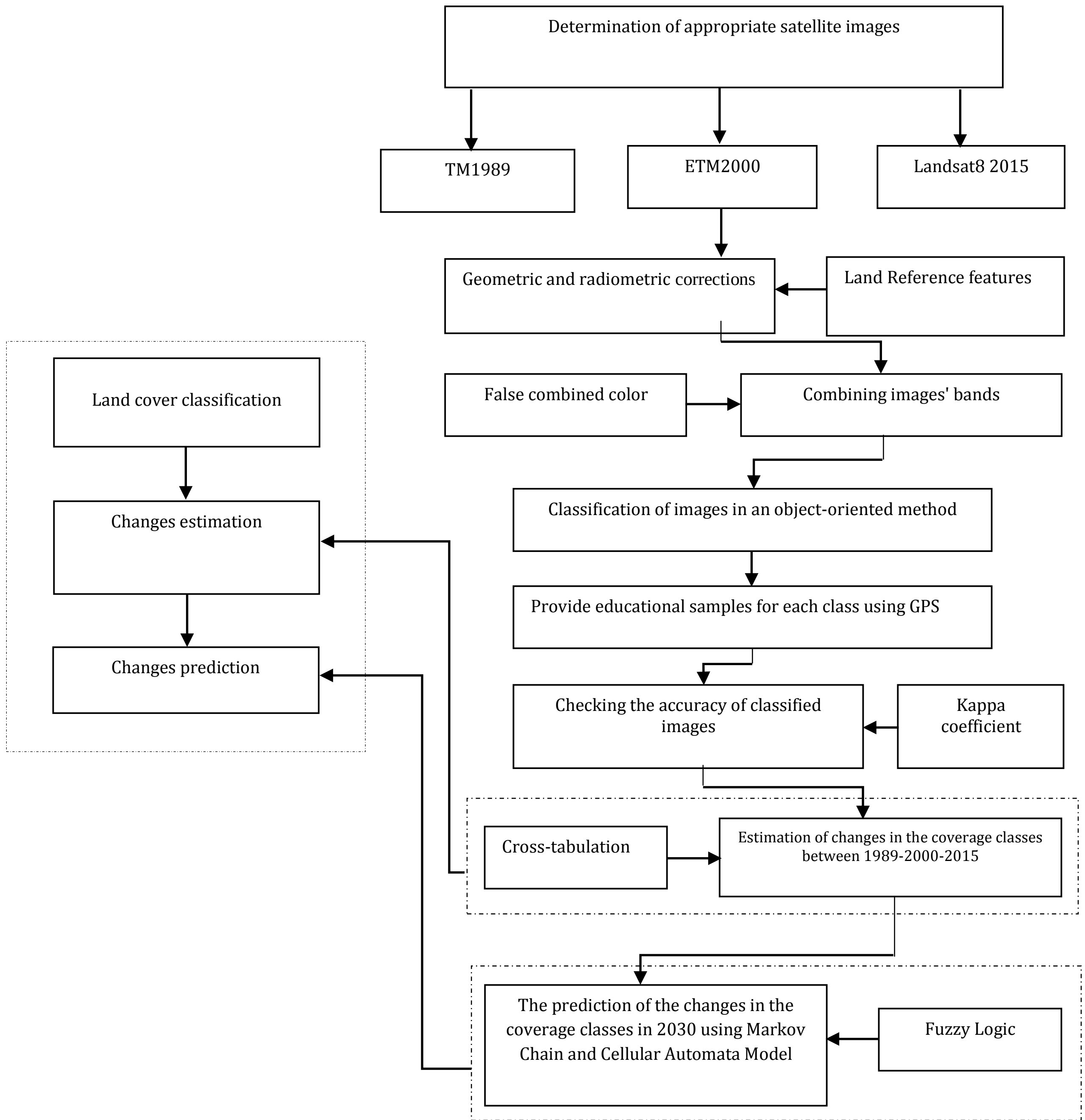


Chart 1. Operational Process of the study

3.1. Study area

The Chaf & Chamkhaleh city is located on the central part of Langrood, between 37° 13' N and 50° 15' E (Fig. 1). Since the establishment of a large part of its land at the sea coasts, this city is composed of two main types of coastal and plain areas in terms of natural features.

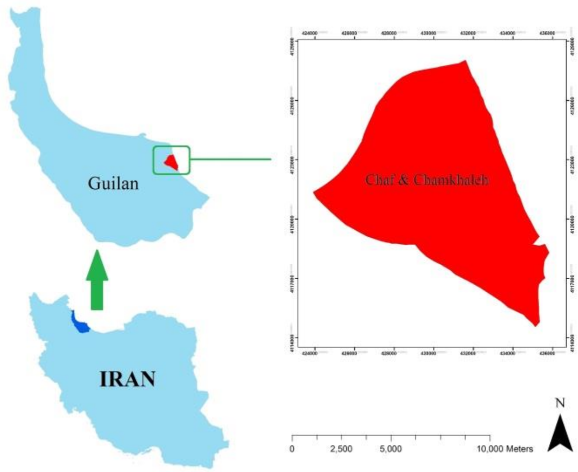
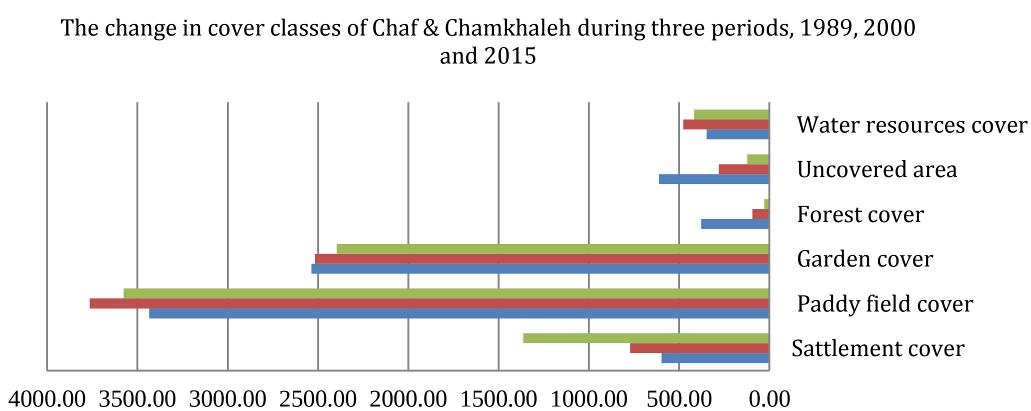


Figure 1. The study area (Source: Generated by author)

4. Results

4.1. Comparison of changes in the six covering classes for in 1989, 2000, and 2015



	Sattlement cover	Paddy field cover	Garden cover	Forest cover	Uncovered area	Water resources cover
2015	1363.84	3577.77	2396.84	29.35	122.28	417.24
2000	771.77	3765.55	2517.39	94.78	281.19	478.01
1989	598.48	3434.73	2536.47	378.73	612.10	347.99

Chart 2. Comparison of cover classes in 1989, 2000, and 2015

According to Chart 2, the total settlement cover increased ascending from 598 ha in 1989 to 1364 ha in 2015. The area under paddy field cover has increased ascending in the first period until 2000, the main reason of which was the rise in the economic value of rice and the beginning of the agricultural mechanization plan making garden lands unsustainable and converting uneven grounds to paddy fields. However, in the next period, due to increased production costs and insignificant rise in crops' price, the improvement of the position of Chaf and Chamkhala in the country's divisions, and thereby, economic boom of urban and tourism activities, the area under cultivation was reduced. The garden cover area has also decreased from 2536 ha in 1989 to 2397 ha in 2015. Forest cover with a reduction from 378 ha in 1989 to 29 ha in 2015 has had the most significant changes. The uncovered class which includes mostly coastal lands has reduced from 612 ha in 1989 to 122 ha in 2015. While, water resources' cover has increased has increased from 348 ha in 1989 to 417 ha in 2015. It was mostly due to the sea fluctuation rather than the watershed management and restoration of water resources (Fig. 2).

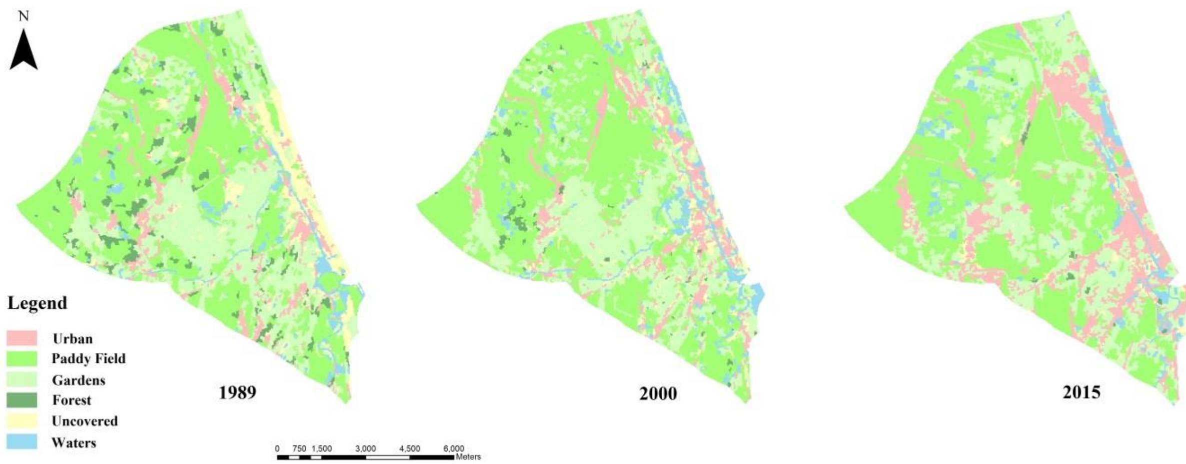


Figure 2. Changes in cover classes for periods, 1989 - 2000 - 2015(Source: Generated by author)

4.2. 4.2. Simulation and Prediction

4.2.1. 4.2.1. Markov cellular model calibration

By using the processed and classified images of 1989 and 2000, the prediction of changes for 2015 was conducted for prediction accuracy test. Since the real changes in 2015 were achieved from the Land Sat satellite image processing, comparison of the similarities and differences between the projected image and the real image was performed and the accuracy was calculated based on the real image. The matrix in Table 1 illustrates the probability of changes calculated by the Markov chain in 2015 based on the images of 1989 and 2000. In fact, the matrix of changes' rate probability indicates the probability percentage of changes in a cover class to the other cover class.

The matrix in Table 1 shows: the probability that the class 1 (urban cover) remains un-changed is 35%. The probability that the class 2 (paddy field cover) stays invariant is 67%, the class 3 (gardens cover) would be as same as previous cover rate with a probability of 46% in 2015, with only one percent, the garden cover (class 4) likely to remain stable (class 4). Uncovered (class5) and water resources' cover (class6) are likely to remain unchanged with probability rates of 6% and 13%, respectively, and the rest covers will transformed to other cover classes. In fact, economic, political, and social events are considered as the fundamental content and roots of the developments, the outcome of which is the formic changes in the macro covers of the region. Then, the probability matrix of the changes in the area was calculated. The matrix in Table 2 shows the probability of changes in the area of the cover classes in 2015.

Table 1. The matrix of the probability of changes in cover classes in 2015

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6
Class 1	0.3592	0.2256	0.2858	0.0125	0.0692	0.0476
Class 2	0.0342	0.6793	0.2032	0.0120	0.0144	0.0569
Class 3	0.0973	0.3295	0.4693	0.0096	0.0426	0.518
Class 4	0.0531	0.5775	0.2857	0.0143	0.0206	0.0488
Class 5	0.2406	0.2377	0.3482	0.0094	0.0696	0.0945
Class 6	0.0819	0.4449	0.2817	0.0102	0.0433	0.1380

Table 2. The changes' probability matrix of cover classes' area in 2015

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6
Class 1	3407	2140	2710	119	657	452
Class 2	1586	31480	9418	556	666	2639
Class 3	3018	10223	14561	298	1323	1606
Class 4	62	676	335	17	24	57
Class 5	831	882	1203	32	241	327
Class 6	482	2617	1657	60	254	812

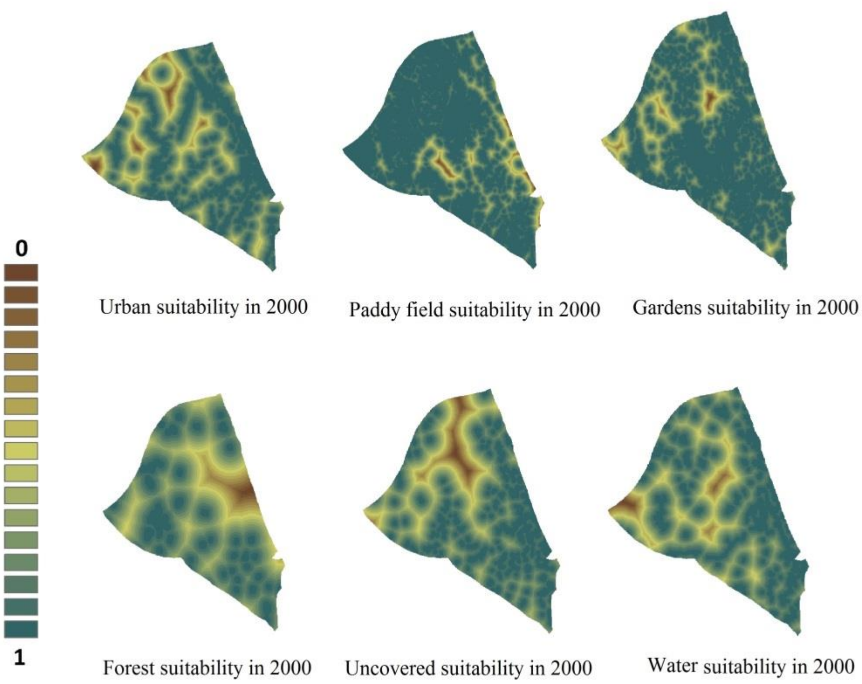


Figure 3. Suitability map of cover classes of image in 2000(Source: Generated by author)

The Markov chain is a method to predict changes. In fact, it calculates the probability of changes. Markov output was 2 matrices in tables 1 and 2. These matrices represent the probability and the area of changes, respectively. However, the Markov chain is not able to show where the changes take place. That is, it lacks a spatial dimension (it has a temporal dimension). Therefore, to eliminate this problem (adding spatial dimension to the change probability matrix), automated cells or cellular automata are used. In fact, cellular automata adds a spatial dimension using the Markov probabilities, and shows where the changes has often taken place. So, a suitability map was created to make possible changes graphical by the cellular automata model. Suitability maps to simulate changes in 2015 were cover classes of 2000, which were separated and their Euclidean distance was calculated, and then, were normalized by fuzzy logic (Fig. 3).

The right side of Figure 4 shows the graphical prediction of cover changes in 2015. To calculate the accuracy of the model, the area of the predicted cover classes and the real cover classes' area in 2015 were calculated. Then, the accuracy of the model was obtained by comparing the percentage of classes.

According to Table 3, the comparison of the percentage of classes in the real and the predicted image of 2015 indicates that there is a total difference of 16.72%. Therefore, 83.28 percent accuracy was obtained which is acceptable. There is a significant difference in the paddy field and garden cover classes, which can be neglected due to the similarities and interferences of the border and the adjacency of these two classes.

Table 3. Area and percentage of real and predicted cover classes' image of 2015

	real image 2015			predicted image 2015		
	Area(Hectare)	Percent		Area(Hectare)	Percent	percent Dispute
Urban	1367.12	17.28	urban	842.46	10.67	6.61
Rice field	3581.08	45.26	Rice field	4024.37	50.96	-5.7
gardens	2391.91	30.23	gardens	2536.90	32.13	-1.9
forest	29.10	0.37	forest	2.19	0.03	0.34
No cover	123.97	1.57	No cover	12.91	0.16	1.41
water	418.50	5.29	water	477.35	6.05	-0.76
total	7911.68	100		7896.18	100	

The following formula was used to calculate prediction accuracy:

$$\text{Accuracy} = \sum |urbanareapercentDispute| + |ricefieldareapercentDispute| + |gardensareapercentDispute| + |forestareapercentDispute| + |nocoverareapercentDispute| + |waterareapercentDispute|$$

4.2.2. The prediction of changes in the cover classes on the horizon of 2030

In order to predict changes in the six cover classes in 2030, images from 2000 and 2015 were used in the IDRISI software environment. Given the trend governing the changes of cover classes in the study area over the years 1989 to 2015, the Markov chain model computed the change probability matrix for the year 2030.

The matrix in Table 4 shows that the probability of the urban cover to be remained unchanged is 60%. The probability of unchanging in paddy field cover is 67%, and the gardens will be the same as the previous, in 2030 with a probability of 46% coverage. The forests, uncovered and water resources' covers will be remain unchanged with probabilities of 0%, 1% and 16%, respectively. The rest classes will convert to other cover classes. Paddy fields will be converted to gardens and built-up covers with probabilities of 21 and 5 percent, respectively. The gardens will also be turned into built-up cover in 2030 by a probability of 19%. The most instability will be assumed for forest cover, uncovered and water resources' cover classes. The paddy fields will be more stable than other cover classes.

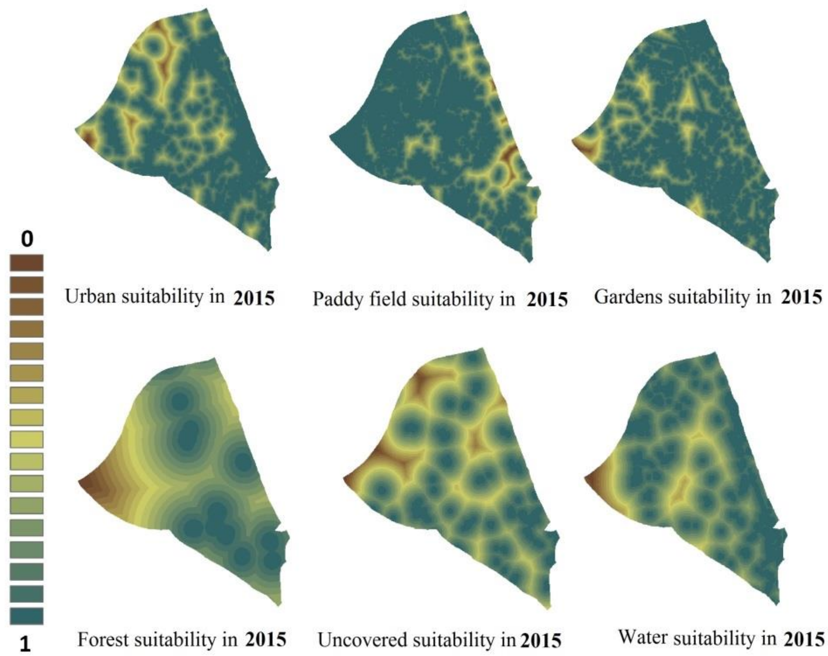


Figure 5. Suitability map of cover classes of 2015 image (Source: Generated by author)

Table 4. The matrix of changes' probability of the cover classes in 2030

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6
Class 1	0.6023	0.1187	0.2132	0.0060	0.0149	0.449
Class 2	0.0541	0.6774	0.2149	0.0020	0.0105	0.0410
Class 3	0.1903	0.2732	0.4612	0.0053	0.0223	0.0477
Class 4	0.1019	0.4101	0.3964	0.0000	0.0051	0.0865
Class 5	0.3780	0.1696	0.3658	0.0035	0.0130	0.0701
Class 6	0.2152	0.3475	0.2403	0.0051	0.0236	0.1683

Table 4 shows the matrix of the probability of changing the area of the cover classes. The unit of this matrix is a cell, and Chart 3 shows the rate of changes in the cover classes in the predicted period after converting unit in hectare. Figure 6 shows the possible changes in the year 2030 graphically simulated using the CA-Markov model. To simulate the changes in 2030, suitability maps were first developed. Suitability maps were cover classes of the 2015 image which were separated and their Euclidean distance was calculated. Finally, they were normalized with fuzzy logic (Fig. 5).

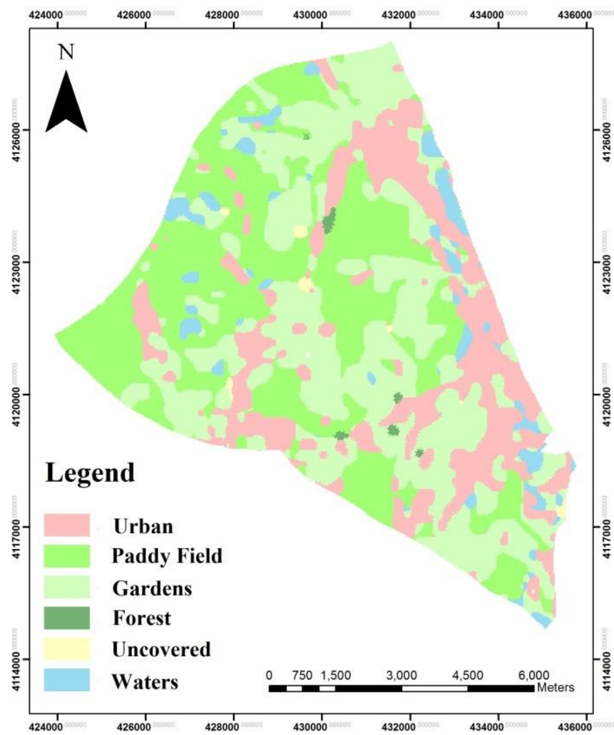
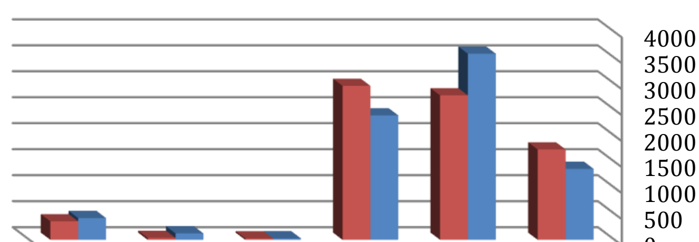


Figure 6: The prediction of changes in the cover classes in 2030 using the Markov cellular model (Source: Generated by author)



	Water resources cover	Uncovered area	Forest cover	Garden cover	Paddy field cover	Urban cover
2015 image	418.5	123.97	29.1	2391.91	3581.08	1363.84
2030 predicted image	355.42	37.04	27.94	2960.69	2779.53	1735.90

Chart 3. Comparison between land cover classes' area in 2015 and prediction of 2030

Chart 3 shows that in 2030, the area of the paddy field cover and uncovered classes coating will be significantly reduced. According to the past trend, the urban cover class will increase by 372 hectares and the gardens cover class will increase by 568 hectares. This increase could be a sign of abandoning the paddy fields and gardens.

5. Conclusion

Dynamic analysis of the change process of land cover showed that in a 26-year period, a total 765.36 hectares of natural-ecosystem-adapted land covers has become an incompatible cover. Comparing the changes in the land cover classes obtained from the satellite images in the studied periods it was indicated that in 7911 hectares of study area covered, the area of water resources and paddy field cover classes was initially increased, and then it decreased. While, the area of gardens, forests and uncovered classes has decreased, but the area of urban cover has increased. Overall, the comparison of the images of the three periods, 1989, 2000, and 2015 in a 26-years period suggested that due to the dispersion of changes, cover changes have been occurred to loss agricultural lands, to loss natural production capacity and to destroy the landscape.

The prediction of changes using the Markov cellular model shows that the area of the paddy field cover and uncovered classes would be significantly reduced in 2030. According to the past trend, the urban and garden cover classes will be increased by 372 and 568 hectares, respectively. This increase could be a sign of the abandoning the paddy fields and gardens due to economic and livelihood issues. In fact, economic, political and social events are considered as the main content and roots of the developments, the outcome of which is the formic changes in the regional land covers.

6. Study limitations and proposed future policies

A limitation to the study is the lack of formulated database for statistical data on the studied area. This study identifies the general guidelines of land allocation; hence studies must be carried out at lower levels to achieve the results of study, so it is proposed to do further research on the subject.

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