RESEARCH

Spatial relationship of Remote Sensing Ecological Indicator (RSEI) and landscape metrics under urban development intensification

Nazanin Naseri[1] · Raoof Mostafazadeh[2]

Abstract

In recent years, environmental issues such as global warming and climate change have led to an increased focus on finding solutions to reduce its impacts, especially in urban areas. Remote sensing data have become an increasingly popular tool for conducting environmental assessment studies. The objective of this study was to assess and analyze the ecological environmental quality of Karaj County using Landsat satellite imagery of 2010 and 2020. In addition, the spatial pattern of landscape metrics has been quantified to assess the spatial pattern of green spaces. The greenness, moisture, dryness, and heat indicators were combined into a comprehensive RSEI index. The importance of the sub-indicators was determined using principal component analysis and weighted to obtain the RSEI index, which consists of the components LST, NDVI, NDBI, and wetness. The results indicate that the overall quality of the ecological environment in Karaj district has decreased, with the mean RSEI decreasing from 0.59 to 0.25. Landscape characteristics of the ecological environment have changed to a more separated, incoherent, and irregular pattern. Specifically, RSEI values had a significant correlation with landscape pattern change. The value of the COHESION metric has decreased and the value of the Edge Density has increased, which indicates the separation of the green space in the study area. These results could be valuable information for decision makers in managing or achieving an optimal eco-environment landscape pattern in urbanized areas.

Keywords Karaj County · Contagion Index · Remote Sensing Ecological Index (RSEI) · Landscape metrics · Spatial patterns · Land surface temperature

Introduction

Urban ecology science plays a crucial role in advancing sustainable development by enhancing the environmental health and livability of urban residents. However, current approaches to quantitatively analyze urban areas using data collection and analysis technologies are insufficient and lack systematicity compared to the relatively mature urban ecology theory (Tan et al. 2022). The ecological impact of urban development has gained increasing importance due to ongoing human-induced landscape modifications, resulting in changes in land use, intensified development, and degradation of natural landscapes (Williams et al. 2009; Mostafazadeh and Talebi Khiavi 2022). According to Ellis et al. (2006), the degradation of the environment caused by urban landscapes poses a significant threat globally, contributing to a substantial portion of environmental changes. Urbanization has given rise to various issues such as congestion, air pollution, waterlogging, and the urban heat island effect. Recent advancements in satellite-based Earth observation systems have the potential to serve as powerful tools for ecosystem management, providing robust insights into ecosystem status at local and global scales (Ellis et al. 2006; Willis 2015; Wang and Xu 2018).

Remote sensing techniques serve as effective tools for measuring ecosystem components, identifying ecological attributes across different spatial scales, and estimating Earth's surface processes, including land use/land cover (LULC) type, leaf area index (LAI), and biomass (Abdullah et al., 2011; Amorim et al., 2022). Kennedy et al. (2014) highlight the extensive use of remote sensing methods in

✉ Raoof Mostafazadeh
raoofmostafazadeh@uma.ac.ir

[1] Department of Environment, Faculty of Natural Resources, Malayer University, Malayer, Iran

[2] Department of Natural Resources and Water Management Research Center, Faculty of Agriculture and Natural Resources, University of Mohaghegh Ardabili, Ardabili, Iran

ecological and environmental assessment and monitoring (Ouyang et al. 2014; Willis 2015; Xu et al. 2018; Hu and Xu 2018). Tang et al. (2015) emphasize that analyzing ecosystem changes using composite indicators leads to improved results. Various ecological indicators have been developed to determine and quantify ecosystems. For example, the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index are suitable examples for monitoring changes in vegetation cover type and percentage (Tang et al. 2015; Brehaut and Danby 2018). Land surface temperature (LST) has been employed in several studies to evaluate the urban heat island effect (Weng 2009; Zhou et al. 2014; Meng et al. 2018; Chakraborty and Lee 2019). Additionally, the normalized difference built-up index (NDBI), index-based built-up index (IBI), and normalized difference impervious surface index (NDISI) have been utilized to delineate built-up and impervious surface areas (Xu 2008; Sekertekin et al. 2018). The normalized difference water index (NDWI) and modified NDWI (MNDWI) have been used to extract water bodies (Sandholt et al. 2002; Meng et al. 2018). Moreover, NDVI and LST have been applied to monitor drought or soil moisture (Sandholt et al. 2002; Marzban et al. 2018). Coutts et al. (2016) employed the bare soil index (BI) (Rikimaru et al. 2002) and dry bare-soil index (DBSI) to map bare soil regions. Given the complexity and diversity of factors contributing to the state of an ecosystem, using multiple indicators to assess its condition yields more reliable results. Various ecological indicators based on remote sensing play a crucial role in determining the characteristics and functional components of ecosystems. Among these indicators, the Normalized Difference Vegetation Index (NDVI) is the most commonly used index to describe spatial and temporal changes in vegetation cover (Tilt et al. 2007; Ochoa-Gaona et al. 2010; White et al. 2016). Other notable ecological indices include the permanent vegetation fraction (PVF) index and the hyperspectral flower index (HFI), which have shown promising results in assessing ecological conditions.

Ivits et al. (2009) utilized the permanent vegetation fraction index to assess the favorable and unfavorable ecological conditions in the coastal areas of Andalusia. Chen et al. (2009) employed the hyperspectral flower index (HFI) to monitor plant flowering status and phenology periods on the Tibetan Plateau. In urban areas, the land surface temperature index (LST) based on remote sensing is commonly used to identify the characteristics and spatial distribution of the urban heat island (UHI). Nichol (2009), Coutts et al. (2016), and Xu et al. (2017) have all utilized LST as an index for this purpose. Additionally, integrated remote sensing-based ecological indicators have been employed to evaluate complex ecological conditions in a spatially explicit manner. For instance, the Remote Sensing Ecological Index (RSEI) incorporates four components related to climate and land surface biophysical variables, along with various

metrics such as the Normalized Difference Vegetation Index (NDVI), humidity (WET), and LST (Xu et al. 2017). The NDVI component indicates the greenness of a specific area, WET reflects soil moisture characteristics, and LST represents the thermal characteristics of the studied environment. Spatial principal component analysis (SPCA) allows for weighing and determining the information value of different layers (Kang et al. 2018). Apart from indicators related to environmental quality assessment, landscape-related criteria are utilized to evaluate the geometric characteristics and spatial patterns of green space. Meng et al. (2016) emphasize that the primary goal of landscape ecology is to investigate and enhance the connections between ecosystem components, the environment, and ecological processes. Pattern recognition and analysis are critical research areas in landscape ecology, focusing on understanding the environmental changes in the composition and arrangement of landscape elements. Wu (2006) highlights pattern analysis as an important topic, and Fan and Myint (2014) as well as Wang et al. (2020) have conducted research in this field. Furthermore, land surface characteristics are important indicators that influence various ecological processes (Hao et al. 2017). Monitoring land use/cover changes and analyzing landscape patterns have been the focal points of numerous researchers (Gillanders et al. 2008). Changes in land use/cover and landscape patterns can result in diverse ecological, hydrological, and geomorphological effects, as suggested by Boongaling et al. (2018). Many studies have examined the impact of landscape pattern changes on ecological processes and the correlation between these changes and their effects. Examples of such research include Echeverría et al. (2012) and Lausch et al. (2015). Talebi Khiavi and Mostafazadeh (2021) conducted a comprehensive assessment of land use change in a mountainous area using satellite imagery and the degree of single and integrated land use change dynamic. The study revealed a significant decrease in the area of natural lands within the study area. Chen et al. (2014) and Meng et al. (2016) investigated the spatial configuration of the urban thermal environment and its correlation with landscape pattern metrics. Yu et al. (2022) developed a remote sensing index (ELI) to assess urban ecological viability in Wuhan. They used Landsat and MODIS data to evaluate Ecological Livability Quality (ELQ) from 2002 to 2017. The study found a moderate ELQ (ELI = 0.6) with initial deterioration but recent improvement. Ecological viability was better near rivers and lakes, as well as during spring and autumn. Urban forestry mitigated external ecological degradation due to urban expansion. This research highlights the value of remote sensing for managing urban ecosystems and promoting sustainable development. Hao et al. (2022) used RSEI from Landsat-8 data to evaluate ecological restoration in an abandoned mine for sustainable regional development. RSEI effectively assessed management in mining areas with bare

soil. Dispersion management increased regional RSEI by 0.029 initially and 0.051 later, showing the positive impact of comprehensive management. This research underscores remote sensing's potential for informing sustainable regional development through effective ecological management. Kurda (2022) created an urban ecosystem service index for sustainable city planning and well-being. Studying Siljan metropolis affected by mining, the research highlighted the importance of natural ecosystems and green spaces in providing essential services and improving quality of life. Integrating green infrastructure into urban planning was emphasized for sustainable development and enhanced well-being. Li et al. (2023) examined land use and landscape pattern effects on vegetation diversity along urban river corridors. They analyzed various areas and found distinct responses from different plant life forms. Industrial areas influenced vegetation clustering, while native plant habitats correlated with surrounding land use and landscape pattern, which supports incorporating nature-based solutions in urban river planning to protect natural habitats.

As a relevant research studies on the landscape ecological functioning in the the study area, Taleshi and Ghobadi (2012) underscore the importance of assessing land use compatibility in Karaj, specifically in district 4. They advocate for the relocation of incompatible land uses, the provision of adequate urban facilities, and the preservation of green spaces as integral components of sustainable planning. Heydarzadeh and Danehkar (2016) focus on identifying environmental factors and strategies that prioritize the development of urban green spaces in Karaj city, specifically in district 2. Their recommendations include the establishment of parks and the implementation of new green space plans, improvements in water networks, and the empowerment of local communities in the development and maintenance of green spaces. Utilizing GIS software, Abdi et al. (2018) conduct an analysis of maps and data to identify influential characteristics and propose a comprehensive plan for a well-coordinated network of green spaces in Karaj city. Their objective is to achieve ecological balance and enhance the quality of urban green spaces. The literature review underscores the potential of remote sensing techniques in evaluating urban ecological conditions and providing valuable insights for sustainable urban development decision-making. Researchers have employed various remote sensing-based indices to assess ecological viability, and landscape pattern analysis has emerged as a critical research area, emphasizing the influence of landscape patterns on ecological processes. However, an important research gap exists in understanding the relationship between different eco-environment grades and landscape metrics, impeding a comprehensive understanding of how landscape patterns impact ecological processes. Bridging this gap is crucial for enhancing environmental health and suitability, as well as guiding

decision-making in sustainable urban planning and development. Although some studies have explored the effects of landscape pattern changes on ecological processes, further research is needed to investigate the correlation between landscape pattern metrics and specific ecological effects. Addressing this knowledge gap would contribute to a more holistic comprehension of the interaction between landscape patterns and ecosystem dynamics. Consequently, conducting further research in these areas is essential for evidence-based decision-making in sustainable ecosystem management and development. However, remote sensing indicators are limited in predicting the impact of population growth on ecological quality because vital indicators like population dynamics are challenging to assess through remote sensing-based approaches. Hence, there is a need for additional research to explore predicting future ecological changes in urbanized areas.

The city of Karaj, situated adjacent to Tehran, was chosen as the focal point for this research due to its unique characteristics. These include its diverse ethnic and cultural composition, significant capabilities in transportation, agriculture, tourism, natural resources, human capital, and potential environmental threats. Karaj serves as a crucial residential hub, located approximately 48 km away from Iran's political and economic center, Tehran. Its accessibility is facilitated by an extensive network of highways, main roads, a dedicated route, and the Tehran-Karaj subway system, thereby enhancing its prominence. The favorable climatic and topographic conditions of the area have further contributed to its appeal, resulting in population growth and industrial development, particularly along the main Tehran-Karaj-Qazvin Road. Considering these factors, the study area was selected for comprehensive analysis. The research aims to achieve the following objectives: (1) Analyzing spatial-temporal changes in the Risk-Screening Environmental Indicators (RSEI). (2) Evaluating the spatial characteristics of green space distribution patterns based on landscape metrics and RSEI values at both the class and landscape levels. (3) Identifying the relationship between RSEI values and the spatial pattern of landscape metrics.

Study area and methodology

Study area

Karaj County, situated in the Alborz province of Iran, serves as a prominent metropolis within the country. With a population of 2,413,041 individuals, it stands as one of Iran's largest cities in terms of immigrant population. Karaj boasts a considerable number of production and industrial units, which are concentrated in various parts of the city, including designated industrial zones. Notably,

significant industrial development has taken place along the main Tehran-Karaj-Qazvin Road. This road serves as a hub for numerous production and industrial facilities spread across different areas of the city, as well as within industrial towns. Karaj offers a range of tourist attractions, such as the renowned Karaj-Chalous Road, the picturesque Mehrshahr apple orchard, the esteemed Pearl Palace, and the historically significant village of Atashgah. The city's accessibility is enhanced by a well-developed network of highways, main roads, a dedicated route, and the Tehran-Karaj subway system, all of which contribute to its overall significance.

Data preparation and RSEI calculation

For this research, satellite imagery was utilized to conduct the analysis. Landsat 5 TM images captured on July 29, 2010, and Landsat 8 OLI and TIRS images from September 2020 were acquired from the US Geological Survey (USGS) website. It was ensured that the images obtained from different time periods were consistent, thus ensuring the comparability of the results. To prepare the satellite imagery for analysis, radiometric correction was performed using ENVI 5 software (Abdullah et al., 2011). This involved converting the digital number values of the satellite images into sensor reflectivity. Additionally, atmospheric correction was conducted for the visible and near-infrared bands of each phase using the FLAASH atmospheric correction tool (Amorim et al., 2022). To calculate the Risk-Screening Environmental Indicators (RSEI), several indicators were computed as raster layers. These indicators included the Normalized Difference Vegetation Index (NDVI) to represent greenness, Wetness (Wet) to reflect environmental dryness, Land Surface Temperature (LST) as a local temperature change indicator, and Normalized Difference Built-Up Index (NDBI) to highlight human-induced environmental pressures (Amorim et al., 2022; Meng et al. 2016; Xu et al. 2018).

Vegetation mapping and assessment

NDVI is widely employed to indicate vegetation growth and coverage status (Pettorelli et al. 2005), which can be expressed as follows (Eq. 1).

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

Where, ρnir and ρred represent the reflectance of the near-infrared and red bands, respectively.

Retrieval of wetness

Kauth-Thomas transformation can produce three components of humidity, greenness, and brightness, which are commonly used in environmental evaluations. The moisture component can estimate the water content of soil and vegetation. The wetness component of TM and OLI has been obtained using specific formulas (Crist 1985; Baig et al. 2014).

$$Wet_{TM} = 0.0315_{\rho blue} + 0.2021_{\rho green} + 0.3102_{\rho red} + 0.1594_{\rho nir} - 0.6806_{\rho swir1} - 0.6109_{\rho swir2} \tag{2}$$

$$Wet_{OLI} = 0.1511_{\rho blue} + 0.1973_{\rho green} + 0.3283_{\rho red} + 0.3407_{\rho nir} - 0.7117_{\rho swir1} - 0.4559_{\rho swir2} \tag{3}$$

In the formula, ρbule, ρgreen, ρswir1, and ρSwir2 represent the reflectance of the blue band, green band, short-wave infrared band1, and band 2, respectively.

Retrieval of land surface temperature

Land surface temperature (LST) was evaluated as follows (Bertolo et al. 2012; Dadashpoor et al. 2019), (Eq. 4):

$$LST = \frac{T_{sensor}}{\left[1 + \left(\lambda \times T_{sensor}/\rho\right)ln\epsilon\right]} \tag{4}$$

Where, λ is the wavelength of the emitted radiance (11.435 µm for Landsat 5/7 and 10.9 µm for band 10 of Landsat 8); ρ is a constant ($1.438 \times 10-2$ m K); ϵ is the land surface emissivity, which can be expressed as (Marzban et al. 2018; Asadi et al. 2019):

$$\epsilon = \begin{cases} 0.995 & NDVI \leq 0 \\ 0.970 & 0 < NDVI \leq 0.157 \\ 1.0094 + 0.047 \ln NDVI & 0.157 < NDVI \leq 0.727 \\ 0.986 & NDVI > 0.727 \end{cases} \tag{5}$$

Also, T_{sensor} is the at-satellite brightness temperature in Kelvin and can be computed through Eq. (6).

$$T_{sensor} = \frac{K_2}{ln(K_1/L_\lambda+1)} \quad L_\lambda = Gain \times DN \times Bias \tag{6}$$

Lλ is the at-sensor spectral radiance, while Gain and Bias are the band-specific multiplicative rescaling factor and the band-specific additive rescaling factor available in the head file of the used image. DN represents the digital number of a given pixel, and K1 and K2 are calibration coefficients for TM/ETM+/OLI sensor thermal band (Crist 1985; Baig et al. 2014).

Retrieval of normalized difference build up

NDBI in next equation is a normalized difference built-up index which is used to extract built-up area, first it was used for TM data by (Zha et al. 2003).

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \qquad (7)$$

RSEI calculation and classification

In the next step, the remote sensing ecological index (RSEI) was calculated based on integrating the NDVI, Wet, LST, and NDBI, which expressed in Eq. (8).

$$RSEI = 1 - PCI\big[f(NDVI, Wet, LST, NDBSI)\big] \qquad (8)$$

The RSEI is a function of four indices (greenness, wetness, dryness, and heat) that has been extracted from remote sensing data (Guo et al. 2017). NDVI stands for greenness index and is used to determine the environmental condition. The humidity component indicates the severity of the dryness of the environment and the LST indicates the indicators related to the thermal condition of the environment, which is used as an index of local temperature changes. NDBI is an indicator that is used to show the pressures caused by human activities on the environment. The PCA technique is used to determine the weight of each factor based on the assignment of the load of each factor to the main components. In the present research, regarding the four indices used, i.e., NDVI, NDBI, Wet, LST, the first component, (PC1), has justified more than 80% of the characteristics of the data set. Since the units and range of data used in calculating the RSEI index are different, before performing PCA, the values of the four indicators used were normalized between 0 and 1. Following the acquisition of the four index constituents, the RSEI index is derived through principal component transformation. The weight assigned to each indicator is objectively established according to their respective contributions to the initial principal component (PCI). The computation of the principal component is conducted using PCA analysis within ArcGIS spatial analyst tools. In order to facilitate index measurement and comparison, the RSEIpci also needs to be normalized. Elevated RSEI values signify greater ecological resilience; specifically, proximity to unity indicates superior

Table 1 The characteristics of selected landscape metrics in the analysis of the spatial pattern of green spaces in the study area

Variable	Unit	Range	level	Description	Formulas
Contagion Index	None	$0 < COHESION < 100$	Class	Patch cohesion index measures the physical connectedness of the corresponding patch type	$\left[1 - \frac{\sum_{i=0}^{n} P_{ij}}{\sum_{i=0}^{n} P_{ij}\sqrt{a_{ij}}}\right] \times \left[1 - \frac{1}{\sqrt{z}}\right]^{-1} \times 100$
Percentage of Landscape area (PLAND)	%	$0 < PLAND < 100$	Class	Percentage of the area of a particular patch type of total landscape area	$\frac{100}{A} \times \sum_{i=0}^{n} (a_i)$
Edge density (ED)	m/ha	$ED > 0$	Class	Amount of edge relative to the landscape area	$\frac{\sum_{i=0}^{n} e_{ik}^2}{A} 10000$
Largest patch index (LPI)	%	$0 < LPI < 100$	Class	Percent of the total landscape that is made up by the largest patch	$\frac{max\, a_{ij}\,_{j=1}^{n}}{A} \times 100$
patch area (MN)	Km^2	$MPS > 0$	Landscape	Average patch size	$\frac{\sum_{i=0}^{n} (aij)}{n_i} \times \left(\frac{1}{10000}\right)$
Shannon's Diversity Index	None	$SHDI \geq 0$	Landscape	Shannon's diversity index is a popular measure of diversity in community ecology	$-\sum_{i=0}^{n} (P_i \times lnP_i)$
Aggregation Index	%	$0 \leqq AI \leqq 100$	Landscape	Aggregation index is calculated from an adjacency matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side-by-side on the map	$\left[\frac{g_{ij}}{max\, g_{ij}}\right] \times 100$
Contagion Index	%	$0 < CONTAG \leqq 100$	Landscape	Contagion is inversely related to edge density. When edge density is very low, for example, when a single class occupies a very large percentage of the landscape, contagion is high, and vice versa	$1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i \times \frac{g_{ik}}{\sum_{k=1}^{m}(g_{ik})}\right] \times \left[ln\left(P_i \times \frac{g_{ik}}{\sum_{k=1}^{m}(g_{ik})}\right)\right]}{2ln(m)} \times 100$

ecological environment quality. Subsequently, RSEI values were categorized into three equal domains within the range of zero to one (poor = 0-0.33, good = 0.33–0.66, excellent = > 0.66).

Calculation of landscape metrics to determine the composition and configuration of the green spaces

The Fragstats software, known for its user-friendly interface, can be employed to calculate landscape metrics (McGarigal et al. 2012). The latest updated version of this software offers enhanced capabilities, including the support and inclusion of criteria at the cellular scale and surface pattern criteria. Moreover, it provides the flexibility to utilize various sampling methods for subsequent analyses. Given the emphasis of landscape ecology on the interconnectedness of spatial patterns and ecological processes, it becomes crucial to establish techniques for defining and measuring these spatial patterns, as highlighted by Jabbarian Amiri and Dezhkam (2020) and Esfandiyari Darabad et al. (2021). A quantitative assessment of the composition and spatial distribution of landscape elements can be achieved by calculating landscape

metrics. These metrics serve as indices for quantifying specific spatial characteristics of patches, classes, or the overall landscape (McGarigal et al. 2012; Alaei et al. 2022). Selecting the proper metrics is highly depend on the objective of the study, landscape properties and ecological characteristics of an area. Landscape spatial pattern, cover type composition, degree of fragmentation, composition, diversity, and connectivity habitat quality are essential considerations in the selection of appropriate landscape metrics. Therefore, choosing the appropriate criteria from among the many calculation criteria is one of the basic factors in the analysis of the landscape pattern (Gillanders et al. 2008; Chen et al. 2014; Wang et al. 2020). In this research, first, all landscape metrics were calculated, and then those that showed no changes in the two study periods were set aside. Subsequently, based on the research objective, the significance and frequency of use in studies related to environmental quality, relevant landscape metrics related to pattern changes, connectivity, and fragmentation were selected through literature review (Nazarneghad et al. 2020). It should be noted that correlation analysis and principal component analysis were utilized for the selection of landscape metrics. The summary of the selected landscape metrics has been shown in Table 1.
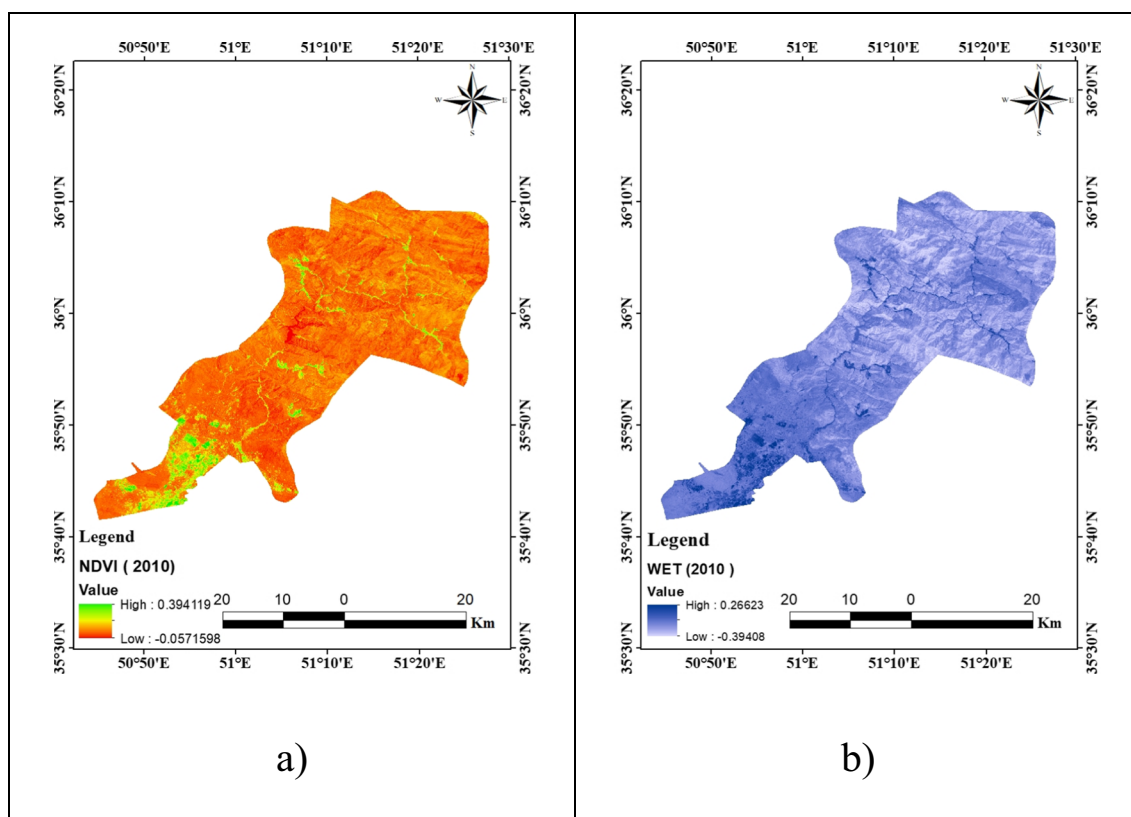
Fig. 1 The map of indices used in the calculation of RSEI in the year 2010, **a** NDVI, and **b** Wet

Results

Analysis of spatio-temporal RSEI changes

The Remote Sensing Ecological Index (RSEI) as a measure of ecological quality, derived by scoring the PC1 of four indices based on their attributes. The results of the calculated indicators used in the calculation of RSEI in 2010 year are presented in Figs. 1 and 2.

Figures 3 and 4 display the outcomes of the computed indicators utilized in the calculation of the RSEI for the year 2020.

Table 2 presents the PCA data for the RSEI of the 2010 Landsat 5 image and the 2020 Landsat 8 image. Notably, PC1 exhibits the highest eigenvalue among the four principal components, accounting for over 70% of the information in both images. This indicates that PC1 effectively represents the four indicators, capturing the majority of their information compared to the other three components. In the PC1 analysis of the 2010 image, Wetness and NDVI demonstrate positive values, indicating a positive contribution to the ecological environment. Conversely, LST and NDBI exhibit negative values, suggesting a negative impact on the ecological quality of the environment.

These findings align with ground observations. Wetness and NDVI exhibit similar behavior, while NDBI and LST share similar characteristics in terms of environmental quality assessment. These two groups display opposite signs, reflecting their contrasting contributions to the ecological quality of the environment, thereby adhering to natural ecological principles. Conversely, the signs of the four criteria in the second to fourth components are not logically categorized like the first component. In the PC1 analysis corresponding to the 2020 image, LST, NDVI, and Wetness values are negative, while NDVI remains positive. However, LST and NDBI consistently belong to the same group for both years, allowing for analysis based on the ecological quality of the study area. The signs of the four indicators in PC2, PC3, and PC4 for both the 2010 and 2020 images do not align.

Figure 5 illustrates the spatial distribution of the RSEI over a 10-years period. The average RSEI value for 2010 was 0.59, whereas it decreased to 0.25 in 2020. This signifies a significant decline in environmental conditions in Karaj during this timeframe. The research findings indicate that the northern region of Karaj exhibited a more favorable eco-environment in 2010 compared to the northwestern, central, and southeastern regions, which experienced
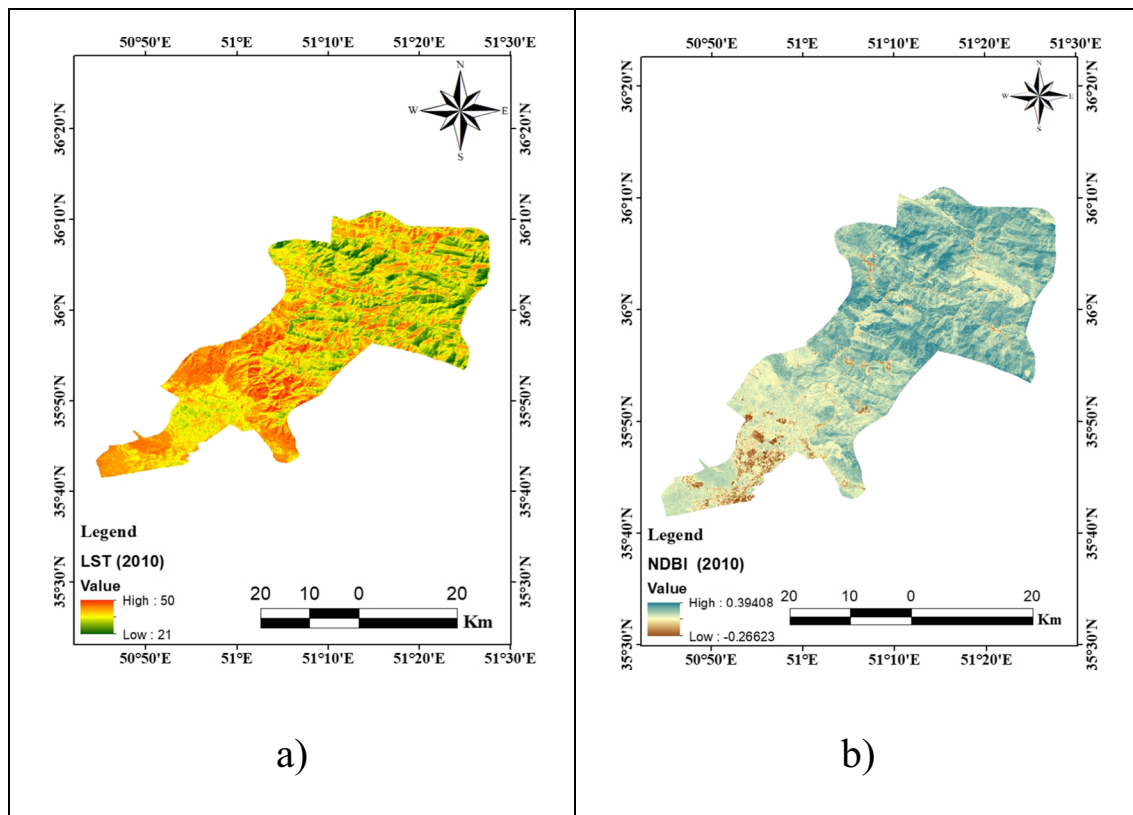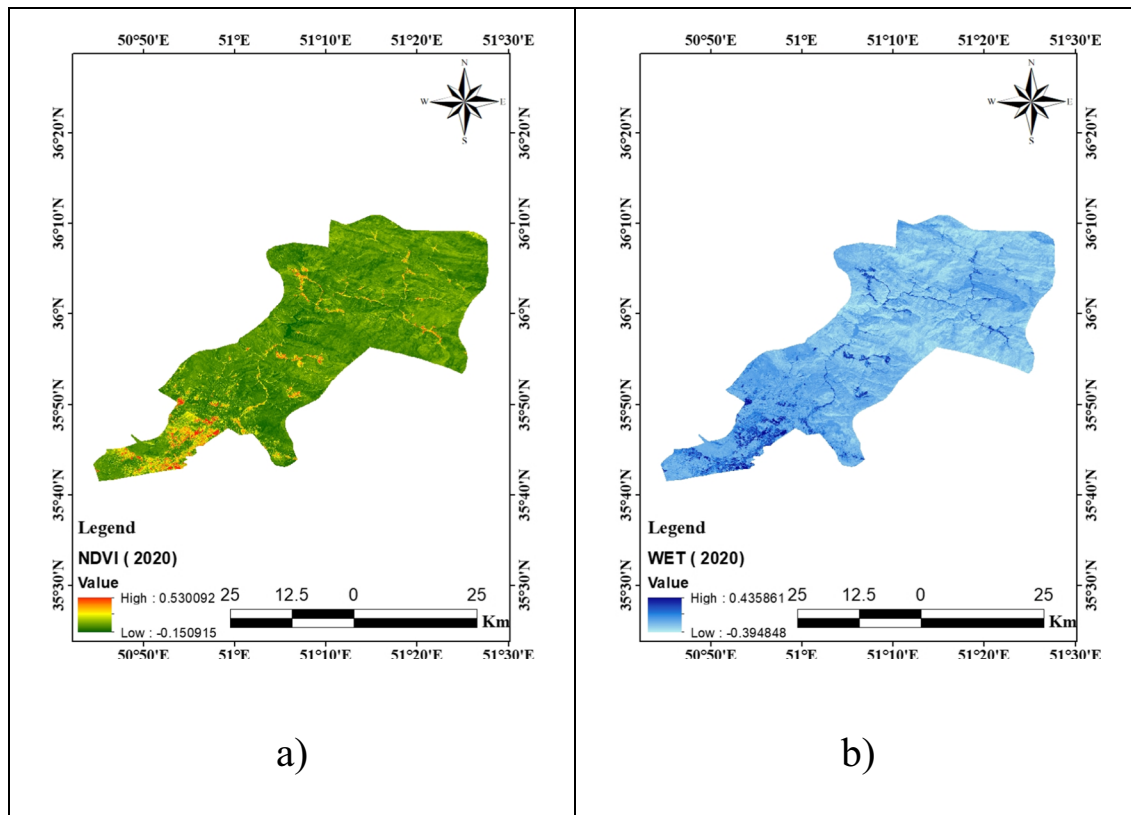

Fig. 2 The map of indices used in the calculation of RSEI in the year 2010, **a** LST, and **b** NDBI

Fig. 3 The map of indices used in the calculation of RSEI in the year 2010, **a** NDVI, and **b** Wet

degradation by 2020. The primary factor contributing to this degradation is the expansion of human settlements and an influx of individuals from other cities seeking employment opportunities in Karaj. Analysis of satellite images and data from the Statistics Center of Iran for both years reveals an increase in population density and heightened human activity, resulting in changes in land use and extensive soil exposure. Consequently, there has been a considerable reduction in the contributions of NDVI and Wetness to the RSEI, whereas the contribution of NDSI has significantly increased when compared to the corresponding data from 2010.

Table 3 shows the statistical results of the three RSEI classes (0 to 0.33, 0.33 to 0.66, and greater than 0.66, which represents poor, good and excellent conditions). The analysis reveals an increase in areas with poor and good environmental quality from 2010 to 2020, indicating a decline in the natural environment quality over this period. The ecological environment in Karaj has undergone significant changes overall. Particularly noteworthy is the substantial reduction in natural quality, which decreased from 55.63% to 2010 to 7.21% in 2020. In light of these findings, it is recommended to incorporate additional indicators to achieve a harmonious development between human activities and the natural environment.

Spatial pattern of landscape change at the class-level metrics in different RSEI conditions

We selected landscape metrics to capture the changes and evolution of the green space landscape metrics and RSEI. Table 4 presents the values of four class-level metrics (PLAND, LPI, AREA_MN, and COHESION), which offer supplementary insights into the class-level characteristics arising from distinct patch arrangements within the landscape, as indicated by the literature. COHESION measures the physical connectivity of the corresponding land type. In both 2010 and 2020, the values of COHESION increase across all three degrees of RSEI. However, this increase in the poor degree suggests landscape fragmentation. Furthermore, the COHESION metric exhibits lower values in the excellent condition compared to the good and poor levels of RSEI, indicating a reduction in the area of excellent-grade land and an increase in the areas classified as poor and good. PLAND examined the percentage of natural green areas within the landscape of the study area. The value of this metric has decreased over the study period, indicating a decline in the NDVI index and a significant deterioration in environmental quality in 2020. Throughout the study period, the index exhibited an increase in the poor class while showing a
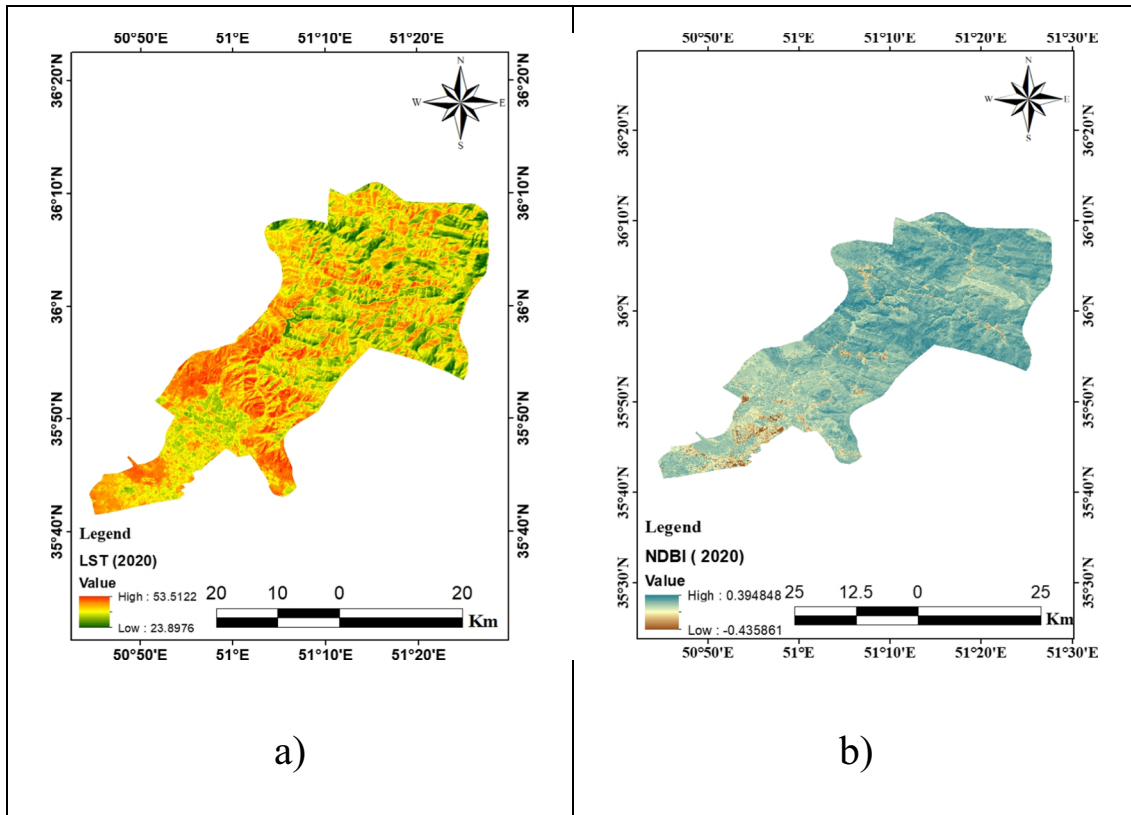
Fig. 4 The map of indices used in the calculation of RSEI in the year 2010, **a** LST, and **b** NDBI

Table 2 Principal components of the four factors used in RSEI calculation

	2010				2020			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
LST	-0.2899	0.6710	0.6769	0.0860	-0.2632	-0.5019	-0.8229	0.0389
NDBI	-0.4256	-0.6257	0.3694	0.5392	-0.6712	-0.2155	-0.3747	0.6021
WET	0.6599	0.1836	0.0079	0.7284	0.08427	0.7793	0.4269	0.4508
NDVI	0.5470	0.3527	0.6365	0.4136	0.6877	0.3070	0.0076	0.6577
Eigenvalue	1.5347	1.1732	0.7398	0.5505	1.5683	1.2675	0.8436	0.3201

decrease in the good and excellent classes, indicating that patches became more scattered in both RSEI classes. The edge density (ED), which represents the proportion of edge length relative to the landscape area, did not undergo significant changes over the period. However, in both 2010 and 2020, the poor class exhibited higher values compared to the good and excellent classes, suggesting that the area covered by the poor class is larger than that of the other classes. Regarding the landscape metric LPI value, it can be said that in the studied period, the size of LPI has decreased, while in the good and excellent classes, a slight increase in the mentioned metric has been observed.

Spatial pattern of landscape change at the landscape-level metrics in different RSEI conditions

In this research, four landscape-level metrics were selected and presented in Table 5 to characterize the landscape. These metrics offer a holistic assessment of the overall structure, function, and changes across the entire area by integrating the characteristics of all patches. Furthermore, they provide insights into fragmentation, connectivity, diversity, and other relevant landscape features. Shannon's Diversity Index (SHDI) was utilized to measure the diversity of Remote Sensing Ecological Index (RSEI) classes. The SHDI
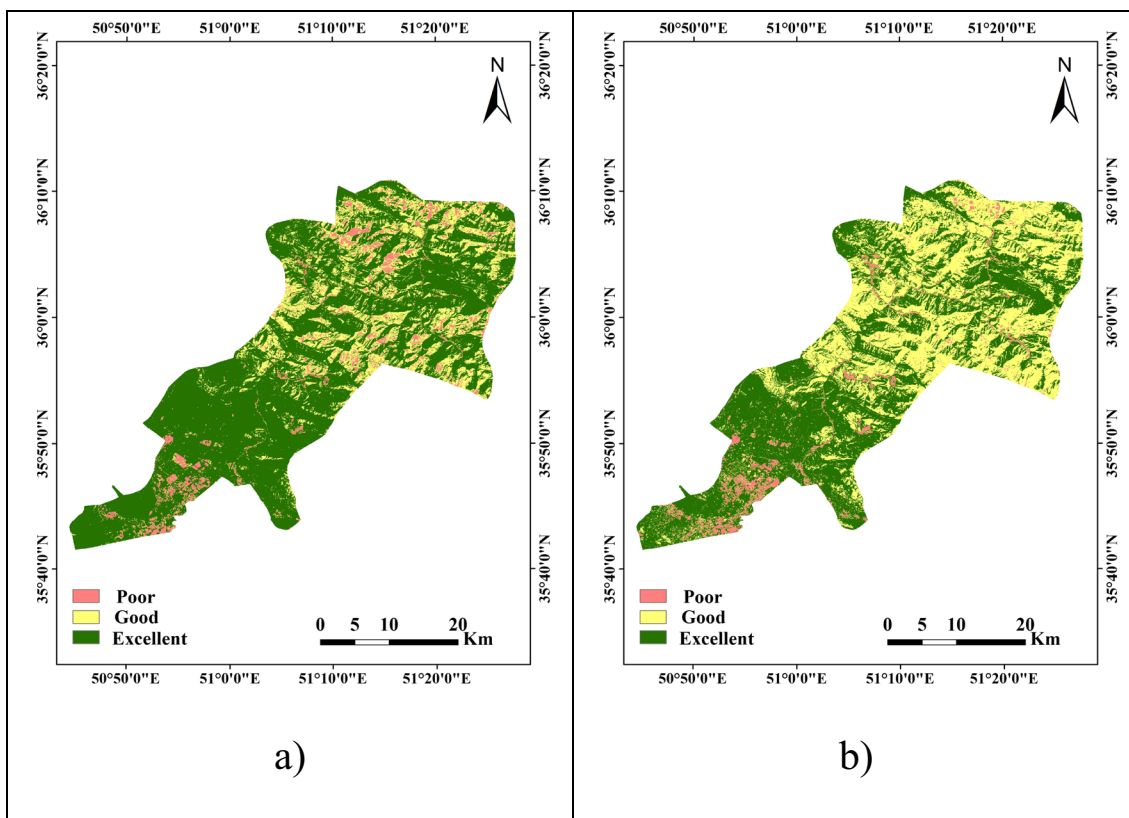
Fig. 5 Spatial distribution of RSEI in the study area, **a** 2010, **b** 2020

Table 3 The difference in total area value of RSEI classes in studied years

	2010		2020	
	Area (km²)	(%)	Area (km²)	(%)
Poor	791.73	35.17	870.70	38.61
Good	208.82	9.20	1221.92	54.18
Excellent	1254.70	55.63	162.59	7.21

Table 4 Average class-level landscape metrics of the green spaces in each RSEI grade in Karaj from 2010 to 2020

Year	Class level	Landscape metrics			
		COHESION	PLAND	ED	LPI
2010	Poor	99.94	96.98	0.091	96.87
	Good	97.04	2.74	0.119	2.74
	Excellent	14.68	0.14	0.032	0.01
2020	Poor	99.96	90.33	0.17	90.31
	Good	98.33	8.84	0.32	8.9
	Excellent	68.76	0.81	0.15	0.20

Table 5 Average landscape level metrics of the green spaces in each RSEI grade 2010 and 2020 in study area

Landscape metric Year	MPS	SHDI	AI	CONTAG
2010	1045.214	0.14	98.86	93.96
2020	619.675	0.34	98.30	80.97

increased to 0.34 in 2015 compared to 2010, indicating that patches became more complex and diverse over time. The contagion index (CONTAG) is inversely correlated with the edge density (ED). A high CONTAG value suggests a dominant single class in the landscape, while a low value indicates greater heterogeneity. From 2010 to 2020, the CONTAG value decreased, implying a reduction in edge density at the class level and an increase in aggregation. The aggregation index quantifies the level of spatial pattern aggregation. Although its value remained consistently high throughout the study period, there were no significant changes observed. The mean patch size (MPS) exhibited

a significant decrease from 2010 to 2020, declining from 1045.2 km2 to 619.6 km2. This indicates a substantial reduction in the average size of patches. Overall, the analysis of landscape metrics demonstrates that the landscape has experienced fragmentation, resulting in a loss of ecological quality over the study period. The changes in the value of AI landscape metric were a slight decreasing during the study period.

The relationship of landscape patterns and RSEI

The analysis in this study focused on examining the relationship between changes in landscape pattern and the corresponding RSEI grade. This investigation was conducted at both the class and landscape levels to gain insights into the correlation between Remote Sensing Ecological Index (RSEI) scores and landscape characteristics. To explore the association between perspective and RSEI, a correlation analysis approach, as described in the cited references, was employed. This approach allowed for a systematic examination of the relationship between different perspectives and the corresponding RSEI values.

Figure 6 presents the correlation between the selected landscape metrics and the average coefficient of determination. The correlation between RSEI and landscape metrics was found to be strongly positive or negative, as supported by the cited sources. The CONTAG metric exhibited a highly robust correlation with RSEI grades. Both CONTAG and AI metrics displayed a strong and positive relationship with the RSEI excellent grade, while demonstrating a strong and negative relationship with the poor and good grades. Conversely, the SHDI and MPS metrics showed a strong and negative relationship with the RSEI excellent grade, but a positive and strong relationship with the poor and RSEI good grades. However, the effects varied. Undoubtedly, a higher diversity in the natural cover of the landscape and larger average size of green space patches would positively influence the environmental quality. The analysis investigating the relationship between landscape-level metrics and RSEI grades revealed predominantly positive or negative correlations between the two.

Conclusions

The current study utilized an approach to directly characterize the regional ecological condition by employing the ecological indicator, RSEI. Subsequently, the research analyzed the spatio-temporal modifications of the Remote Sensing Ecological Index (RSEI) and the diversity in landscape patterns at both the class and landscape levels. The calculation and spatial changes of RSEI in Karaj city demonstrated the possibility of evaluating the ecological quality of the urban area based on environmental conditions. This quantitative approach enables the classification of ecological conditions, and its spatial mapping facilitates the analysis of factors influencing changes in different regions. Moreover, RSEI can be utilized to predict regional ecological changes in various geographical areas. As an innovation, this study quantified the spatial pattern of green spaces using landscape metrics, allowing for a detailed assessment of the changes in the landscape characteristics over the studied period. The assessment of the correlation between landscape metrics and RSEI values provide additional information in the present study. In this study, the relationship between land metrics and RSEI was investigated using correlation analysis. According to Fig. 6, it is evident that the condition in 2010 was superior to that in 2020. In 2010, the excellent grade was assigned to the northern and eastern parts of Karaj city. This allocation was because Karaj city had recently been separated from Tehran province and had become an independent city, with limited growth in the built-up area at that time. However, as the city gradually developed and the population density increased, the natural area decreased. Poorly planned expansion led to negative changes in the area, ultimately resulting in a decline in environmental quality. The analysis of landscape metrics also revealed that RSEI indicators are influenced by these metrics, exhibiting a linear relationship between them. Increased fragmentation and decreased cohesion in the landscape had a detrimental effect on wet and NDVI indexes. The study found that the quality of Karaj's eco-environment had declined over the course of ten years, as indicated by a decrease in the Remote Sensing Ecological Index (RSEI) value from 0.59 to 0.25. Additionally, the research identified a progressive increase in fragmentation, isolation, and irregularity in the landscape characteristics of the Karaj region. Furthermore, it was found that human activities have an escalating impact on regional environmental changes, and varying degrees of RSEI show positive or negative correlations with landscape pattern diversity, providing valuable insights for managing and achieving optimal environmental landscape patterns, as cited. According to the results, improved spatial arrangement can be achieved through the implementation of green-based management strategies. In other words, the development of existing green spaces and the construction of new green spaces should focus on enhancing connectivity and increasing the size of green patches. Regional ecological landscape managers should consider the landscape pattern of the entire region in their management plans. Additionally, the development of urban plans on a regional scale should be aligned with efforts to improve environmental quality and elevate the poor levels of the RSEI index towards the good and excellent classes. The study has limitations in terms of its time frame, which may not capture long-term ecological changes in the region. Although valuable in assessing the spatial pattern of green spaces, the study does not explore the underlying
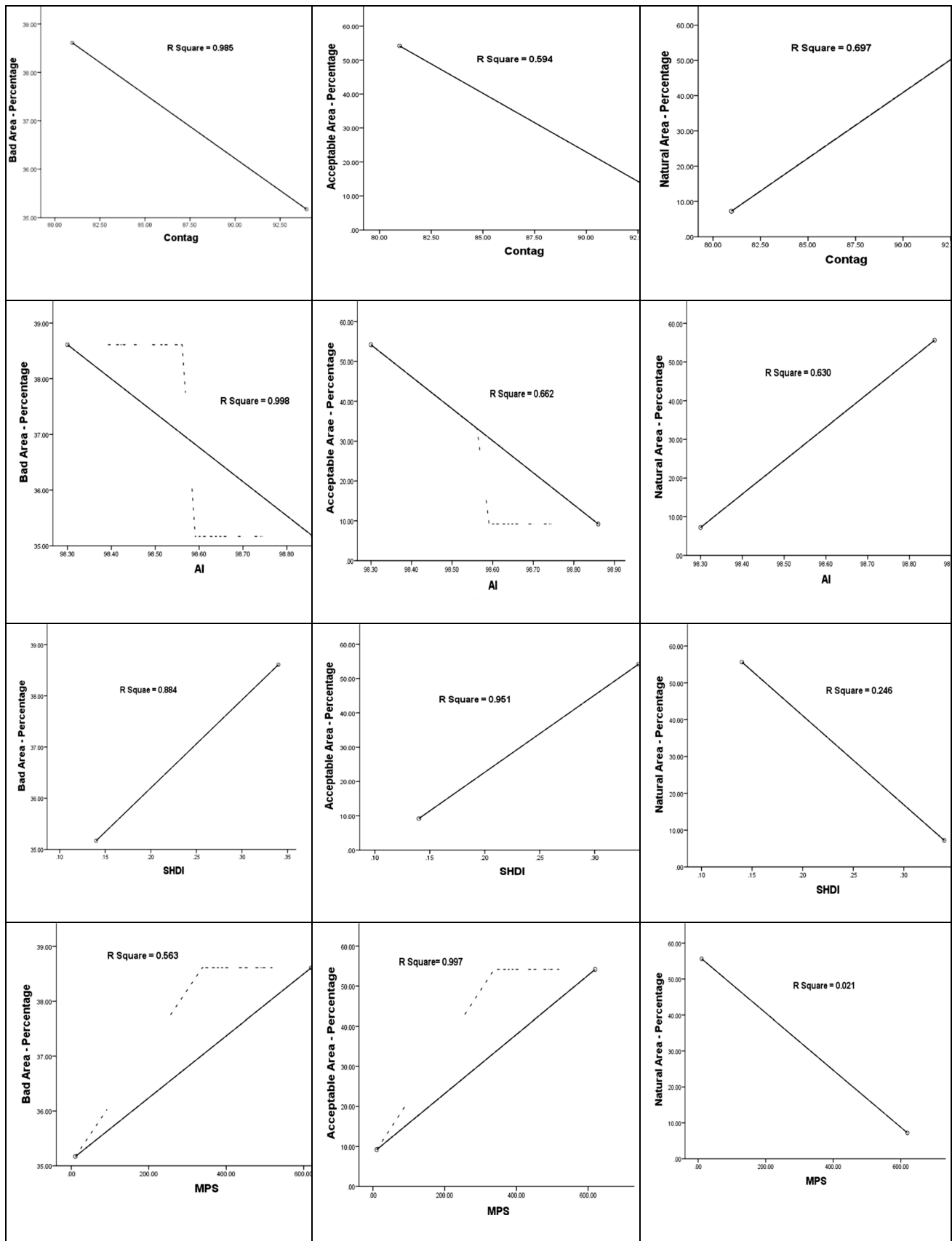
Fig. 6 Relationships between four landscape-level metrics and the area percentage of RSEI grades

causes of these changes, such as urbanization and land-use changes. Additionally, important aspects like biodiversity and specific habitat types are not considered in the assessment of ecological conditions. Future research should conduct a more comprehensive analysis, incorporating a broader temporal scale and multidimensional factors, to gain a deeper understanding of the ecological condition in the study area.

Declarations

Competing interests The authors declare no competing interests.

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