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Forecast of temporal-spatial changes of Iran's vegetation using Markov Chain- Automated Cell Model

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Original Research

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Abstract:

Vegetation changes are the main criteria for desertification and that is important in land management and monitoring. This research aimed to investigate the vegetation cover changes in different provinces of Iran. In the present study, vegetation changes were forecasted for 2024 using the Normalized Difference Vegetation Index (NDVI) obtained from MODIS satellite images to monitor temporal-spatial vegetation changes in different provinces of Iran and apply a Markov forecast model. To this end, vegetation maps were initially drawn for 2000, 2008 and 2016, and then changes were detected based on the comparison after classification according to different provinces. Results revealed that more descending vegetation changes belong to Markazi, Lorestan, Khuzestan, North Khorasan, Razavi Khorasan, Bushehr and Ilam Provinces, respectively. Finally, vegetation changes were forecasted for 2024 using Markov chain-automated cell model. The results of the vegetation changes matrix based on maps from 2008 to 2016 showed that the vegetation classes of no vegetation, low vegetation, medium vegetation, and high vegetation with probabilities of 95, 90, 89, and 93%, respectively, would remain unchanged from 2016 to 2024 so that the class without vegetation will have the highest stability, and on the other hand, the normal class will have the lowest stability.

Keywords: MODIS; NDVI; Remote sensing; Simulation; Change detection

Introduction

Land use and vegetation cover are two main environmental research issues that are influenced by natural processes and human activities (Mendoza et al., 2011). Plants are integral parts of terrestrial ecosystems and play important roles in the climate system. They also help to maintain climate stability through various processes such as photosynthesis, evapotranspiration, Albedo change, surface roughness, and the global carbon cycle adjustment (Begue et al., 2011). Vegetation criterion is an important determinant of the desertification phenomenon. When the soil surface is free of vegetation, the field of action of wind increases, the wind speed increases, and thus, it directly hits the soil surface, thereby increasing the severity of wind erosion and desertification (Khenamani et al., 2011). The land cover change is an ecological global trend (Agarwal, 2002) that is mainly related to the transformation of about 1.2 million km^2 of forest and 5.6 million km^2 of grasslands including pastures, and other land uses over the past three centuries (Ramankutty and Foley, 1999). Tazeh (2016) conducted a research about the use of landscape metrics using maps obtained from the classification of satellite images Also, in a research conducted by Kamali et al. (2023), the relationship between Normalized Difference Vegetation Index (NDVI) and its effect on wind erosion was investigated. Heydari et al. (2023) investigated the use of quadcopter and thermal bands, along with Moderate Resolution Imaging Spectroradiometer (MODIS). Zarei et al. (2021) used other applications of remote sensing for classification and trends in wetlands. Therefore, the understanding of changes in plant activities and their reactions to environmental variables, the vital efforts of natural resource managers, the environment and policymakers can forecast the plant growth process, environmental changes and ecosystem evolution in the future (Neigh et al., 2008; Piao et al., 2014). In a study, the possibility of using the NDVI index on the changes in lichen cover was investigated. This study showed that the correlation between NDVI values and lichen cover was different in different regions (Erlandsson et al., 2023).

The lack of precise location information about the past is an important issue in the study of vegetation changes (Alavi Panah, 2011). Over the past two decades, many research projects have been conducted on land use/cover changes based on the remote sensing data; and various techniques have been developed in this regard (Miao et al., 2012). In addition, in the process of examining past land use changes, remote sensing allows users and researchers to forecast land use changes, determine the extent of expansion and degradation of natural resources, and lead changes in appropriate ways (Hathout, 2002). For ecologists, satellite remote sensing has become a repeatable approach to monitoring and predicting changes in plant activities in large areas (Chen et al., 2014). Vegetation indices are widely used as criteria for analyzing land cover changes including vegetation and other factors (Morawitz et al., 2006). Over the past few decades, it has been proven that the NDVI represents the success of plant activities (Neigh et al., 2008; Piao et al., 2014). Long-term data on the NDVI became available in the early 1980s, and since then, the reaction of plant activities to environmental changes has attracted considerable attention (Piao et al., 2011; Ven Leeuwen et al., 2006). In another research, the dynamic characteristics of vegetation in Shengnongjia forests in central China were monitored using MODIS images and removing clouds from them. This study was conducted between 2010 and 2020. In this study, the time series of NDVI data was used in vegetation studies. The results of this research showed that changes in vegetation were influenced by the temperature of the earth, rainfall, and the reaction of vegetation growth (Li et al., 2023).

Various methods to forecast changes such as the Markov chain model have been proposed (Muller and Middleton, 1994). Some studies have been conducted using this model to forecast land use/cover changes as follows: Memarian et al. (2012) simulated land cover changes using the Markov model in Malaysia's Langat District. They validated the CA-Markov model using the validation, allocation of disagreement, and disagreement rate, and suitability criteria in a three-dimensional space. Subedi et al. (2013) evaluated the application of the Markov chain model and automated cells in forecasting vegetation changes. In another study, plant growth cycles were investigated based on NDVI time series data obtained from MODIS images. In this study, a plant growth monitoring technique was proposed for monitoring agricultural fields on plant patterns of major one-way and two-way changes during the growth of different crops (Ahmed and Singh, 2020). Fathizad et al. (2014) forecasted the land use and cover changes using satellite data and the Markov chain model in Doiraj Basin, Ilam province, Iran. In another study, Ileri and Koc (2022) in Bozdag Rangeland in Turkey, the amount of available fodder was monitored using the NDVI values obtained from the Sentinel 2 satellite data in the sustainable management of pastures. They showed that the satellite-derived NDVI values of Sentinel 2A provide promising results for monitoring the forage vegetation of semi-arid rangeland, but further research was needed to develop new vegetation indices to consider woody textures in the vegetation. They suggested higher resolution for greater monitoring accuracy. Zare et al. (2017) using the Markov chain-automated cell model forecasted the land use location changes in the Kasilian Watershed in Mazandaran province, Iran. Tsakmakis et al. (2021) used NDVI Sentinel satellite data to reduce uncertainty in field studies on vegetation. They showed that the remotely acquired canopy cover time series could be successfully used as an alternative means to validate canopy cover simulations. Das (2021) used NDVI values obtained from Moody's satellite images in the Indian state of Uttarakhand over 20 years. They showed that the negative impact of the reservoir on vegetation was limited up to 815 m altitude and the high-altitude classes had a positive role.

Various methods have been proposed to forecast changes including models based on automated networks. Markov chains have vast applications in modeling land use and cover changes for urban and non-urban areas (Wu et al., 2006). In the Markov chain analysis, the cover classes are used as the chain states. In this analysis, two raster maps called model inputs are used. In addition to these two maps, the interval between the two images and the predicted interval are also considered in the model. The output of the model also includes the state transition probability, the matrix of transformed areas of each class, and finally, the conditional probability images for converting different uses (Weng, 2002; Gelman et al., 1996).

Models of automated cells are dynamic and discrete systems that can have very complex behavior for the global simulation of dynamic systems using local rules and interactions (White and Engelen, 2000). The CA model is taken into consideration due to its similarity with Raster data in the geographic information system (GIS). CA and Markov chains both are discrete dynamic models in time and space. The inherent problem of the Markov chain is that it does not consider spatial information and location. The transition probability may be associated with accuracy on each base group, but it lacks knowledge of the random spatial distribution within each land use group. In other words, there is no spatial component in the output of the model. Therefore, the CA-MARKOV model is used to add a spatial attribute to the model. In this model, the Markov chain process controls time changes among the land use/cover class based on the transition probability, while spatial changes are controlled by local rules that are determined through spatial filtering of CA with suitability maps (Eastman et al., 2005).

By examining this process, one can gain the necessary knowledge to manage vegetation resources. Of course, a part of these changes is due to climate changes and a part of it is due to management policies. Also, by studying the changes in the vegetation cover, we have tried to predict the future conditions for the vegetation cover in the region. The use of Modi's products on a local and macro scale together in the study of vegetation index is one of the Innovations of this research. Also, by evaluating the results obtained in the first and second periods, the vegetation condition was predicted in the following. Therefore, this research was conducted to investigate the vegetation cover changes in different provinces of Iran.

Materials and methods

Study area

Iran is a country in the Southwest of Asia with an area of about 1648000 km^2 and is located approximately between the latitudes of 25º to 45º N and longitudes of 44º to 64º E (figure 1). The average annual rainfall is 250 mm which is less than a third of the global average rainfall. The average annual temperature is 31.4 ºC. Iran has a very diverse geomorphology and includes mountainous, plain and playa areas. Climatic diversity in this country has led to the formation of vegetation diversity.

Research method

The research used vegetation output of MODIS sensors for 2000, 2008, and 2016 on a monthly scale with code MOD13A3 relating to TERRA satellite with a spatial resolution of 1 km and a HDF format. Due to the large area of the study region, the easy access to MODIS satellite data and the availability of its ready products, the images of this satellite were used in the present study.
This output included the monthly NDVI. Furthermore, remote sensing software and geographic information systems including Idrisi selva, Envi5.1 and Arc GIS10.3 were used for analysis. Since the output from the MODIS sensor is processed, there is no need for georeference and definition of the coordinate system, and their coordinate system types can be changed using the software. The coordinate system of images changed to the longitude and latitude coordinate system by ENVI 5.1, and the NDVI became ready for processing after performing initial processing on images and data of the website. Afterward, the annual NDVI map was drawn based on the average maps of months, and then, the annual average maps were prepared for three periods. The vegetation class type was determined according to uncovered soil class or no vegetation (0.05 to 1), low vegetation (0.05 to 0.1), medium vegetation (0.1 to 0.5) and high vegetation (more than 0.5) after classification of NDVI values in order to detect changes by a differential method (Fatemi and Rezaei, 2014). The area percentage of each land cover class was calculated in the studied region to reveal changes using classified maps for each period. From 2000 – 2016, the vegetation change diagram was prepared in terms of decreasing and increasing vegetation classes. Subsequently, the area of vegetation was calculated for each province based on decreasing, incremental and unchanged cover classes. The classified images of 2000, 2008, and 2016 were then used as cover maps for preparing the state-transition matrix. The interval of both images was 8 years, and the same period was used to forecast changes in vegetation classes. The state-transition matrix of vegetation classes was measured between both periods using the obtained maps for each period. The first state-transition matrix was obtained from maps of 2000 and 2008, the second state-transition matrix maps from 2008 and 2016, and a general state-transition matrix from 2000 to 2016. The matrices contained information on the transformation percentage of each class to other classes (figure 2).

Figure 1. The map of study area in Iran.

2008-9996[https://doi.org/10.57647/j.jrs.2025.1503.29]

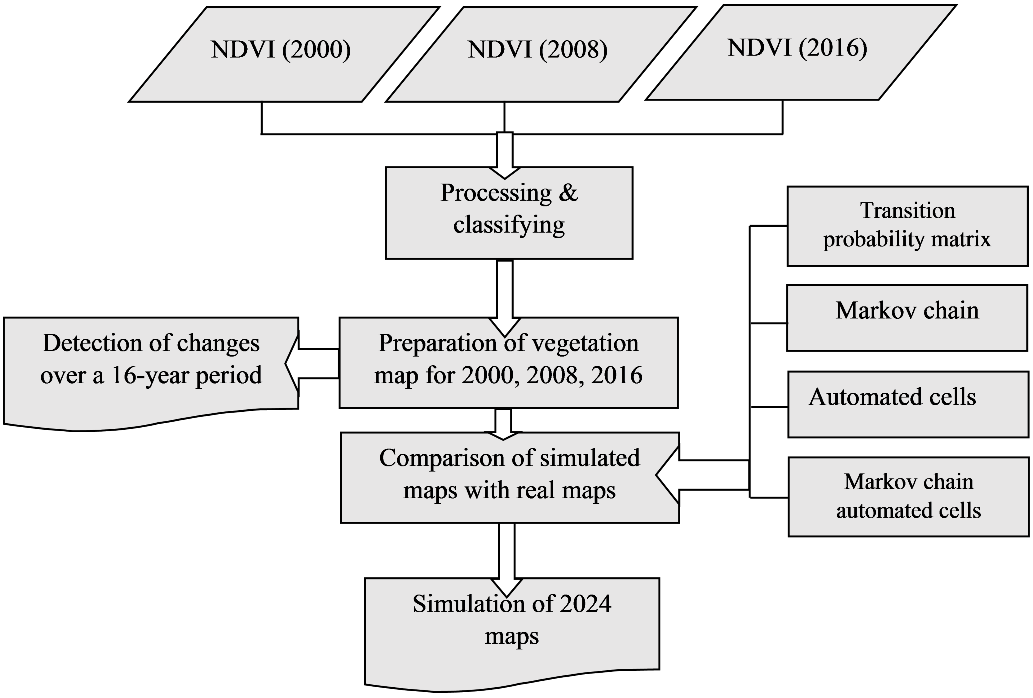

Figure 2. Flow diagram of research method.

Normalized difference vegetation index (NDVI)

It is a widely used index in the vegetation survey of various issues. The index was developed by Rouse (1974), but its concept was first introduced by Kriegler et al. (1969). The NDVI is an important index in determining changes in land phenomena, and it is significantly important in vegetation studies. NDVI was applied using the equation (1) (Kogan, 1995).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (1)$$

where:
NIR is Reflection in the near-infrared band; and RED is the Reflection in the red band. Values of this index converge to 1 are for dense vegetation; and negative values of this index indicate the absence of vegetation (Pettorelli et al., 2005).

Results

Vegetation classification map

In the present study, the NDVI classification map of the studied region was prepared in four classes for 2000, 2008, and 2016. As shown, there are no- vegetation, sparse, medium, and dense cover zones in 2000, 2008 and 2016, respectively (figures 3, 4 and 5).

Classification comparison

After classification, the areas and percentages of each class were calculated for 2000, 2010, and 2016 (Table 1). Results from 2000 to 2016 indicated that areas of some applied classes such as the medium vegetation class were decreased, and areas with low vegetation and no vegetation classes increased, but the high vegetation class area had a slight increase (figure 6). Based on the results of Table 1, the medium vegetation class with an area of 48.10% in 2000 was changed to an area of 38.57% in 2016; and the low vegetation class reached 53.63% from 46.13% in 2016, and the largest areas belonged to these two classes during these three periods.

Changes in the vegetation area of Iran in provinces are presented based on the results of classified maps' differences from 2000 to 2016 so that the vegetation and areas of regions decreased in most provinces during these 16 years (Table 2). Therefore, the highest descending trends belonged to Markazi, Lorestan, Khuzestan, North Khorasan, Razavi Khorasan, Bushehr and Ilam provinces with the descending area values of 36.99%, 25.25%, 26.47%, 20.85%, 20.68%, 20.22%, and 18% respectively.

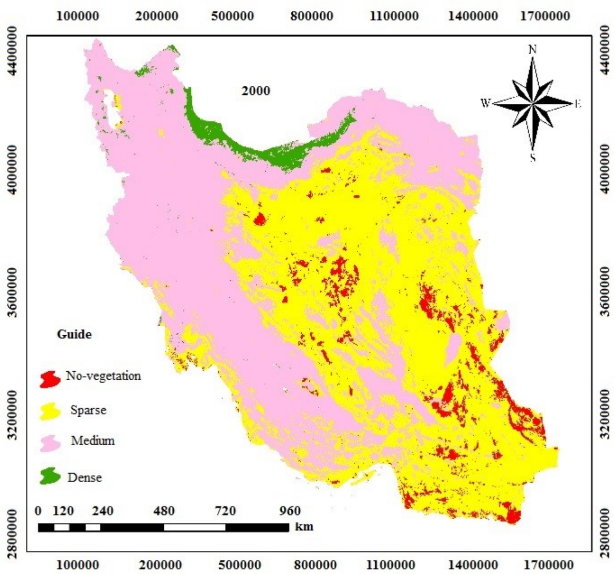

Figure 3. Map of vegetation classes in 2000.

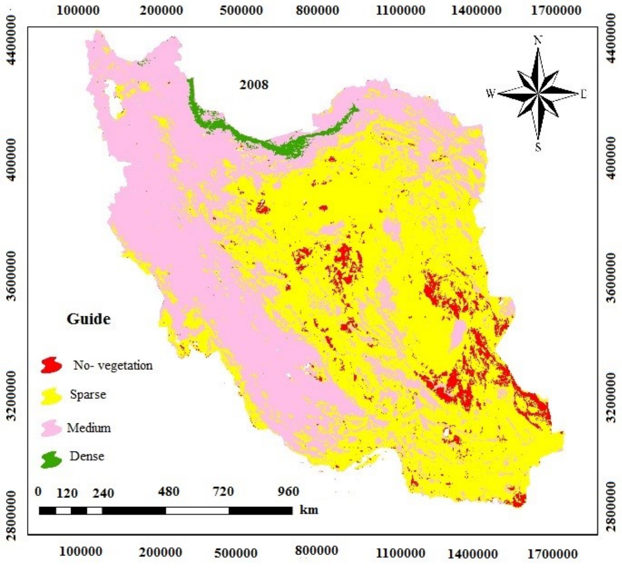

Figure 4. Map of vegetation classes in 2008.

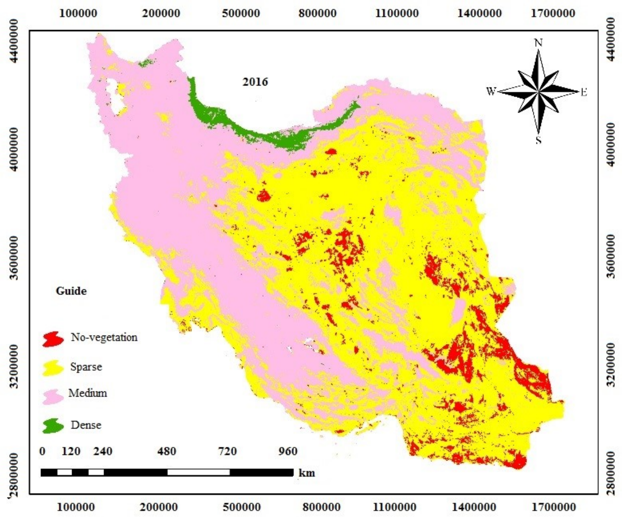

Figure 5. Map of vegetation classes in 2016.

Markov Chain analysis

The model calibration was first performed to simulate changes in vegetation classes. The results of forecasting changes in the NDVI map related to the area of each class were used to evaluate Markov model using a vegetation map for 2016 (Table 2). The obtained results indicated various class differences with a magnitude of less than 8% indicating the usefulness and usability of Markov model in forecasting land use changes.

Considering the future trend equivalent to current changes, The obtained probability matrix from maps of 2008 and 2016 using the Markov Chain were used for forecasting the changes in the next 8 years (Table 3). This matrix is used as an input in Markov chain-automated cells model along with the related changes in vegetation classes resulting from the subtraction of constructed land classes during 2008 – 2016 and four classes of vegetation.

The results showed that the area without vegetation had increased and its cause due to land use changes, along with intensifying desertification and destruction of vegetation (figure 7). The continuation of the process will lead to a decrease in the amount of vegetation in the middle class and an increase in lands with low coverage. Lands with high coverage had not changed much, the main reason for which was the location of forest areas in this class.

The matrix table shows the probability of transfer in percentage between 2016 and 2020 (Table 4). The numbers in this table indicate the probability of moving each class in the first time to the same class or other classes in the second time. The transition probability matrix is explained as follows. The most important thing to know when studying stochastic processes is the Transition Probability Matrix because transition matrices represent the probabilities of how the systems can change. These tools are essential in presenting and examining the probability of changes from

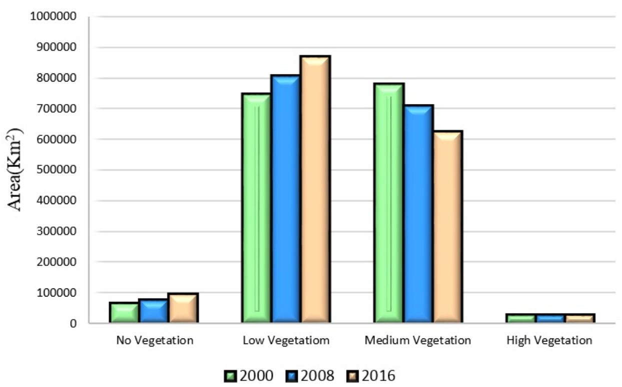

Figure 6. Area change process of vegetation from 2000 to 2016.

Table 1. Areas of studied vegetation zones in Iran (2000, 2008 and 2016).

Changes class	2000		2008		2016	
	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
No Vegetation	66236.73	4.08	77379.91	4.76	97527.22	6
Low Vegetation	749464.21	46.13	808423.07	49.76	871214.63	53.63
Medium Vegetation	781403.04	48.10	710162.73	43.71	626578.42	38.57
High Vegetation	27461.01	1.69	28599.28	1.76	29244.72	1.8
Total	1624565	100	1624565	100	1624565	100

Table 2. Changes in areas of vegetation classes in provinces of Iran (2000 – 2016).

Province	Classes changes	Area (%)	Province	Classes changes	Area (%)
	Unchanged	88.66	Northern Khorasan	Unchanged	78.8
East Azerbaijan	Decreasing	9.27		Decreasing	20.85
	Increasing	2.07		Increasing	0.35
West Azerbaijan	Unchanged	91.17	Khuzestan	Unchanged	70.62
	Decreasing	6.59		Decreasing	26.47
	Increasing	2.24		Increasing	2.91
Ardebil	Unchanged	96.51	Zanjan	Unchanged	92.55
	Decreasing	0.72		Decreasing	7.4
	Increasing	2.78		Increasing	0.05
Esfahan	Unchanged	86.54	Semnan	Unchanged	89.5
	Decreasing	10.55		Decreasing	8.76
	Increasing	2.91		Increasing	1.74
Alborz	Unchanged	83.97	Sistan & Baluchestan	Unchanged	87.02
	Decreasing	15.4		Decreasing	11.62
	Increasing	0.63		Increasing	1.31
Ilam	Unchanged	81.62	Fars	Unchanged	85.27
	Decreasing	18		Decreasing	13.8
	Increasing	0.24		Increasing	0.93
Bushehr	Unchanged	77.9	Qazvin	Unchanged	93.26
	Decreasing	20.22		Decreasing	6.44
	Increasing	1.88		Increasing	0.3
Tehran	Unchanged	87.06	Qom	Unchanged	79.29
	Decreasing	11.62		Decreasing	15.35
	Increasing	1.32		Increasing	5.36
Chaharmahal & Bakhtiari	Unchanged	92.94	Kurdistan	Unchanged	98.71
	Decreasing	6.65		Decreasing	1.09
	Increasing	0.41		Increasing	0.2
South Khorasan	Unchanged	92.89	Kerman	Unchanged	84.47
	Decreasing	5.27		Decreasing	14.27
	Increasing	1.83		Increasing	1.26
Razavi Khorasan	Unchanged	76.75	Kermanshah	Unchanged	91.88
	Decreasing	20.68		Decreasing	8.08
	Increasing	2.57		Increasing	0.05

one state to another within a given system. A Markov chain is a kind of stochastic process, which fulfills the Markov property, i.e., the probability that the next state will occur only depends on the present state and not on the sequence of states which preceded it. Markov's process principle of Transition Probability Matrix which is also noted as P is an important thing. By this property, Markov chains can be an effective and comfortable way of modeling random processes. The Transition Probability Matrix consists of the transition probabilities from the initial state to the final state. Working with this matrix, if we set the matrix P as the Transition Probability Matrix, the matrix elements Pij are the probability of transition from the ith state to jth state at a single step. This matrix is also the one that highlights the

Table 3. Comparison of forecast results and extracted areas from the land use map (in km^2) in 2016.

Vegetation class	No vegetation	Low vegetation	Medium vegetation	High vegetation
2016- Maps area	97527.22	871214.63	626578.42	29244.72
Forecast for 2016	95615.27	824137.4	674211.8	30600.53
Area difference	+1911.95	+47077.23	−47633.33	−1355.82
Area percentage	−2	5.71	−7.07	−4.43

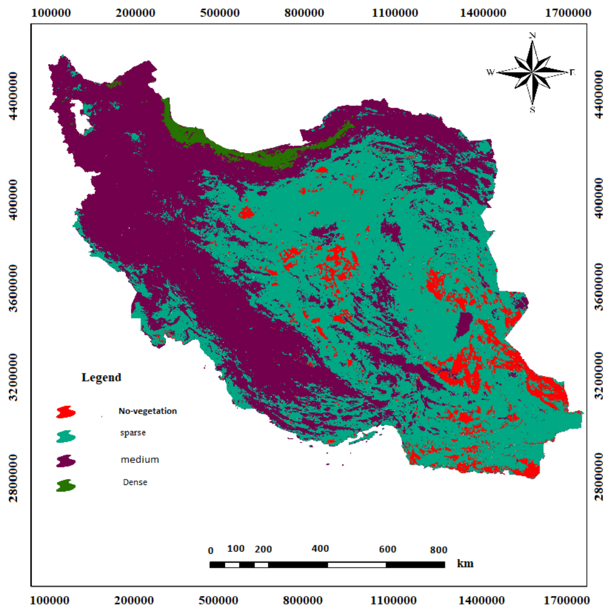

Figure 7. Vegetation forecast map of 2024.

fact of the summation of the total probability of transition from one state to any other state and it equals 1, which is the row elements sum to 1.

The results of this research showed that in 2024, it is likely that 95% of the uncovered class, 90% of the thin class, 89% of the medium class, and 93% of the dense class will remain unchanged, and the class without vegetation has the highest stability and on the other hand, the middle class will have the least stability (figure 7). Also, in the years from 2016 to 2024, the conversion of medium class to thin class and thin to no cover one has the highest probability. The percentage of the predicted area of vegetation classes for 2024 is shown in each class (Table 5).

Discussion

Since land use and vegetation changes play important roles in desertification, the extent of expansion and degradation of resources can be determined. These changes can be guided in appropriate ways to help managers make decisions by providing maps of modeling and forecasting changes in vegetation and land use. Results of the comparison of density maps of NDVI classes during the mentioned periods indicated the changed areas of all land uses so that the areas of some applied classes like the medium class decreased, but the low vegetation and no vegetation classes increased, and the high vegetation class slightly increased. The changed area of the medium vegetation class was from 48.10% in 2000 to 38.57% in 2016, and the low vegetation class changed from 46.13% to 53.77% in 2016. The largest area belonged to the above classes during three periods. Changes in the three periods indicated that from 2000 to 2008, the areas of sparse, no vegetation, and high vegetation classes increased by 3.63%, 0.69%, and 0.07%, respectively while the medium vegetation class with a value of 4.39% had a downtrend. During these 8 years, the highest changes belonged to the medium vegetation and low vegetation classes. Results of changes during the period of 2008 – 2016 were the same as the period of 2000 – 2008. The results of our study on the trend of vegetation changes in different provinces of Iran indicated that almost all provinces had descending changes. However, the Ardabil, Mazandaran, and Gilan provinces with areas of 2.78%, 7.33%, and 5.53%, respectively, had ascending changes from 2000 to 2016. In general, the results of the studied trend of vegetation changes indicated the vegetation decline in the studied area due to the substitution of medium vegetation and low vegetation classes for low vegetation and no vegetation classes indicating the degradation of vegetation and increased barren soil probably due to recent droughts in Iran, mismanagement of land and wrong and uncontrolled exploitation of resources.

Table 4. The probability matrix of class transition by Markov method (in percent) during 2016 – 2020.

Vegetation class	No vegetation	Low vegetation	Medium vegetation	High vegetation	Total
No-vegetation	95	5	0	0	100
Low vegetation	7	90	3	0	100
Medium vegetation	2	8	89	1	100
High vegetation	0	0	7	93	100

Table 5. Areas of different NDVI classes in 2024.

Vegetation class	Area (km^2)	Area (%)
No vegetation	120104.81	7.39
Low vegetation	898186.78	55.29
Medium vegetation	579765.40	35.69
High vegetation	26448.42	1.63
Total	1624565	100

According to the results of forecasting changes based on 2008 and 2016, probably 95% of the areas without vegetation class, 90% of the low vegetation class, 89% of the medium vegetation class, and 93% of the high vegetation class would remain unchanged in 2024 and the no vegetation class would have the highest sustainability. However, the medium vegetation class would have the least sustainability. During 2016 – 2024, the transformation of medium vegetation to low vegetation class, low vegetation to no vegetation class, and high vegetation to medium vegetation class had the highest probabilities with values of 8%, 75 and 7%, respectively. On the contrary, the transformation of land uses had a probability of less than 6% and even 0%. The obtained results of our study are consistent with previous studies by Zhang et al. (2015), Fathizad et al. (2014) and Kamusoko et al. (2009) on the possibility of using a Markov model to forecast land cover changes. The utilization of the Markova model to forecast changes and prepare maps of different vegetation maps was the important innovation of the present study. The simulated map of this model can be a good guide for managers and planners in the natural resources sector.

Conclusion

The comparison of Tables related to the area percentage in different vegetation classes in the previous time showed that the land area without cover increased. This was due to two reasons; a) the conversion of low-covering lands to non-covering lands and b) the change of uses and the destruction and transformation of other classes into the bare lands. The large number of predicted changes was related to lands with medium coverage. This showed that these lands and this class of cover need more management and planning compared to other classes of vegetation. Medium rangelands need better and more management to protect them. In areas with high coverage, the predicted changes were not large that was due to the forest cover being located in this class, and the area with high coverage had a small area compared to the lands with medium and low coverage.

Authors Contributions
All authors have contributed equally to prepare the paper.

Availability of Data and Materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of Interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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