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Spatial analysis of land use/land cover (LULC) changes using landscape metrics and VIKOR method in the Kashkan watershed, Iran

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ABSTRACT

The monitoring and assessment of land use/land cover (LULC) changes are critical issues in sustainable land management. The aim of the study was to assess LULC changes in the watershed using landscape metrics. The study utilized remote sensing and FRAGSTAT to analyze satellite imagery and landscape metrics from 1991 to 2021. Eight metrics were employed to quantify changes in the landscape structure and identify areas of potential degradation. The study applied the VIKOR method for vulnerability priority assessment, emphasizing the importance of considering multiple landscape metrics in the evaluation. The study highlighted the significance of each metric and its impact on land use sustainability, employing a weighted approach. The results indicated significant changes in the LULC of the Kashkan watershed over the 30-year period. The primary changes included a decrease in forest cover (18.35%) and an increase in rangeland (20.85%). Landscape metrics revealed that these changes resulted in decreased landscape connectivity and increased fragmentation. The vulnerability assessment showed that forests and rangelands have the highest and lowest vulnerability, respectively, with values of 0.997 and 0.074. The study underscores the importance of monitoring and assessing LULC changes for sustainable land management. The landscape metrics used in this study provide a useful tool for quantifying changes in landscape structure and identifying areas of potential degradation. This information can be utilized by land managers and policymakers to develop effective strategies for sustainable land management.

KEYWORDS

Landscape Ecology
Remote Sensing
FRAGSTAT
VIKOR
GIS

1. Introduction

Land use/land cover (LULC) changes are an essential aspect of landscape ecology, a field of study that focuses on the interactions between organisms and their environment at a large scale (Wang et al. 2021). Human activities, such as urbanization, agriculture, and forestry, have a profound impact on the natural environment and can result in significant changes to the landscape (Shastri et al. 2020). Monitoring and assessing LULC changes is crucial for understanding the impacts of these activities and developing sustainable land management practices (Darvishi et al. 2020). Landscape metrics are a set of quantitative tools that can be used to analyze and measure the spatial patterns and characteristics of LULC changes (Liu et al. 2020). These metrics are designed to capture the complexity and diversity of the landscape and provide information on various aspects of its structure and function, such as connectivity, fragmentation, and habitat suitability (Topaloğlu et al. 2021). They can also be used to assess the ecological health and resilience of the landscape and to identify areas that are at risk of degradation or loss (Kumar et al. 2018). Landscape metrics provide a way to analyze and measure the spatial patterns and characteristics of LULC changes (Sertel et al. 2018). These metrics are based on a set of mathematical formulas and algorithms that can be applied to spatial data, such as maps, satellite images, and aerial photographs (Effati et al. 2021). Landscape metrics can be used to quantify a wide range of landscape features and

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processes, including the size, shape, and distribution of patches, the connectivity and fragmentation of habitat, and the diversity and complexity of vegetation (Getu & Bhat, 2021). In recent years, landscape metrics have been applied in a variety of research and management contexts, including , forestry (Morelli et al. 2018; da Silva et al. 2020; Ersoy et al. 2020), agriculture (Cervelli et al. 2020), and urban planning (Magidi & Ahmed, 2019; Motlagh et al. 2020; Effati et al. 2021). One of the key advantages of using landscape metrics for monitoring and assessment of LULC changes is their ability to capture the complexity and heterogeneity of the landscape (Kumar et al. 2018). Unlike traditional measures of LULC, such as land cover maps or simple area statistics, landscape metrics provide a more nuanced and detailed understanding of the spatial patterns and processes of change. This can help identify areas that are at risk of degradation or loss, and can inform management decisions aimed at promoting sustainable land use practices. Another advantage of using landscape metrics is their ability to integrate with other data sources, such as remote sensing and geographic information systems (GIS) (Berila & Isufi 2021). This allows for a more comprehensive and integrated analysis of LULC change over time and space, and can help identify the drivers and impacts of change. Additionally, the use of remote sensing data can help overcome some of the challenges associated with ground-based monitoring, such as limited accessibility or high costs (Azareh et al. 2021). Over the years, researchers have used various methods to study and quantify land use and land cover changes, including traditional methods such as field surveys and more advanced techniques such as remote sensing and GIS (Azareh et al. 2021; Berila & Isufi, 202; Getu & Bhat, 2021). In recent years, landscape metrics have emerged as a promising approach for analyzing and quantifying the spatial patterns and characteristics of land use and land cover changes (Magidi & Ahmed, 2019). Several studies have demonstrated the effectiveness of landscape metrics in monitoring and assessing LULC changes (Qiu et al. 2017; Mugiraneza et al. 2019; Phiri et al. 2019; Cervelli & Pindozzi, 2022; Firozjaei et al. 2022). Qiu et al. (2017) used landscape metrics to assess the impacts of urbanization on vegetation cover in the rapidly developing city of Shanghai, China. The results showed that urbanization had led to a significant reduction in vegetation cover, fragmentation of green spaces, and loss of habitat connectivity (Qiu et al. 2017). Mugiraneza et al. (2018) employed landscape metrics to evaluate the impacts of LULC changes on the provision of ecosystem services. The results showed that forest loss and conversion to pastureland had led to a significant decline in the provision of ecosystem services, including carbon sequestration, water regulation, and biodiversity conservation (Mugiraneza et al. 2019). Phiri et al. (2019) used landscape metrics to analyze the spatial patterns and trends of land use and land cover changes in the Zambia over the past four decades. The results showed that agricultural land use had expanded at the expense of natural vegetation, leading to fragmentation and loss of habitat (Phiri et al. 2019). In a study by Smiraglia et al. (2020), landscape metrics were used to assess the impacts of LULC changes on soil erosion in Italy. The results showed that conversion of natural vegetation to agricultural land had led to a significant increase in soil erosion, as well as changes in soil structure and properties (Smiraglia et al. 2019). Another study by Ersoy Mirici et al. (2020) used landscape metrics to evaluate the impacts of LULC changes on biodiversity in the Eastern Mediterranean of Turkey. The results showed that forest fragmentation and loss had led to a significant decline in species richness and abundance, as well as changes in community composition (Ersoy Mirici, et al. 2020). Xie et al. (2022) applied landscape metrics to assess the impacts of LULC changes on the connectivity of landscape in a small Watershed. The results showed that urbanization and agricultural expansion had led to a significant reduction in landscape connectivity and fragmentation, which could have negative impacts on environment and ecosystem functioning (Xie et al. 2022). Dezhbani et al. (2022) used landscape metrics to evaluate the spatial and temporal changes in in the Koozeh Topraghi Watershed. The results showed that conversion of natural vegetation to urban and agricultural land had led to a significant decline in the provision of ecosystem services (Dezhbani et al. 2023). These studies highlight the potential of landscape metrics for monitoring and assessing LULC changes in different ecosystems and regions. The use of landscape metrics for monitoring and assessment of LULC changes has become increasingly important in recent years, as the pace and scale of human activities continue to impact the natural environment (Zhang et al. 2022). These metrics can be applied to a wide range of spatial and temporal scales, from local to global, and can be used to analyze changes in LULC over time (Morelli et al. 2018). Landscape metrics can also be integrated with other data sources, such as remote sensing, to provide a more comprehensive understanding of the landscape. The review of existing literature underscores the efficacy of traditional and advanced methodologies, encompassing remote sensing and GIS, in the examination of LULC changes. Despite their effectiveness, there is a cognizance that these methods, while valuable, may lack the requisite granularity for conducting intricate spatial analyses. Moreover, the literature recognizes limitations associated with the application of landscape metrics in specific contexts. To address these identified gaps, our study adopted a comprehensive approach, utilizing remote sensing and FRAGSTAT to analyze satellite imagery and landscape metrics. The study emphasized a weighted approach, highlighting the significance of each metric and its distinct impact on land use sustainability. Through this integrated methodology, our research aims to contribute to a refined understanding of land use and land cover changes, taking into account the limitations identified in the existing literature. The purpose of this study is to provide an overview of the importance of monitoring and assessing LULC changes and to highlight the potential of landscape metrics as a promising approach for analyzing and quantifying these changes in Kashkan watershed, Iran. The application of landscape metrics emerges as a central theme, offering a nuanced approach to dissect and measure the spatial transformations occurring within this specific geographical region. Through this exploration, the study aspires to bridge existing knowledge gaps, offering a foundation for informed decision-making and sustainable land management practices in the Kashkan watershed. The intention is to not only illuminate the importance of monitoring LULC changes but also to advocate for the efficacy of landscape metrics as a strategic tool in enhancing the understanding and management of these changes within the unique environmental context of Iran's Kashkan watershed.

2. Method and material

2.1. Case study

The Koshkan Basin, with an area of 9275.7 square kilometers, is located in the southwest of Iran in the Lorestan province (Figure 1), at geographic coordinates ranging from 47°12' to 48°59' E and 33°8' to 34°2' N. The Koshkan Basin is one of the important sub-basins of the Karkheh River Basin. Geographically, the basin has a structural heterogeneity, with the highest altitude of around 3566 meters and the lowest altitude of around 572 meters. In terms of climate, the absolute difference between the maximum and minimum temperatures recorded is more than 80 degrees Celsius. The highest recorded temperature is 47.4 degrees Celsius, and the absolute minimum recorded temperature is -35 degrees Celsius. The average annual precipitation is between 550 and 600 millimeters. Generally, three distinct climatic zones are observed in the basin: cold mountainous, central temperate, and warm southern. This basin is located within the Zagros forests and a significant part of the LULC in this area consists of forest and rangeland. In recent years, changes in land cover in the Koshkan Basin have disrupted the balance of the elements and components of the land in the basin (Japelaghi et al. 2019).

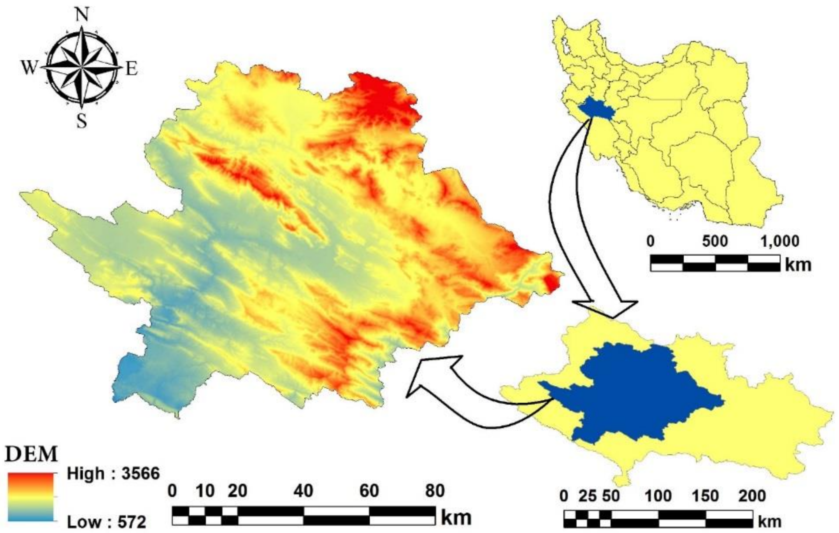


Figure 1. Geographic Location of the Kashkan Area in the West of Iran

2.2. Methodology

The research process is illustrated in Figure 2. The study offers a model for assessing LULC changes using landscape metrics. The procedure involves five steps:

Step 1: Data collection

- Obtain satellite imagery for the years 1991 and 2021
- Preprocess the images to remove any distortions and to ensure that they are in the same projection and resolution
- Collect ground truth data on LULC classes for both years, using a combination of field surveys and existing maps

Step 2: LULC classification

- Use a supervised classification algorithm to classify the satellite imagery into LULC classes
- Validate the classification accuracy using the ground truth data collected in Step 1

Step 3: Calculation of landscape metrics

- Use FRAGSTAT software to calculate landscape metrics for both 1991 and 2021 LULC maps
- Select appropriate metrics that are relevant to the study based on literature review and expert opinion

- Calculate the metrics at multiple scales to capture the effects of different spatial resolutions on the landscape metrics

Step 4: Comparison of landscape metrics

- Compare the landscape metrics between the two years to identify changes in the landscape over time
- Use statistical analysis to determine the significance of the changes observed
- Vulnerability priority assessment of LULC using VIKOR-based Landscape metrics

Step 5: Interpretation of results

- Interpret the results of the analysis in the context of the study area and the broader landscape
- Discuss the implications of the changes observed
- Identify opportunities for LULC planning and management to promote sustainable LULC practices in the future

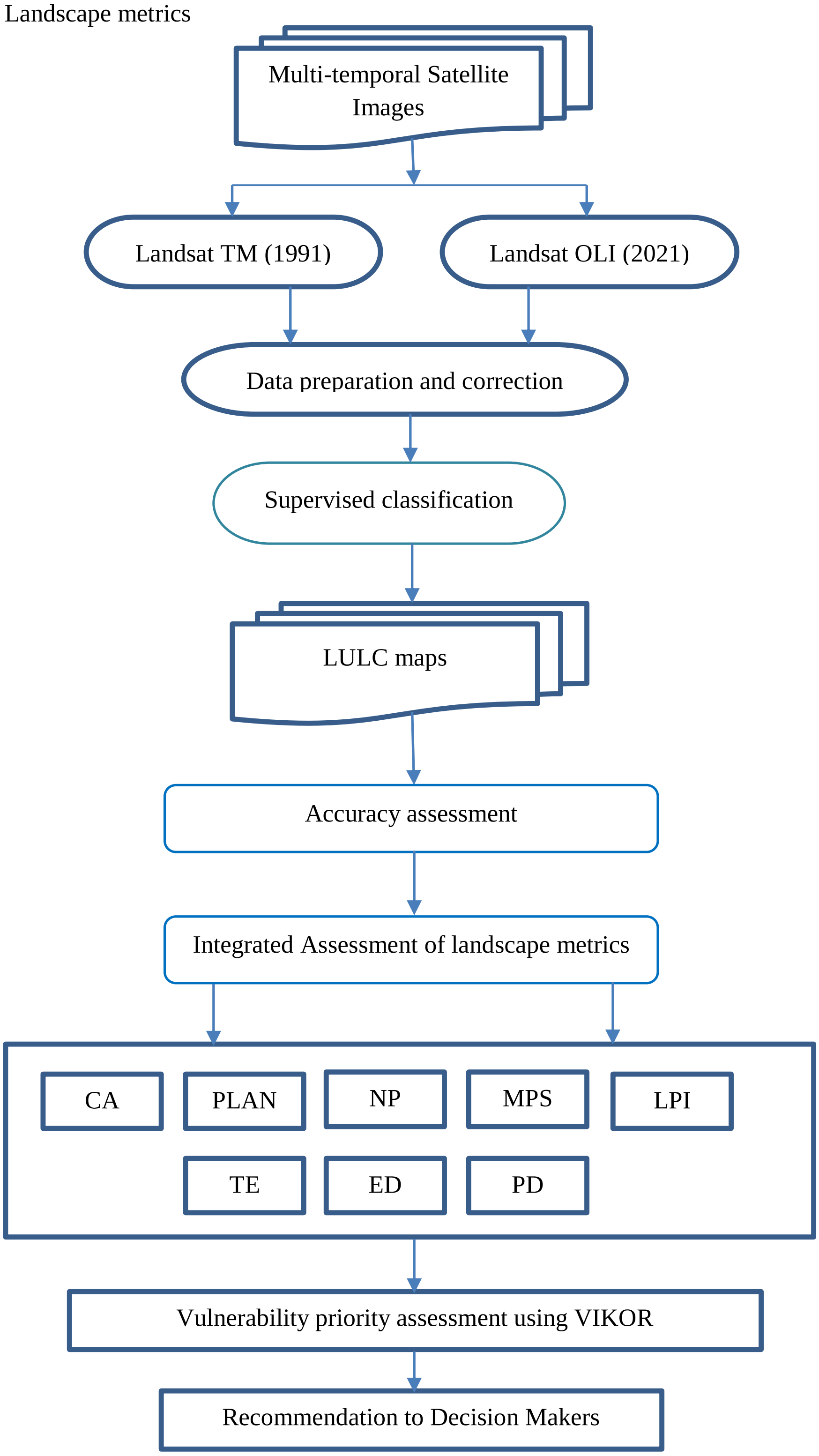


Figure 2. The research process

2.2.1. Data Acquisitions and Preparation

LULC change was assessed using Landsat imagery, with consideration given to data quality, availability, and the dry season when selecting dates. The USGS Global Visualization Viewer was used to obtain two Landsat images for the Kashkan catchment area, captured in 1991 and 2021, using Path/Row 166/37. These images were used to create LULC maps within a GIS, with analysis carried out using software packages including TerrSet, ArcGIS, and Fragsts. Although the images all had a spatial resolution of 30 m, they were sensed by different sensors and satellites at different times of the year. As a result, each scene was subjected to radiometric correction to adjust raw digital numbers (DNs) to top of atmosphere (TOA) reflectance values, to account for variations in sun angles and surface reflectance changes. Government records, land surveys, and cadastral maps were consulted to obtain historical information about LULC. These documents provided legal and administrative data that could support the interpretation of LULC changes.

2.2.2. Classification and Change Detection

To examine land cover changes, Landsat images were classified into seven categories using maximum likelihood and object-oriented methods via TerrSet software. The seven classes were forest (LC1), scattered dry farming (LC2), irrigated farming (LC3), dry farming (LC4), rangeland (LC5), residential (LC6), and water zones (LC7). Maximum likelihood classification is a widely used method for determining a known class of distributions as the maximum for a given statistic, with the assumption of normality for the training samples (Das and Angadi 2022). The algorithm generates probability density functions for each category and assigns membership to unclassified pixels based on their relative likelihood within each category's density function (Gul et al. 2023). Training areas were established by selecting one or more polygons for each class, with the selection criteria based on the properties of uniformity and representativeness of the same class throughout the entire image. The classification process involved selecting training samples for each land cover category, which were used to define the spectral signatures for each class. The training samples were selected based on visual interpretation of the imagery, and ground-truthing was performed to verify the land cover classes. The spectral signatures were then used to classify the entire image using the maximum likelihood algorithm, which assigned each pixel to a specific land cover class based on its spectral characteristics. To detect changes in land cover, two images taken at different time periods were compared. A post-classification comparison technique was used, which involved comparing the land cover classifications of the two images. The changes in land cover were identified by comparing the categories of land cover that changed between the two time periods.

The accuracy of the output of land cover change analysis can be assessed using different indexes, depending on the specific goals and requirements of the study. One commonly used indexes is the overall accuracy, which measures the proportion of correctly classified pixels over the total number of pixels in the study area (Seyam et al. 2023). The overall accuracy can be calculated using the following equation:

$$\text{Overall accuracy} = N/TN \tag{1}$$

Where N is number of correctly classified pixels, and TN is total number of pixels. Another useful index is the kappa coefficient, which takes into account the chance agreement between the observed and expected classifications, and provides a more robust measure of accuracy than the overall accuracy (Das & Angadi, 2022). The kappa coefficient can be calculated using the following equation:

$$\text{Kappa} = (Po-Pe)/(1-Pe) \tag{2}$$

Where Po is the observed proportion of agreement between the classifications, and Pe is the expected proportion of agreement due to chance. The kappa coefficient ranges from -1 to +1, with values closer to +1 indicating higher agreement between the classifications than expected by chance, values around 0 indicating no agreement between the classifications, and values closer to -1 indicating lower agreement between the classifications than expected by chance. In addition to the overall accuracy and kappa coefficient, other metrics such as user's accuracy and producer's accuracy can be used to assess the accuracy of land cover change analysis and identify land cover changes in detail (Seyam et al. 2023).

2.2.3. Calculation of Landscape Metrics

Landscape matrices are used to measure landscape pattern, spatial configuration, and spatial heterogeneity of land cover types within a study area. FRAGSTATS is a commonly used software tool to calculate landscape metrics. Calculating landscape matrices using FRAGSTATS requires careful consideration of the input data, metric selection, and parameter setting, as well as a solid understanding of landscape ecology principles (Teimouri et al. 2023). In the study, a set of metrics were used to evaluate the landscape pattern characteristics. These metrics were chosen based on their effectiveness in capturing different aspects of landscape structure, literature review and expert opinions. The study utilized eight metrics including Core Area (CA), Percentage of Landscape (PLAND), Number of Patches (NP), Mean Patch Size (MPS), Largest Patch Index (LPI), Total Edge (TE), Edge Density (ED), and Patch Density (PD). These metrics were explained in detail in Table 1, and their values were computed using an 8 x 8 meter cell neighborhood rule in the FRAGSTAT software. Subsequently, the findings were analyzed.

Table 1. The characteristics of landscape metrics in the study

	Metric	Index	Range	Unit	Description
C1	Class Area	CA	0<CA	ha	The total area of each land cover class within the landscape
C2	Percentage of Landscape	PLAND	0<PLAND<100	%	The proportion of the landscape that is covered by each land cover class
C3	Number of Patches	NP	1<NP	-	The number of patches of each land cover class within the landscape
C4	Mean Patch Size	MPS	-	ha	The average size of patches of each land cover class within the landscape
C5	Edge Density	ED	0<ED	m/ha	The amount of edge between different land cover classes within the landscape
C6	Landscape Pattern Index	LPI	0-100	%	The degree of fragmentation of the landscape by calculating the ratio of the observed mean patch size to the expected mean patch size
C7	Total Edge	TE	0<TE	m	The total length of edge between different land cover classes within the landscape
C8	Patch Density	PD	0<PD	n/ha	The number of patches of each land cover class per unit area of the landscape

2.2.4. Vulnerability priority assessment of LULC using VIKOR-based Landscape metrics

In the study, we present a methodology for vulnerability ranking of LULC using the VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) method. The VIKOR method is a multi-criteria decision-making tool that can be used to determine the alternative ranking based on several criteria (Bhattacharya et al. 2020) . In the study, VIKOR is used to evaluate the vulnerability of different land cover types based on landscape metrics. In the study, the VIKOR method involves several steps, which are outlined below:

Step 1: Determine the criteria and their weights: The first step is to identify the criteria that will be used to evaluate the alternatives and assign weights to them based on their relative importance (Ameri et al. 2018). In this study, we used expert judgment to assign the weights to the criteria.

Step 2: Normalize the decision matrix: The next step is to normalize the decision matrix to ensure that all criteria are on the same scale. This is done by dividing each value in the matrix by the corresponding maximum value in the same column (Ameri et al. 2018).

Step 3: Determine the values of the positive and negative ideal solutions: The positive ideal solution (PIS) is the best value that can be achieved for each criterion, while the negative ideal solution (NIS) is the worst value that can be tolerated for each criterion (Arabameri Pal et al. 2021). The PIS and NIS are calculated by taking the maximum and minimum values for each criterion, respectively.

Step 4: Calculate the distance of each alternative from the ideal solutions: The next step is to calculate the distance of each alternative from the PIS and NIS. The distance from the PIS is calculated using the following formula (Moradpanah et al. 2022):

$$D+(i) = \sqrt{(\sum w(j) * (s(j,i) - s(j,PIS))^2)} \quad (3)$$

where D+(i) is the distance of alternative i from the PIS, w(j) is the weight of criterion j, s(j,i) is the normalized value of alternative i for criterion j, and s(j,PIS) is the normalized value of the PIS for criterion j.

The distance from the NIS is calculated using a similar formula:

$$D-(i) = \sqrt{(\sum w(j) * (s(j,i) - s(j,NIS))^2)} \quad (4)$$

where D-(i) is the distance of alternative i from the NIS, w(j) is the weight of criterion j, s(j,i) is the normalized value of alternative i for criterion j, and s(j,NIS) is the normalized value of the NIS for criterion j.

Step 5: Calculate the VIKOR index and ranking: The VIKOR index is calculated using the following formula:

$$Q(i) = (\lambda * R(i)) + ((1 - \lambda) * S(i)) \quad (5)$$

where Q(i) is the VIKOR index of alternative i, R(i) is the relative rank of alternative i, S(i) is the “closeness” of alternative i to the ideal solution, and λ is a weight that reflects the decision maker’s attitude towards the trade-off between the two factors. The value of λ is usually set between 0.5 and 1. The relative rank of alternative i is calculated as follows:

$$R(i) = (m+1 - r(i)) / m \quad (6)$$

where R(i) is the relative rank of alternative i, m is the number of alternatives, and r(i) is the rank of alternative i based on its “closeness” to the ideal solution. The alternative with the smallest distance from the ideal solution is given a rank of 1, and the alternative with the largest distance is given a rank of m. The “closeness” of alternative i to the ideal solution is calculated as follows:

$$S(i) = (D-(i) - D+(i)) / D \quad (7)$$

The “closeness” of alternative i to the ideal solution measures the compromise between the two factors. The smaller the value of S(i), the closer the alternative is to the ideal solution.

3. Results

The results of object-based classification of images and LULC maps for the years 1991 and 2021 are presented in Figure 3. At first glance, the change from dry farming to rangeland and the reduction in irrigated agricultural lands can be clearly seen on the map. Table 2 shows the results of the accuracy assessment of LULC maps, including the area of LULC classes and their changes. The overall accuracy and Kappa coefficient for the 1991 image are 95.33% and 0.9624, respectively. The lowest producer's accuracy for the rangeland class in the 1991 map is about 81.8%, which can be attributed to the weakness of the TM sensor in separating this land use from other land uses compared to the OLI sensor. The overall accuracy and Kappa coefficient for the 2021 map are 96.4% and 0.9453, respectively. In 2021, rangeland has the lowest producer's accuracy of 90.1%. The assessment of LULC changes between 1991 and 2021 showed an increase in the area of dry farming, rangeland, and residential areas and a decrease in the forest, irrigated agriculture, and scattered agriculture.

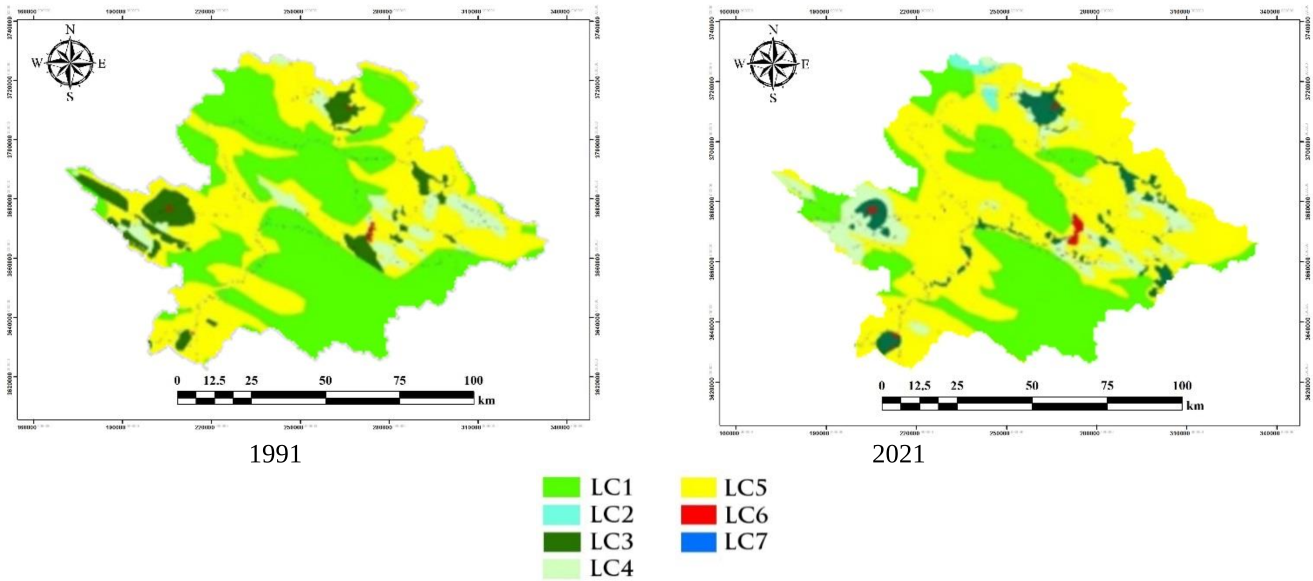
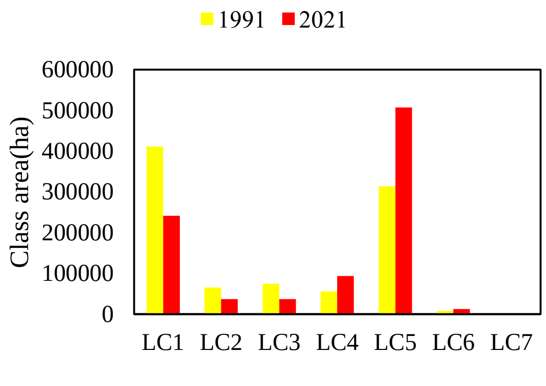


Figure 3. Map of LULC changes in the case study

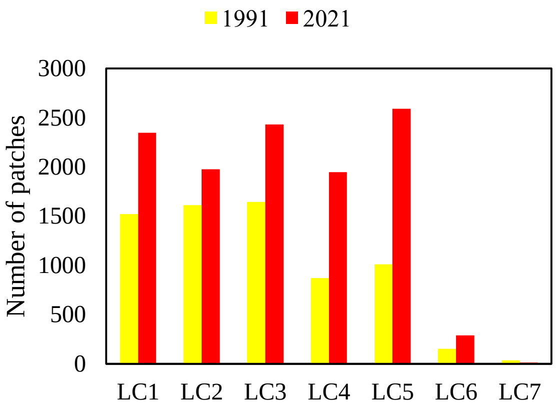
Table 2. Accuracy assessment, area and changes of each of LULC classes

Land cover	Area(ha)			Accuracy assessment (1991)		Accuracy assessment (2021)	
	1991	2021	Changes	user	producer	user	producer
LC1	411377.3	241168.2	-170209.1	84.6	97.4	92.8	96.2
LC2	64929.9	37102.8	-27827.1	95.3	99.1	98.2	99.4
LC3	74205.6	37102.8	-37102.8	86.4	88.4	96.4	92.6
LC4	55654.2	93128.0	37473.8	93.7	94.1	93.4	96.8
LC5	313518.7	506917.1	193398.4	81.8	86.2	90.1	95.3
LC6	7420.6	12058.4	4637.8	95.4	86.7	99.2	93.6
LC7	463.7	92.7	-371.0	100	100.0	100.0	100.0
Total	927570	927570	-	-	-	-	-
Overall accuracy				95.33		96.4	
Kappa coefficient				0.9624		0.9453	

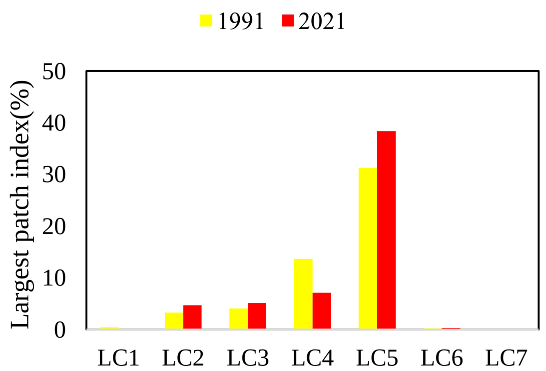
The results of evaluating LULC changes using landscape metrics at the class level for various land covers have been calculated and presented in Figure 4. The largest LULC area in 1991 belonged to forests with an area of 411,377.3 hectares, while in 2021 it belonged to rangelands with an area of 506,917.1 hectares. The smallest area in both 1991 and 2021 belonged to the water zones (463.7 and 92.7 hectares, respectively). The greatest change in LULC area between 1991 and 2021 was related to rangelands with an increasing trend (37,473.8 hectares), and the smallest change was related to the water zones with a decreasing trend (371 hectares). The highest percentage of landscape in 1991 was forests (44.35%), and in 2021 it was rangelands (54.63%), while the lowest percentage in both 1991 and 2021 was the water zones (0.05 and 0.01%, respectively). The greatest change in the percentage of landscape between 1991 and 2021 was related to rangelands with an increasing trend (20.85%), and the smallest change was related to the water zones with a decreasing trend (0.04%). The highest number of patches in 1991 was related to irrigated agriculture (1645), while in 2021 it was related to rangelands (2589), and the lowest number of patches in both years was related to water zones (33 and 12, respectively). The highest change in the number of patches between 1991 and 2021 was related to rangelands with an increasing trend (1578 patches), and the lowest change was related to water zones with a decreasing trend (21 patches). The highest mean patch size in both 1991 and 2021 was related to rangelands (3.10 and 1.96 hectares, respectively), while the lowest mean patch size in both years was related to water zones (0.14 and 0.08 hectares, respectively). The highest change in mean patch size between 1991 and 2021 was related to forests with a decreasing trend (1.28 hectares), while the lowest change was related to residential areas and water zones with a decreasing trend (0.06 hectares). The highest edge density in both 1991 and 2021 was related to dry farming (7.31 and 11.38 meters per hectare, respectively), while the lowest edge density in both years was related to water zones (0.37 and 0.48 meters per hectare, respectively). The highest change in edge density between 1991 and 2021 was related to rangelands with an increasing trend (6.65 meters per hectare), while the lowest change was related to water zones with an increasing trend (0.11 meters per hectare). The largest patch in both 1991 and 2021 was related to rangelands (31.25 and 38.41 percent, respectively), while the smallest patch in both years was related to water zones (0.02 and 0.04 percent, respectively). The highest change in the largest patch between 1991 and 2021 was related to rangelands with an increasing trend (7.16 percent), while the lowest change was related to blue areas with an increasing trend (0.02 percent). The highest total edge in both 1991 and 2021 was related to rangelands, and the lowest edge density in both years was related to water zones. The highest change in the total edge between 1991 and 2021 was related to rangelands with an increasing trend (3966118 meter), while the lowest change was related to water zones with a decreasing trend (86165 meter). The highest accumulation of patches in 1991 and 2021 was related to water zones (0.71 and 1.29, respectively), and the lowest patch density in both years was related to rangelands (0.03 and 0.05, respectively). The highest change in patch density between 1991 and 2021 was related to water areas with an increasing trend (0.58), and the lowest change in patch density was related to rangelands with an increasing trend (0.02 meters).



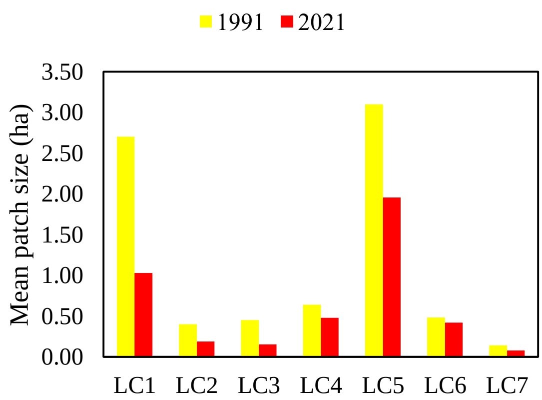
CA



NP



LPI



MPS

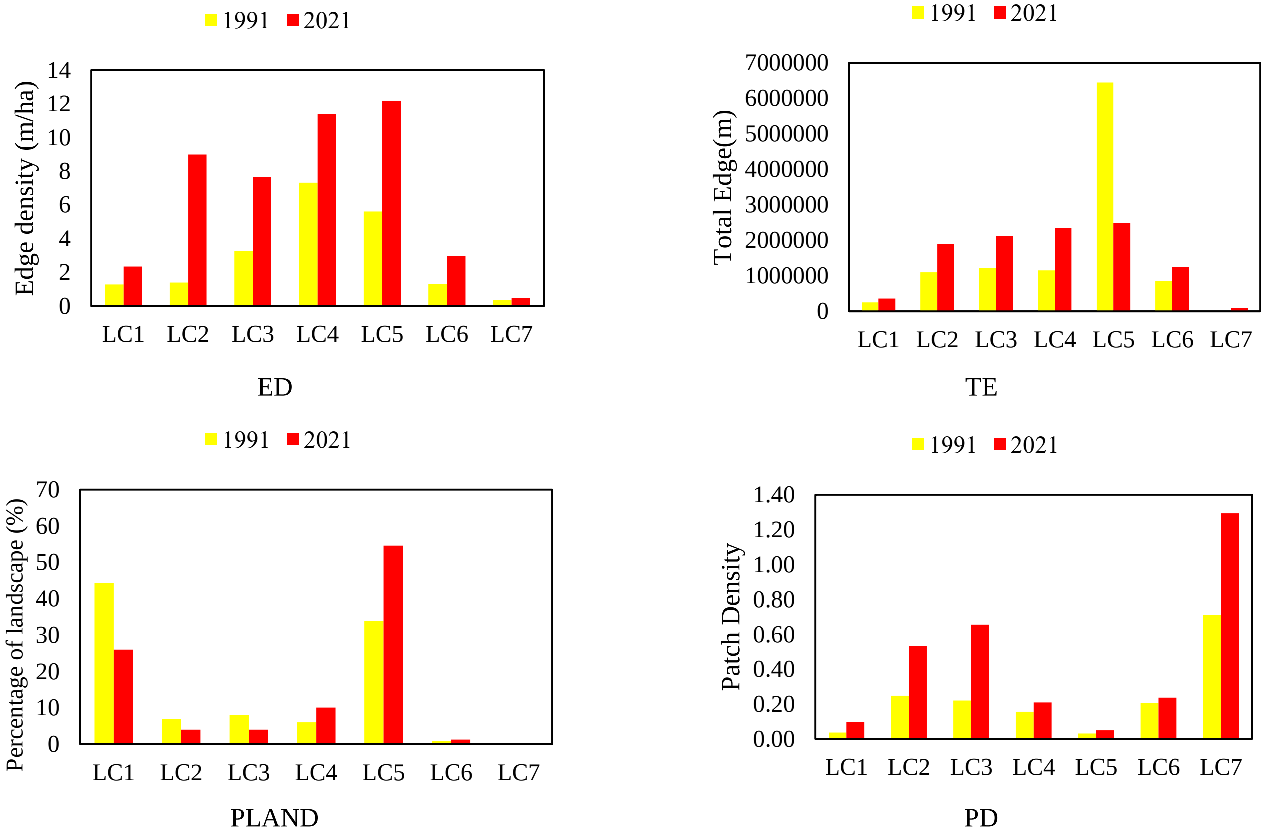


Figure 4. Landscape metrics at the class level for various LULC in 1991 and 2021

The weighting analysis results highlight the importance of considering multiple land cover metrics when assessing LULC vulnerability. Each metric provides a unique perspective on landscape characteristics that contribute to LULC vulnerability, and collectively, they provide a comprehensive understanding of the factors affecting LULC sustainability. The results of the land cover metrics analysis indicate that certain metrics hold more weight in determining the sustainability of LULC types than others (Table 3). The analysis was conducted using a weighted approach, and the importance of each metric was assessed based on its impact on LULC sustainability. The CA metric held the highest weight with a score of 0.187, followed closely by PLAND at 0.165 and MPS at 0.144. NP and TE scored 0.143 and 0.106, respectively, while LPI, ED, and PD held scores of 0.095, 0.083, and 0.077, respectively (Table 4). These findings provide valuable insights into the most significant factors that should be considered when assessing the vulnerability of LULC types and can help inform land-use planning and management decisions. By considering multiple landscape metrics and their weighted scores, the R, S, and Q indexes calculated by VIKOR method provide a comprehensive assessment of land vulnerability (Table 5). This study found that forest and rangeland have the highest and lowest vulnerability, respectively, with Q values of 0.997 and 0.074 (Table 6). These results highlight the importance of incorporating various criteria and metrics when assessing land use sustainability, as different LULC types can have varying degrees of vulnerability and resilience to environmental stressors. This information can help land use planners and decision-makers make informed choices that support sustainable land use practices while minimizing potential environmental and human risks.

Table 3. Normalized decision matrix

LULC	C1	C2	C3	C4	C5	C6	C7	C8
LC1	0.428	0.304	0.377	0.360	0.367	0.325	0.375	0.383
LC2	0.308	0.397	0.286	0.447	0.366	0.274	0.225	0.269
LC3	0.359	0.407	0.386	0.365	0.358	0.335	0.489	0.456
LC4	0.420	0.360	0.395	0.374	0.401	0.435	0.359	0.428
LC5	0.447	0.309	0.360	0.296	0.344	0.263	0.216	0.258
LC6	0.332	0.419	0.411	0.399	0.390	0.443	0.472	0.372
LC7	0.327	0.427	0.416	0.388	0.414	0.502	0.414	0.430

Table 4. The importance of each metric

Metrics	C1	C2	C3	C4	C5	C6	C7	C8
w	0.143	0.144	0.083	0.095	0.106	0.077	0.187	0.165

Table 5. The distance of each alternative from the ideal solutions

D+(i)	0.0639	0.0615	0.0345	0.0425	0.0439	0.0387	0.0915	0.0753
D-(i)	0.0441	0.0437	0.0237	0.0282	0.0364	0.0202	0.0405	0.0426
(D+(i)- D-(i))	0.0198	0.0178	0.0108	0.0143	0.0075	0.0184	0.0510	0.0327

Table 6. The VIKOR index and ranking

LULC	Si	Ri	Qi
LC1	0.8027	0.1871	0.997
LC2	0.5107	0.1441	0.523
LC3	0.7434	0.1808	0.916
LC4	0.2991	0.1184	0.205
LC5	0.3192	0.0895	0.074
LC6	0.2345	0.1231	0.172
LC7	0.3218	0.0904	0.082

4. Discussion

The evaluation of LULC changes using landscape metrics at the class level provides valuable insights into the trends and patterns of land use changes over time. The study results indicate that there have been significant changes in LULC between 1991 and 2021 in the study area. The forest area has decreased, while the rangeland area has increased during the study period. The landscape metrics used in the study include CA, PLAND, NP, MPS, ED, LPI, TE, and PD. The highest percentage of landscape in both 1991 and 2021 was rangelands, while the lowest percentage was water zones. The high percentage of rangelands in both 1991 and 2021 may reflect the importance of this land cover type for livestock production and grazing activities in the study area. It is in accordance with other studies (Das & Angadi, 2022; Dezhbani et al. 2023), the increasing trend in the number of patches and total edge in rangelands also indicates a higher level of fragmentation, which could have negative implications for biodiversity conservation and ecosystem services. The low percentage of water zones highlights the importance of water resource management in the study area, particularly in the context of climate change and water scarcity. Conforming to the results derived from study conducted by Ersoy Mirici et al. (2020), the trend of increasing patches in land cover is a concerning issue that requires further investigation. It could be an indication of land-use changes or a result of climate change. Whatever the cause, it highlights the need for sustainable management practices in these areas to preserve their ecological function and prevent further degradation. Additionally, monitoring and tracking changes in patch numbers can aid in assessing the effectiveness of management strategies and identifying areas that require more attention. In line with other studies such as Gul et al. (2023) and Moradpanah et al. (2022) highlighted the decreasing trend in mean patch size of forests indicates that there may be fragmentation or loss of forested areas over time. This could be due to human activities such as deforestation or urbanization, which can have negative impacts on biodiversity and ecological systems. Consistent with prior research, as illustrated by Phiri et al. (2019) and Seyam et al. (2023), It is important to monitor changes in mean patch size and take actions to protect and preserve natural habitats, as they provide crucial ecosystem services and support a wide range of species. Conservation efforts such as reforestation and sustainable land use practices can help mitigate the effects of habitat fragmentation and loss. The high edge density in dry farming areas suggests that these regions may have experienced significant land use changes or alterations, resulting in more fragmented and diverse landscapes. On the other hand, water zones, which have the lowest edge density, may indicate relatively undisturbed or stable environments with less human impact. Understanding changes in edge density can provide valuable information about the impacts of land use and development on ecological systems and can guide conservation efforts to protect biodiversity and ecosystem services in these areas. In a comparable investigation conducted by Shastri et al. (2020), the increasing trend in the largest patch index of rangelands suggests that these areas have experienced changes in land use, such as conversion from forest or agricultural land to rangeland. The results align with the study conducted by Zhang et al. (2020), indicating that It is important to monitor changes in the largest patch index as it can provide insight into the spatial structure and connectivity of the landscape. Large, contiguous patches of natural habitats are important for biodiversity conservation as they support a variety of species and maintain ecological processes. Corresponding to the outcomes found in similar research (Cervelli et al. 2020; da Silva et al. 2020; Dezhbani et al. 2023), the increasing trend in total edge in rangelands suggests that these areas may have undergone significant land use changes, such as fragmentation or expansion of agricultural or urban areas, resulting in increased edges between natural and human-dominated landscapes. Changes in total edge can impact ecological processes, such as nutrient cycling and the movement of species, and can lead to the loss of natural habitats and species. It is important to monitor changes in total edge and prioritize conservation efforts to maintain connectivity and protect biodiversity in these landscapes. In accordance with the results documented by Azareh et al. (2021) and Zhang et al. (2022) the increasing trend in patch density in water areas indicates that there may have been changes in water levels, shoreline erosion or other disturbances in aquatic ecosystems. These changes can affect the availability of suitable habitats for aquatic species and can alter the functioning of the ecosystem as a whole. Understanding changes in patch density can inform management and conservation strategies to maintain healthy aquatic ecosystems and support biodiversity. Conservation efforts such as restoration of degraded shorelines or protection of key habitats can help mitigate the impacts of changes in patch density. Specifically, the findings of this study can be used to guide land managers in making informed decisions about the allocation of resources to different land uses, particularly in the context of balancing economic development and environmental conservation. For instance, the increase in rangeland areas could be a positive trend for livestock production, but it could also result in habitat fragmentation and loss of biodiversity if not properly managed. The decrease in forest areas could also have negative implications for carbon sequestration and climate regulation, as well as ecosystem services such as water regulation and soil conservation. Therefore, land managers could use the landscape metrics results to prioritize conservation efforts in areas with high forest cover or to implement reforestation programs to restore degraded forest areas. Furthermore, the use of landscape metrics provides a standardized framework for evaluating LULC changes, which can facilitate comparisons across different regions and time periods. This could help to identify regional and global trends in land use change and the drivers behind these changes, such as population growth, urbanization, and agricultural expansion. Overall, the results of this study demonstrate the importance of using landscape metrics to evaluate LULC changes and their ecological consequences. By providing a quantitative and standardized approach, landscape metrics can help to inform sustainable land use and conservation practices and support evidence-based decision-making in the context of global environmental challenges. Despite the benefits of using landscape metrics for monitoring and assessment of land use/land cover changes, there are also challenges associated with their use. One of the main challenges is the need for high-quality data, particularly in areas with limited or no ground-based monitoring. This requires the use of remote sensing data, which can be expensive and require specialized training and equipment. Additionally, the interpretation of landscape metrics requires expertise in landscape ecology and statistical analysis, which may not be readily available in some areas. Our study has many differences from the other studies:1) Holistic approach to LULC changes: Unlike many studies focusing solely on specific aspects of land use or cover changes, our research takes a comprehensive approach. We assess a wide range of changes over a substantial period, from 1991 to 2021, providing a holistic view of the dynamic landscape transformations in the Kashkan watershed; 2) Utilization of advanced techniques: Our study employs cutting-edge methodologies, combining remote sensing and FRAGSTAT, to analyze satellite imagery and landscape metrics. This integration allows for a more nuanced understanding of LULC changes and their implications, setting our research apart in terms of analytical sophistication; 3) Application of VIKOR method for vulnerability assessment: The use of the VIKOR method for vulnerability priority assessment is a distinctive feature of our study. This approach adds depth to our evaluation, emphasizing the importance of considering multiple landscape metrics in vulnerability assessments. The weighted approach applied to highlight the significance of each metric contributes to a more nuanced vulnerability analysis; 4) Identification of areas of potential degradation: The utilization of landscape metrics not only aids in quantifying changes but also serves as a practical tool to identify areas of potential degradation. This proactive approach allows for targeted interventions and the development of strategies to mitigate negative impacts, showcasing the practical applicability of our findings.

While the study contributes valuable insights to the assessment of land use/land cover (LULC) changes and their implications for sustainable land management, it is essential to acknowledge certain limitations that may impact the interpretation and generalization of the findings:

- The spatial resolution of the remote sensing data and landscape metrics may limit the precision of the analysis, especially in areas with heterogeneous land cover. Higher resolution data might provide more detailed insights into specific landscape changes.
- Although the study employed eight landscape metrics, the choice of metrics is subjective and may not capture all relevant aspects of landscape changes. Different metrics or combinations could potentially yield varied results and interpretations.
- The study primarily focuses on the biophysical aspects of land use changes. While emphasizing the importance of land management strategies, the study does not extensively address socio-economic factors that may influence or be influenced by these changes.
-The current study establishes a foundational understanding of land degradation by employing landscape metrics. However, to expand the breadth and depth of knowledge in this crucial field, it is advisable for future investigations to explore additional influential factors. This may encompass a comprehensive analysis of anthropogenic influences, climate factors, and socio-economic drivers.

5. Conclusion

Landscape metrics serve as a crucial tool for evaluating Land Use/Land Cover (LULC) changes, offering a quantitative and standardized approach that informs sustainable land management and conservation practices.

Their ability to provide a consistent framework facilitates cross-regional and temporal comparisons, unveiling patterns in local-level alterations to land use. This quantitative approach, grounded in factual data, supports decision-making by objectively assessing LULC changes. Notably, the benefits extend to the identification of vulnerable areas, including ecologically sensitive zones, high biodiversity regions, and those with significant carbon storage. This insight empowers prioritized conservation efforts and bolsters evidence-based decision-making amid global environmental challenges like climate change and biodiversity loss.

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