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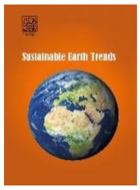

Assessment of land-use changes and landscape pattern through Landsat data in the Chalus watershed, north of Iran

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A B S T R A C T

Land use change represents a critical challenge, potentially altering the landscape pattern. This study aims to evaluate land-use changes in the Chalus watershed in northern Iran and analyze its landscape patterns from 1982 to 2022. Land-use maps were generated using Landsat 3, 5, 7, and 8 imagery within the Google Earth Engine platform, and the changes were assessed with the Land Change Modeler (LCM) in TerrSet. Key landscape metrics, including patch density (PD), number of patches (NP), largest patch index (LPI), landscape shape index (LSI), edge density (ED), and patch cohesion index (PCI), were measured at the landscape scale (entire watershed) using Fragstats. The findings revealed that the rangeland, forest, agricultural land, built-up areas, and water bodies experienced changes of +23736, -25124, +274, +1016, and +99 ha, respectively, from 1982 to 2022. The results indicate that significant changes occurred across the watershed landscape regarding patch number, density, shape, and size, demonstrating substantial habitat fragmentation over this period. The study findings demonstrate that development trends over the past four decades have led to increases in land-use change within the region, which in turn has perpetuated landscape fragmentation and a reduction in natural habitats. This study identified the expansion of built-up areas and agricultural activities as significant contributors to the intensification of habitat fragmentation. Consequently, strategic measurements and planning are essential to prevent further fragmentation and degradation of the landscape.

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1. Introduction

Landscape structure pertains to the genesis and evolution of ecosystem patterns, as well as the ramifications of pattern-process relationships at the population, community, and ecosystem levels. It is a critical aspect of environmental characteristics, essential for the maintenance of ecosystem health and biodiversity conservation, and provides insights that are crucial for advancing sustainable development (Urban, 2006). Landscape metrics have been extensively utilized as pivotal indicators in the investigation of planning and sustainable development. These metrics quantify the composition and configuration of ecosystems across a landscape, including such variables as patch size, shape, nearest-neighbor distance, and proximity index. This enables quantitative comparisons between different landscapes or within a single landscape over time. When spatial information from landscapes is derived from remote sensing data, pattern analysis can be conducted by considering each landscape unit (e.g., land-use/land cover type) as part of a discrete patch mosaic. This approach can provide useful information about habitat fragmentation and its changes (Liu & Yang, 2015; Kumar et al., 2018; Qi et al., 2018; El Jeitany et al., 2024).

The assessment and classification of landscape structure for ecological purposes necessitates the mapping of land use/land cover types and their changes (Laforza et al., 2010). Land use changes have ecological consequences, including carbon sequestration, runoff, soil erosion, and landscape habitat loss. Land use/land cover is essential for landscape structure and indirectly affects ecosystem sustainability. Information on land use/land cover obtained from remote sensing data and other qualitative assessment data can serve as a valuable tool for assessing human impacts on landscapes and, consequently, on ecosystem sustainability (Burkhard et al., 2009).

Land-use change is a process through which human activities transform natural landscapes, specifically how land is utilized, often emphasizing its functional role in economic activities. It is frequently the case that land-use changes are nonlinear, with the potential to introduce feedback mechanisms within ecosystems. This can result in a strain on living conditions and expose communities to vulnerabilities. Therefore, it is essential to evaluate land-use change trajectories and project possible future scenarios under specific assumptions. This is a fundamental aspect of ensuring landscape sustainability (Paul and Rashid, 2017; Nehzak et al., 2022).

A variety of models have been developed for the assessment and classification of land use, which can be grouped into six categories: cellular automata (CA), statistical analyses, Markov chains, artificial neural networks (ANN), economic models, and agent-based systems. CA and agent-based systems excel at spatial dynamics and interactions. Statistical analyses provide simpler insights into relationships. Markov Chains focus on probabilistic transitions effectively, while ANNs have been shown to utilize large datasets for the recognition of complex patterns. Economic models are key to understanding the financial aspects that drive land use change (Guan et al., 2011; Basse et al., 2014). The implementation and execution of these models necessitate the utilization of remote sensing products, including Landsat, Sentinel, and MODIS imagery (USGS, 2020).

Land use is a significant factor in ecological processes and interactions, affecting climate characteristics, biodiversity, water resources, and soil. However, changes in land use have emerged as a significant environmental issue, driven by population growth, economic development, and social needs. When land use changes are made without due consideration of scientific principles and environmental concerns, significant environmental problems can result. For instance, deforestation results in elevated greenhouse gas emissions, which, over time, contribute to climate change. Similarly, agricultural activities, urban sprawl, and road construction result in soil degradation, erosion, and increased environmental pollution. Therefore, studying and understanding land use conversion processes provides valuable insight into the environmental conditions of a region and facilitates the implementation of appropriate planning and management strategies (Liu and Yang, 2015; Sun and Zhou, 2016; Boongaling et al., 2018; Mulatu et al., 2024).

The Chalus River watershed constitutes a portion of the larger Chalus watershed, which has been subjected to the effects of developmental trends and land-use conversion in recent decades. Kheybari et al. (2017) acknowledged a decrease in the extent of forests in the Chalus watershed from 1987 to 2015. The extensive alterations in land use in this region have resulted in deforestation, accelerated erosion, and the loss of habitats. Accordingly, this study aims to assess land-use changes and analyze spatial characteristics and landscape patterns in the Chalus watershed over four decadal intervals (1982 to 2022) to gain a comprehensive understanding of the impact of development on the prevailing ecological conditions and to inform land planning and management efforts. In accordance with the aforementioned, the objectives of this research are as follows: The study will accomplish the following: (1) modeling land-use changes in the study area using Landsat imagery in the Google Earth Engine platform over the 1982 to 2022 period, and (2) analyzing landscape patterns based on landscape metrics for understanding land-use change trends in the study area.

2. Material and methods

2.1. Study area

The Chalus River watershed represents a portion of the larger Chalus watershed, encompassing an area of approximately 102,000 hectares in Mazandaran Province (Fig. 1). This watershed is part of the Caspian Sea basin and is comprised of 18 sub-watersheds.

he maximum and minimum elevations within the Chalus River watershed are 4,260 meters and 158 meters above sea level, respectively. The region is distinguished by precipitous topography with a prevailing northward orientation. The prevailing climatic conditions are cold semi-humid and cold humid, with some lower elevations exhibiting a cold semi-arid climate. The annual precipitation ranges from 3,288 mm to 2,153 mm. The Chalus watershed has experienced significant environmental challenges due to anthropogenic activities, particularly land use change and the discharge of wastewater into the river over the past decade.

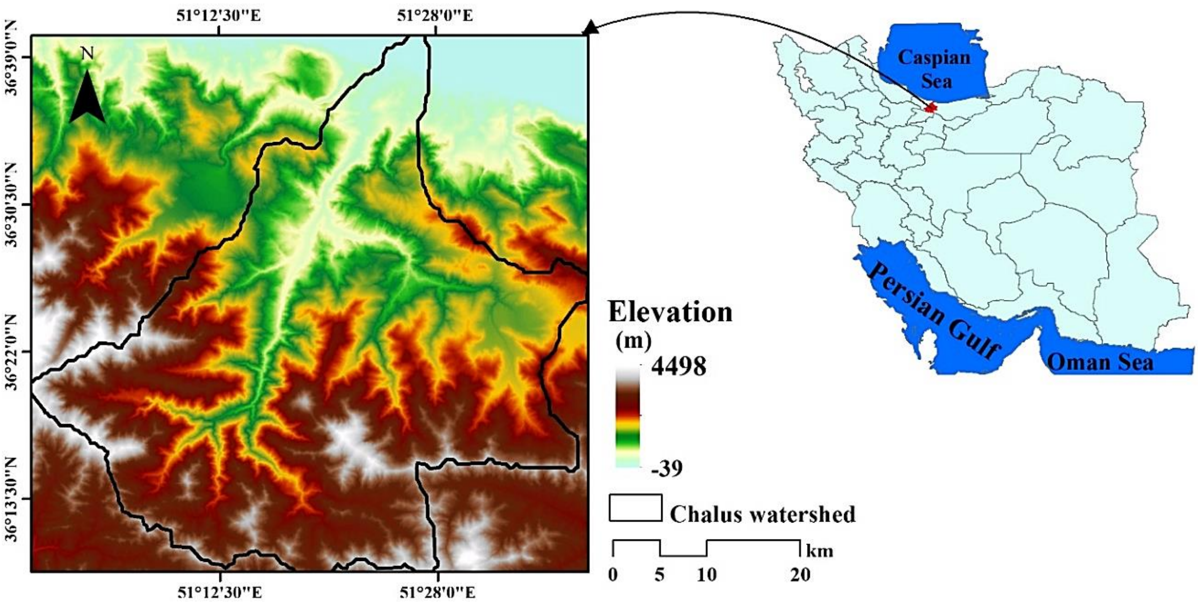

Fig. 1. Geographic location of the study area.

2.2. Data collection

The necessary data for this study were gathered through on-site observations and the utilization of remote sensing products to map the land use of the region and measure the changes over different time periods. Corrected images (Landsat collectrion 2, level 2) from various Landsat series (Landsat 3 through Landsat 8) were utilized, including multispectral images from the MSS, TM, ETM+, and OLI sensors for the years 1982, 1992, 2002, 2012, and 2022. It is important to note that images from these years were selected between July 1 and September 30, with cloud cover below 10 percent. The Digital Elevation Model (DEM) was derived from the Shuttle Radar Topography Mission (SRTM) imagery. Training samples for land-use mapping for the years 1982, 1992, 2002, and 2012 were prepared based on Google Earth images. Training samples for 2022 were collected through a combination of Google Earth images and GPS-based field samples gathered during site visits. The image acquisition and processing were conducted within the Google Earth Engine platform.

2.3. Image preparation

To create land-use maps for 1982, 1992, 2002, 2012, and 2022, surface reflectance images from the Landsat 3, 5, 7, and 8 satellites were utilized in the Google Earth Engine. These images were selected due to their high spatial resolution to provide detailed information about the surface characteristics of the Earth's land masses. The images were acquired with path 35 and row numbers 177 and 178, subsequently processed using the Google Earth Engine software. Subsequently, the surface reflectance images for each sensor were imported into the Google Earth Engine environment and aligned with the boundaries of the study area using the spatial filter designated as "FilterBounds." Subsequently, the images were filtered to encompass the temporal range between July 1 and September 30, utilizing the `FilterDate` function. Furthermore, images exhibiting cloud cover in excess of 10 percent were excluded through the implementation of the "LessThan" filter. Once the requisite filters had been applied, a mosaic of the images was created using the Mosaic function, and the images were cropped according to the boundaries of the study area using the Clip function.

2.4. Land use classification

In this study, the random forest method was employed for the purpose of image classification. Training samples were gathered for the land-use classes within the region, including forest, grassland, barren land, agriculture, built-up areas, and water bodies, using the "Add a Marker" tool. An effort was made to ensure an even distribution of training samples across the image, with the objective of improving classification accuracy. It was hypothesized that precise location and adequate distribution of training areas across the image would enhance classification precision. Subsequently, the samples for each land-use class were merged using the "Merge" function. Subsequently, the "sampleRegions" command was employed to train the classifier, followed by clustering with the "smileRandomForest" function. The number of trees in the random forest was set to 6. Subsequently, the classified map was generated using the `classify` command, and the resulting output was exported using the `Export.image.toDrive` function.

2.5. Accuracy assessment

The accuracy of a classification may be validated through the use of both quantitative and qualitative methods. Quantitative methods include the use of an error matrix, whereas qualitative methods may entail visual interpretation. The error matrix method allows for the calculation of four parameters: producer's accuracy, user's accuracy, overall accuracy, and the Kappa coefficient. The producer's accuracy is calculated by dividing the number of correctly classified pixels in a row by the total number of pixels in that row and multiplying the result by 100. The user's accuracy is calculated by dividing the number of correctly classified pixels in a column by the total number of pixels in that column, and then multiplying the result by 100. Overall accuracy is calculated by dividing the total number of correctly classified pixels by the total number of pixels evaluated. The Kappa coefficient is derived based on the overall accuracy and the random accuracy (Eastman, 2012). In the present study, the land-use maps were validated using both an error matrix and visual interpretation. A total of 300 control points was utilized to evaluate the accuracy of the classification. The control points employed for 2022 were obtained randomly using GPS during field visits, while samples were prepared based on Google Earth images for 1982, 1992, 2002, and 2012.

2.6. Land-use change assessment

After generating and validating the land-use maps for the study area for the years 1982, 1992, 2002, 2012, and 2022, land-use change was assessed for four ten-year intervals (1982–1992, 1992–2002, 2002–2012, and 2012–2022) as well as the entire forty-year period (1982–2022). It was performed using the Land Change Modeler (LCM) in the TerrSet software.

2.7. Landscape metrics

In this study, land-use changes in the study area were analyzed using key and widely-used landscape metrics, including patch density (PD), largest patch index (LPI), number of patches (NP), edge density (ED), landscape shape index (LSI), and Cohesion index at the landscape scale (entire watershed). Additional details of the metrics are described in Table 1 (McGarigal et al., 2012; Kumar et al., 2018; Arora et al., 2021; Shim and Choi, 2024). These metrics represent the main features of the landscape, including fragmentation and discontinuity, which can provide valuable insights into the effects of land use changes. Based on the land-use maps generated in the preceding step, the aforementioned metrics were calculated for different time points using the Fragstats software.

2.8. Land-use change assessment based on landscape metrics

Following the calculation of landscape metrics at the landscape scale, land-use changes were subjected to analysis and comparison according to the metrics. Change diagrams for each metric were generated in the Excel 2016 environment for the purpose of visualization.

Table 1. Descriptions of the landscape metrics (McGarigal et al., 2012).

Metric	Unit	Description
Number of Patches (NP)	Unitless	NP demonstrates the number of patches present within a specified area. A higher value indicates a greater degree of landscape fragmentation.
Patch Density (PD)	Number per 100 Hectares	This index represents the ratio of the number of patches within a specified area to the total area, with a higher value indicating greater landscape fragmentation.
Edge Density (ED)	Meters per hectare	ED is defined as the ratio of the total length of edges to the total area of the landscape. A higher value indicates a greater degree of fragmentation.
Largest Patch Index (LPI)	Percentage	The LPI quantifies the proportion of the total landscape represented by the largest patch. Values range from 1 to 100, with higher values indicating reduced landscape fragmentation.
Cohesion Index	Unitless	This index assesses the physical connectivity of patches of the same land use type within a given area. Lower values indicate increased habitat fragmentation.
Landscape Shape Index (LSI)	Unitless	This index is a standard measure of the total edge or edge density in a given landscape. A higher value indicates a more complex landscape boundary structure.

3. Results and discussion

In this study, land-use maps for the study area were generated for the years 1982, 1992, 2002, 2012, and 2022 based on Landsat images using Google Earth Engine. The results are illustrated in Fig. 2. The maps were validated using an error matrix, and the results are presented in Table 2. Table 3 presents the area designated to each land-use category over the specified time periods, while Fig. 3 illustrates the trends in these changes. The investigation of land-use changes was conducted over four ten-year periods: 1982-1992, 1992-2002, 2002-2012, and 2012-2022. Additionally, the analysis was extended to encompass the entire 40-year period from 1982 to 2022, utilizing the Land Change Modeler (LCM). The findings of this evaluation are presented in Table 4 and illustrated in Fig. 4. Fig. 5 additionally illustrates the areas of gain and loss for each land use type across the specified time periods. Furthermore, Fig. 6 illustrates the trend of land use changes.

Table 2. Results of accuracy assessment for Land-use classification.

Parameter	1982	1992	2002	2012	2022
Overall accuracy (%)	84	84	85	86	88
Kappa coefficient	0.80	0.80	0.81	0.82	0.84
User’s accuracy (%)	81	82	83	84	85
Producer’s accuracy (%)	81	81	82	83	84

Table 3 Area allocated to each land-use in different years

Land-use		1982	1992	2002	2012	2022
Rangeland	ha	88279	92827	98001	104757	112115
	%	51	53	56	60	64
Forest	ha	84063	79053	73759	66607	58939
	%	48	45	42	38	34
Agriculture	ha	1216	1505	1546	1334	1490
	%	0.7	0.9	0.9	0.8	0.9
Built-up areas	ha	301	546	601	1175	1317
	%	0.2	0.3	0.3	0.7	0.8
Waterbodies	ha	81	110	135	168	180
	%	0.05	0.06	0.08	0.1	0.1

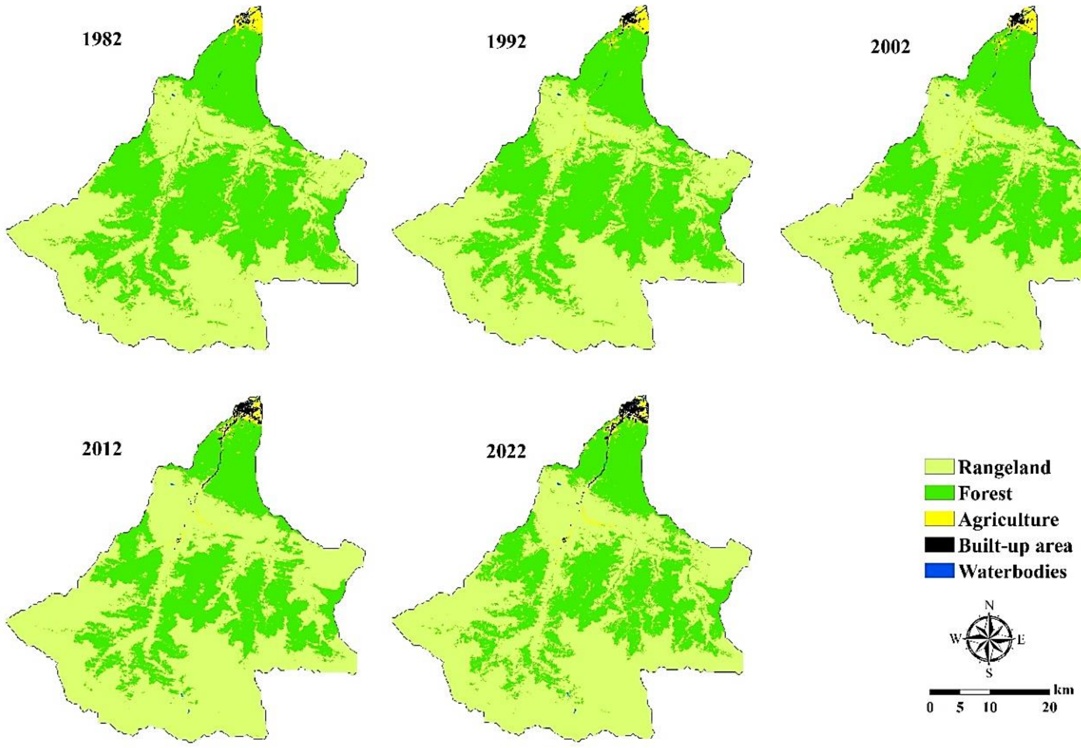

Fig. 2. Land-use maps of the study area in different years.

Table 4. Changes in the area (ha) of land use in different periods.

Land-use	1982-1992	1992-2002	2002-2012	2012-2022	1982-2022
Rangeland	4448	5174	6756	7358	23736
Forest	-5010	-5294	-7152	-7668	-25124
Agriculture	289	41	-212	156	274
Built-up areas	245	55	574	142	1016
Waterbodies	29	25	23	12	99

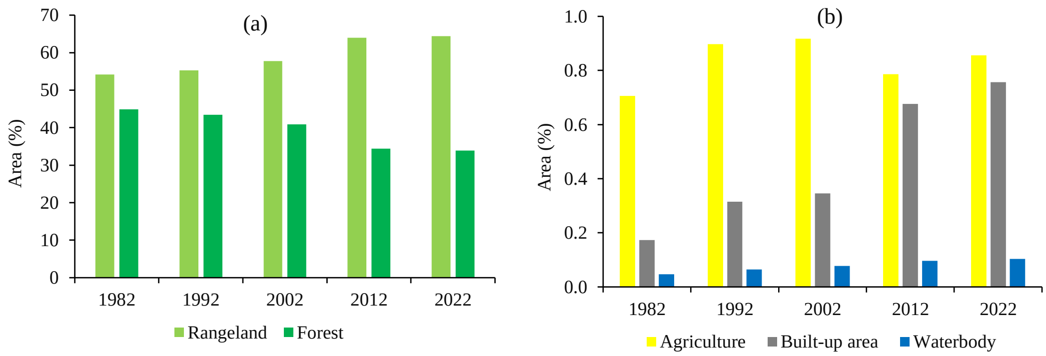

Fig. 3. Ternds of the area allocated to each land-use type during the different years.

In this study, landscape metrics were calculated at the landscape scale (entire watershed). These included PD, NP, LPI, LSI, ED, and cohesion index. The results of these metrics are presented in Table 5. Additionally, the variations in landscape metrics across different years were compared, with the results shown in Figure 7. Table 6 displays the differences in the metrics at the land-use level between 1982 and 2022.

The results indicated that five predominant land-use categories—forest, agriculture, rangeland, built-up areas, and water bodies—are present in the study area. The Kappa coefficient, overall accuracy, producer accuracy, and user accuracy values for the generated land-use maps were, respectively, 0.80, 84%, 81%, and 81%, in 1982, 0.80, 84%, 81%, and 82% in 1992, 0.81, 85%, 82%, and

83% in 2002, 0.82, 86%, 83%, and 84% in 2012, and 0.84, 88%, 84%, and 85% in 2022. These findings substantiate the satisfactory degree of accuracy and reliability in the land-use map classification. As calculated by Ambarwulan et al. (2023), Kappa coefficient and overall accuracy of approximately 83% for modeling land-use changes in the Cisadane watershed in Indonesia. Similarly, Sisay et al. (2023) estimated the overall accuracy and Kappa coefficient for land-use classification in the Guang watershed in Ethiopia to be above 86% and 0.84, respectively.

It was clarified that rangeland, forest, agriculture, built-up areas, and water bodies in 1982 covered 88379, 84063, 1216, 301, and 81 ha, respectively, accounting for 51%, 48%, 0.7%, 0.2%, and 0.05% of the watershed, respectively. By 1992, these land-use categories varied 92827, 79053, 1505, 546, and 110 ha, respectively, representing 53%, 45%, 0.9%, 0.3%, and 0.06% of the region. In 2002, the aforementioned land-use categories exhibited a notable shift in their respective areas, which were recorded at 98001, 73759, 1546, 601, and 135 ha. This corresponded to 56%, 42%, 0.9%, 0.3%, and 0.08% of the watershed, respectively. Moreover, in 2012, the areas designated for land uses were 104757, 66607, 1334, 1175, and 168 ha, representing 60%, 38%, 0.8%, 0.7%, and 0.1% of the study area, respectively. By 2022, the aforementioned land uses had reached 112115, 58939, 1490, 1317, and 180 ha, respectively, accounting for 64%, 34%, 0.9%, 0.8%, and 0.1% of the watershed.

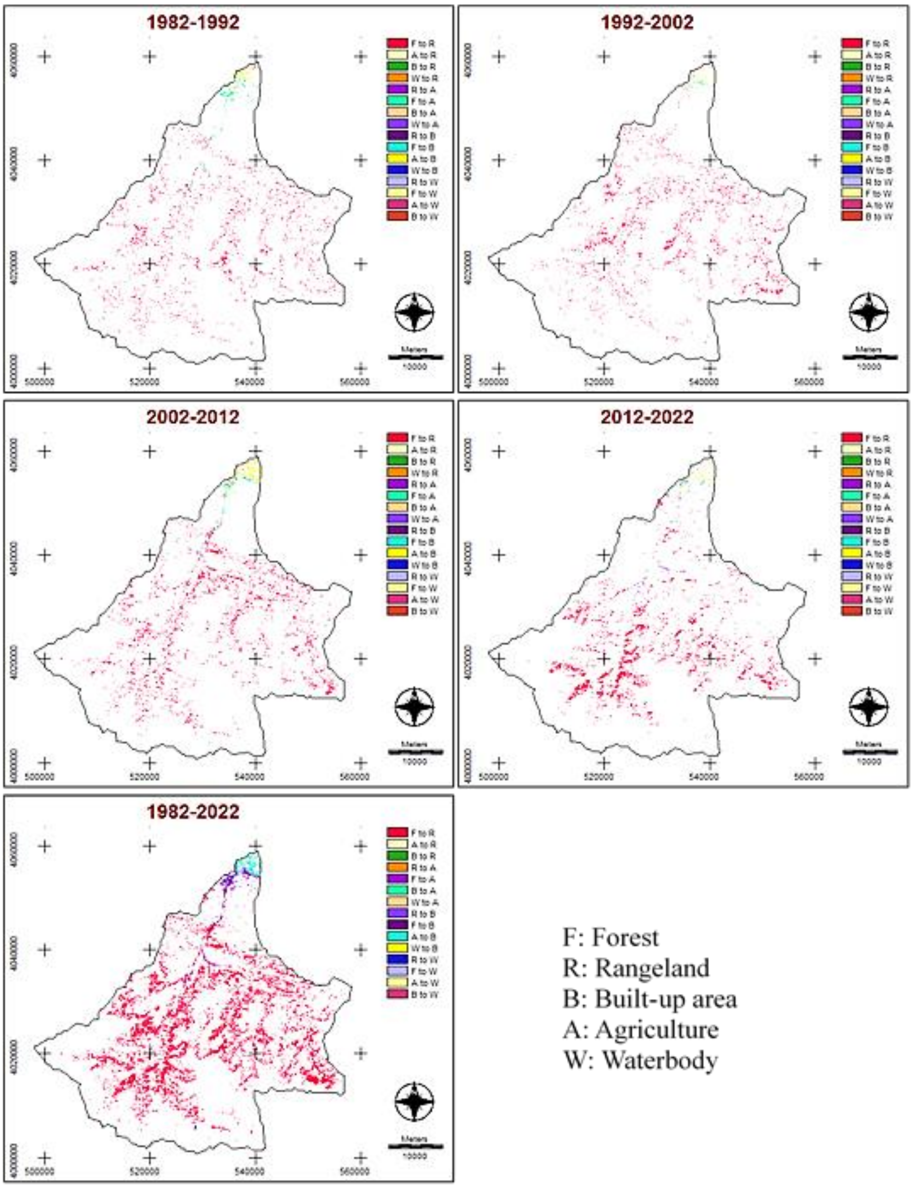

Fig. 4. Land use conversion in the desired periods.

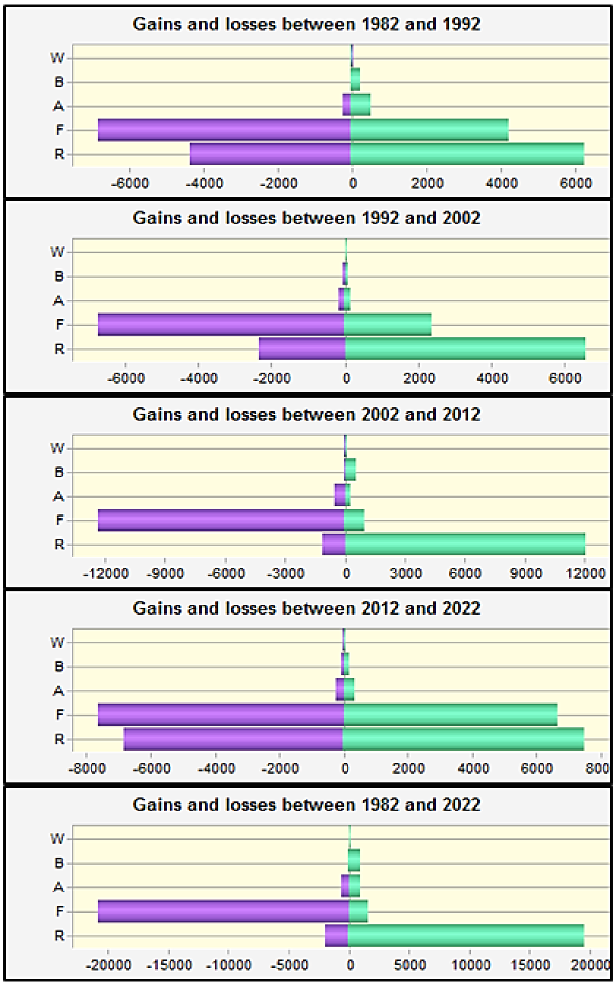

Fig. 5. Gains and losses area for each land use (W: Waterbody, B: Built-up area, A: Agriculture, F: Forest, and R: Rangeland) in different periods.

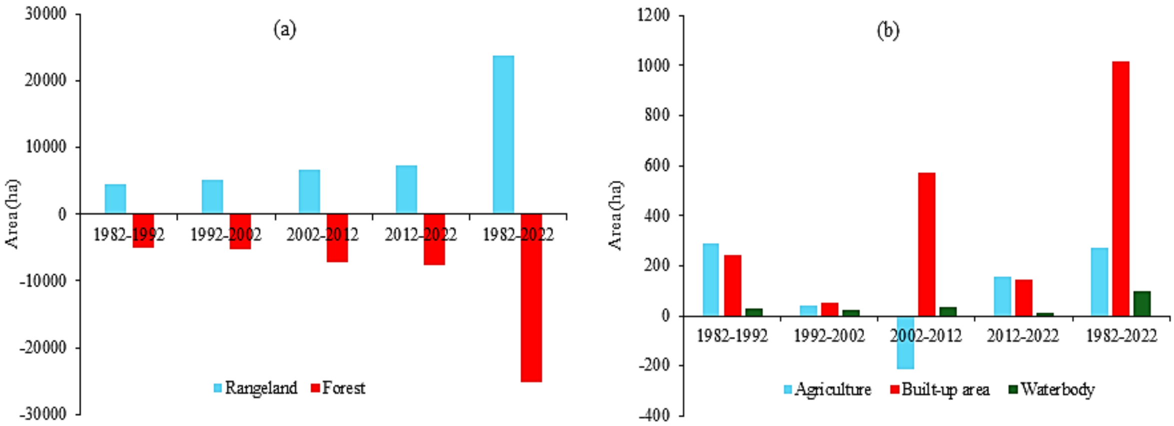

Fig. 6. Trends of land-use changes across different periods.

Table 5. Results of metrics calculation at the landscape scale.

Year	NP	PD	LPI	ED	LSI	Cohesion
1982	5725	303	34	21	24	99.8
1992	8803	5.1	35	26	28	99.8
2002	9660	5.6	37	26	28	99.8
2012	7881	4.5	59	22	25	99.8
2022	13702	7.9	62	32	35	99.8

*Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Edge Density (ED), and Landscape Shape Index (LSI)

The land uses of rangeland, forest, agriculture, built-up areas, and water bodies exhibited changes in the area, by 4448, -5010, 289, 245, and 29 ha during the first decade (1982–1992). In the second decade (1992–2002), the changes were 5174, -5294, 41, 55, and 25 ha, respectively. In the third decade (2002–2012), the areas of these land uses exhibited fluctuations of 6756, -7152, -212, 574, and 33 ha, respectively. Similarly, during the fourth decade (2012–2022), these land uses exhibited variations of 7358, -7668, 156, 142, and 12 ha, respectively. Furthermore, over the forty-year period (1982-2022), the total changes in area for the land uses of rangeland, forest, agriculture, built-up areas, and water bodies were 23736, -25124, 274, 1016, and 99 ha, respectively.

The results demonstrate that the land-uses of rangelands, built-up areas, and water bodies exhibited an overall increase across all four periods. However, the most notable alterations in built-up areas and water bodies occurred during the third decade (2002–2012), whereas changes in rangeland were most evident during the fourth decade (2012–2022). The utilization of agricultural land exhibited an upward trajectory during the first, second, and fourth decades, while it demonstrated a decline during the third decade. The most substantial alterations in agricultural land use were documented during the first decade (1982–1992), whereas the least pronounced changes were observed during the second decade (1992–2002). The reduction in agricultural land use during the third decade can be primarily attributed to the conversion of agricultural areas to built-up areas, particularly in the northern part of the region. Forest land use demonstrated a uniform decline across all four time periods. The smallest and largest decreases were observed in the first (1982–1992) and fourth (2012–2022) decades, respectively. The highest rate of land-use conversion occurred in the fourth decade (2012–2022), while the lowest was in the first decade (1982–1992). The changes observed in the fourth decade were approximately 1.5, 1.4, and 1.04 times greater than those observed in the first, second, and third decades, respectively. The fourth decade was characterized by population growth and increased human activities in the region, which were among the main factors contributing to the greater extent of land-use changes during this period.

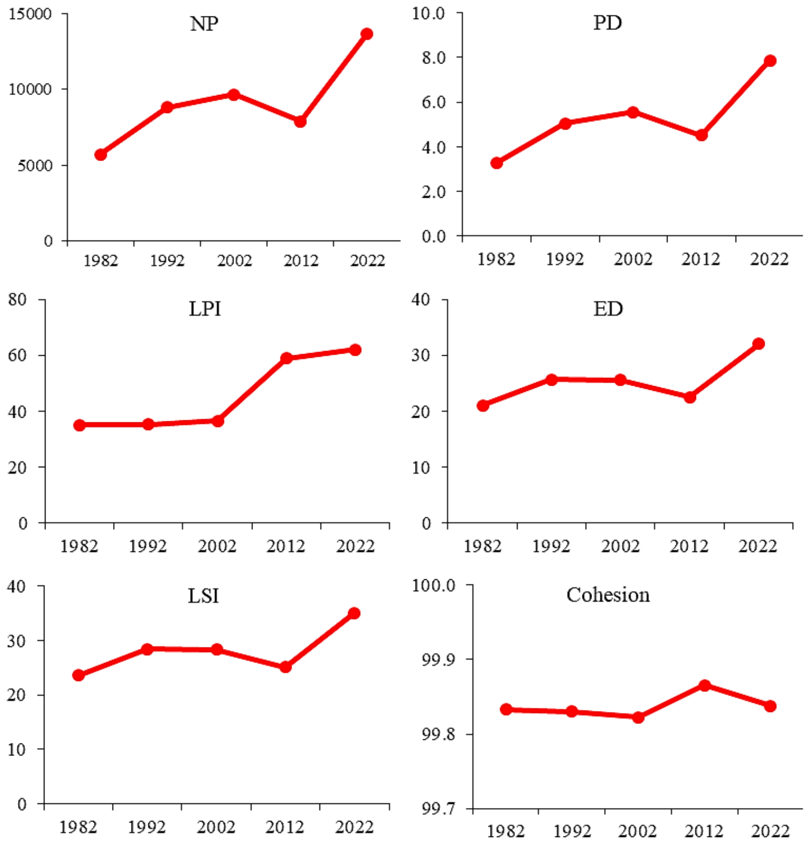

Fig. 7. Trends of landscape metrics in the study area across different periods.

Table 6. Differences in landscape metrics between 1982 and 2022.

Land-use	NP	PD	LPI	ED	LSI	Cohesion
Rangeland	2.9	2.9	1.8	1.5	1.3	1.0
Forest	1.7	1.7	0.2	1.4	1.7	1.0
agriculture	15.0	15.0	0.2	3.8	3.2	0.9
Build-up areas	2.8	2.8	11.4	2.9	1.4	1.1
Water bodies	11.4	11.4	2.5	2.9	1.9	1.0

*Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Edge Density (ED), and Landscape Shape Index (LSI)

The results indicate that over the past forty years (1982–2022), there has been an increase in the extent of rangeland, agriculture, built-up areas, and water bodies. The construction of dams in the region has been identified as a contributing factor to the observed increase in water bodies. The growth rates for these land-uses were 27%, 23%, 338%, and 122%, respectively, compared to 1982. These findings indicate a growing trend of land use changes influenced by anthropogenic activities. In contrast, forest land use exhibited a decline, with a reduction of 30% over the specified period. These findings indicate that built-up areas have experienced the highest growth rate among all land-use categories over the past four decades. In summary, by 2022, the area of rangelands, forests, agricultural lands, built-up areas, and water bodies had increased to approximately 1.3, 0.7, 1.2, 4.4, and 2.2 times their respective areas in 1982. The reduction of one-third of forest areas, coupled with the expansion of built-up areas and agricultural lands, indicates a regressive ecological trend in the study area over the past forty years. This significant loss of forest land, largely replaced by built-up, agricultural, and rangeland areas, represents a profound alteration in the region's ecosystem structure. Such transformations have resulted in the degradation of natural habitats, a decline in biodiversity, and a deterioration of ecological conditions in the area. Prior studies have similarly evaluated land-use alterations across diverse Iranian and global regions, underscoring the considerable influence of expanding human activities on land transformation and land-use conversion. Zare et al. (2017) examined land-use changes in Noor County from 1986 to 2013, emphasizing that the most significant land-use change involved the conversion of agricultural land to urban areas in Noor. The study revealed a negative trend for forest and agricultural land use, while residential land use exhibited a positive trend, with the extent of residential areas increasing fivefold between 1986 and 2013. Similarly, Bogale et al. (2024) demonstrated that the intensity of land cover change in the northwestern Ethiopian highlands has continued over three time periods: 1990–2000, 2000–2010, and 2010–2020. Bachri et al. (2024) examined land-use changes in the Rejali watershed in Indonesia from 2002 to 2022. Their findings revealed a decrease in water bodies (5.31%), forest areas (23.80%), built-up areas (3.15%), open land (0.48%), agricultural land (23.71%), and undeveloped land (0.01%) over the study period.

This study employed landscape metrics, including Edge Density (ED), Patch Density (PD), Number of Patches (NP), Landscape Shape Index (LSI), Largest Patch Index (LPI), and Cohesion Index, to assess the landscape fragmentation in the study area at the landscape level (entire watershed) over designated time intervals. The results demonstrated that the lowest values of NP, PD, LPI, ED, and LSI across the watershed were observed in 1982, with values of 5,725, 3.3, 34, 21, and 24, respectively. In contrast, the highest values of these metrics were observed in 2022, amounting to 13,702, 7.9, 62, 32, and 35, respectively. The analysis of changes revealed that the selected metrics have exhibited an upward trajectory from 1982 to 2022. These findings confirm that, influenced by land-use changes in the region over this period, the level of landscape fragmentation and disintegration has continued to increase. However, the values obtained for the Cohesion Index across the specified years showed no significant variation. Analyses indicate that over the past forty years, the metrics of NP, PD, LPI, ED, and LSI in the entire watershed have clarified an increasing trend, while the Cohesion index has remained relatively stable. These findings corroborate the hypothesis that, from 1982 to 2022, the landscape patches in the watershed have undergone significant changes in terms of number, density, shape, and size. This evidence substantiates the assertion that the region has experienced fragmentation and disintegration of habitats during this period.

The findings of this study demonstrated that landscape metrics can effectively assess land-use changes from various perspectives, including patch number, density, shape, size, and connectivity, at both the landscape and land-use type scales. This approach provides valuable information to support land management and planning. Previous studies have also highlighted the importance of landscape metrics in evaluating land-use changes. Sithole et al. (2024) utilized landscape metrics such as PLAND, LSI, SHDI, SIDI, PD and Cohesion in assessing land-use changes and emphasized their significance. Sertel et al. (2018) investigated the impact of land-use changes on various landscape metrics, including NP, ED, LPI, Euclidean nearest neighbor distance (ENN), split index (SPLIT), and aggregation index (AI) in the metropolitan area of Izmir, Turkey. They confirmed that using landscape metrics allows for a more detailed examination of landscape characteristics.

4. Conclusion

The objective of this study was to evaluate land use alterations in the Chalus watershed and analyze the landscape pattern in different periods. The results demonstrated that over the past four decades (1982-2022), there have been notable changes in the distribution of land use types, including rangeland, forest, agricultural areas, built-up regions, and waterbodies. Furthermore, it was determined that the extent of rangeland, built-up areas, and waterbodies exhibited a consistent increase in all time periods. The utilization of agricultural land exhibited an upward trajectory during the 1982-1992, 1992-2002, and 2012-2022 decades, whereas a decline was discerned during the 2002-2012. However, forest land exhibited a persistent decline across all four periods. The findings substantiated that from 1982 to 2022, considerable alterations in the number, density, configuration, and dimensions of landscape patches were observed across the entire watershed, indicating an increased fragmentation and disconnection of regional habitats. It was confirmed that landscape metrics are an effective tool for assessing land use changes at various dimensions, including the number, density, shape, size, and connectivity of patches at the landscape scale. Such metrics provide valuable insights for land management and planning. Furthermore, it was demonstrated that the expansion of built-up areas and agricultural activities pose significant challenges and exacerbate the fragmentation and disintegration of natural habitats in the region. Accordingly, it is essential to implement strategic measures and sound planning to prevent further fragmentation and degradation of the region's landscape.

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