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Evaluation of the environmental quality of semi-arid areas based on improved remote sensing ecological index (case study: Isfahan city, central Iran)

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ABSTRACT

This research was carried out to provide a suitable method to evaluate the environmental quality of semi-arid areas through the amendment of the Remote Sensing Ecological Index (RSEI). To determine the environmental quality of Isfahan City, Landsat images from 2002, 2011, and 2020 were used to extract five indicators of vegetation, humidity, dryness, heat, and salinity. Then, the Improved Remote Sensing Ecological Index (IRSEI) was obtained by Principal Component Analysis (PCA). The findings showed that the inhibiting effect of heat, dryness, and salinity indicators is significantly more than the promoting effect of vegetation and humidity indicators on the environmental quality of the study area. The average values of IRSEI indicated a decrease in the environmental quality of Isfahan City. The area with poor and moderate environmental quality increased from 19372.77 and 14363.46 hectares in 2002 to 16527.51 and 12141.63 hectares in 2020, respectively. Excellent and good qualities were observed mainly throughout the vegetation around the Zayandeh-Rud River. Based on the results of comparing the land use map to IRSEI; Land use changes were identified as one of the main factors in reducing the environmental quality of Isfahan City. Moreover, vegetation increase, climate regulation, and human activities significantly improve the environment, although soil salinization has a negative effect that should not be ignored. It is suggested that factors such as meteorological conditions, biodiversity, airborne particles, and other human activities that may affect the environmental quality in semi-arid regions should be applied in future studies.

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1. Introduction

Nowadays, urbanization phenomenon has led to unprecedented changes of land cover and land use in and around cities (Cahya et al., 2018). This type of unsustainable urbanization not only affects the local environment but also seriously impact the global environment, the carbon cycle and climate change (Salem et al., 2020). Hence, a comprehensive index is required for evaluation of the environmental quality of complex urban ecosystems consisting of various types of land uses including urban areas, hills, agricultural lands, forests and wetlands (Hang et al., 2020). Whereas human activities are amongst undeniable factors affecting the process of urbanization (Xiang et al., 2023).

Environmental quality refers to suitability of the total or partial combination of ecological factors throughout a specific spatial and temporal area for human survival and sustainable socio-economic development (Zhang et al., 2023). Currently, the environment is mainly evaluated using land cover type, vegetation index, ground surface temperature and humidity, water index and other Remote Sensing Ecological Indices (Song et al., 2019). However, the environment is a dynamic and comprehensive system so a single factor is unable to reflect changes of it. Therefore, knowhow to create a comprehensive evaluation index is a vital scientific issue for monitoring the environmental quality.

Xu (2013) proposed Remote Sensing Ecological Index (RSEI) to describe the regional environment by combining four ecological indicators of vegetation, humidity, heat and dryness. Occasionally, adjusting the weight of each indicator is subjected to a certain degree of subjectivity whereas the environmental differences in the region are not taken into account. RSEI provides a new direction to evaluation of the environmental quality. RSEI integrates four ecological indicators of vegetation, humidity, heat and dryness based on remote sensing technology and then uses Principal Component Analysis (PCA) to automatically and objectively determine the weight of each indicator (Ye and Kuang, 2022). In fact, RSEI has been widely used in various land cover evaluation studies. Yang and Su (2023) evaluated the environmental quality in Xi'an, China for 2000, 2005, 2010, 2015 and 2020 using RSEI whereas the value of RSEI were 0.665, 0.653, 0.623, 0.644 and 0.651, respectively. Yang et al. (2022) investigated the environmental quality of the Yellow River basin using RSEI. During the last 30 years, the environmental quality in this basin improved and this improvement can be divided into two periods: fast improvement (1990-2000) and slow improvement (2000-2020). However, the initial development of RSEI focused on the assessment of various types of ecological conditions that may not fulfill the necessities for monitoring the environmental quality of arid and semi-arid regions. Arid environments have distinctive features such as limited rainfall, drought, little vegetation, significant temperature fluctuations, expansion of soil salinity and irrational use of water resources (Chen et al., 2023). As the third most populous City in Iran and an important tourism hub, Isfahan joined the UNESCO Creative Cities network in 2015 (Karbalaei Saleh et al., 2021). Many changes and intensive development in recent years, the geographical location and different ecological conditions of this City compared to the Cities in previous studies, have made this study somehow different. In addition, the international importance of Isfahan as a cultural heritage increases the importance of examining its ecological quality. Isfahan City is located in a semi-arid region and is exposed to challenges such as soil salinity. The results of researches (Fathi and Rezaei, 2013; Habashi et al., 2017; Jahanbazi et al., 2024) showed that in recent years, a large part of Isfahan City with dense vegetation has turned into low-density vegetation and saline lands. Soil salinity is one of the main forms of land degradation in arid and semi-arid regions, and its occurrence and evolution are complex dynamic processes that include multiple factors such as climate, hydrology, raw materials, and vegetation (Khajehzadeh et al., 2022). Soil salinity directly and indirectly affects agricultural production and resources sustainability and environmental development. Proper assessment and prevention of soil salinization is crucial for improving agricultural production and sustainable regional development (Hou and Rusuli, 2022). It is of great importance to include the salinity indicator in the theoretical framework of RSEI and propose an IRSEI model. This study aims to transform the primary RSEI into IRSEI which considers human activities.

2. Material and Methods

2.1. Study area

Isfahan City is expanded between N32°33′30″ to N32°44′30″ latitude and E51°31′30″ to E51°52′30″ longitude located in central Iran (Fig. 1) with the Zayandeh-Rud River flowing west to east throughout the middle of the city. The altitude of the study area ranges from 1550m at the eastern vicinity of the river to 2232m at the mount Sofeh in the south. The climate of the region is semi-arid having average annual temperature of 16.2°C and average annual rainfall of 121.1mm (Shirani-bidabadi et al., 2019). Isfahan is the third largest Iranian City with an area of 550.247Km^2 continuing to expand due to constructional activities and intensive land use changes during the recent years because of its unprecedented population growth.

2.2. Land use map

Depending on the quality of Landsat satellite images, maximum vegetation and lack of cloud cover across the study area; Landsat 5 satellite images for 2002 and 2011 and Landsat 8 satellite images for 2020 were selected from the US Geology website (https://earthexplorer.usgs.gov). The characteristics of the satellite images applied are presented in Table 1.

The mapping of land use was monitored by the classification method using the maximum likelihood algorithm in ENVI5.3 software. The study considered five land uses including built-up area, bare land, agricultural land, water body and vegetation. The accuracy of the classification was determined through the error matrix and statistical parameters as overall accuracy and kappa coefficient (Table 2). Finally, land use maps were extracted in the Arc GIS10.6.1 software for the years targeted.

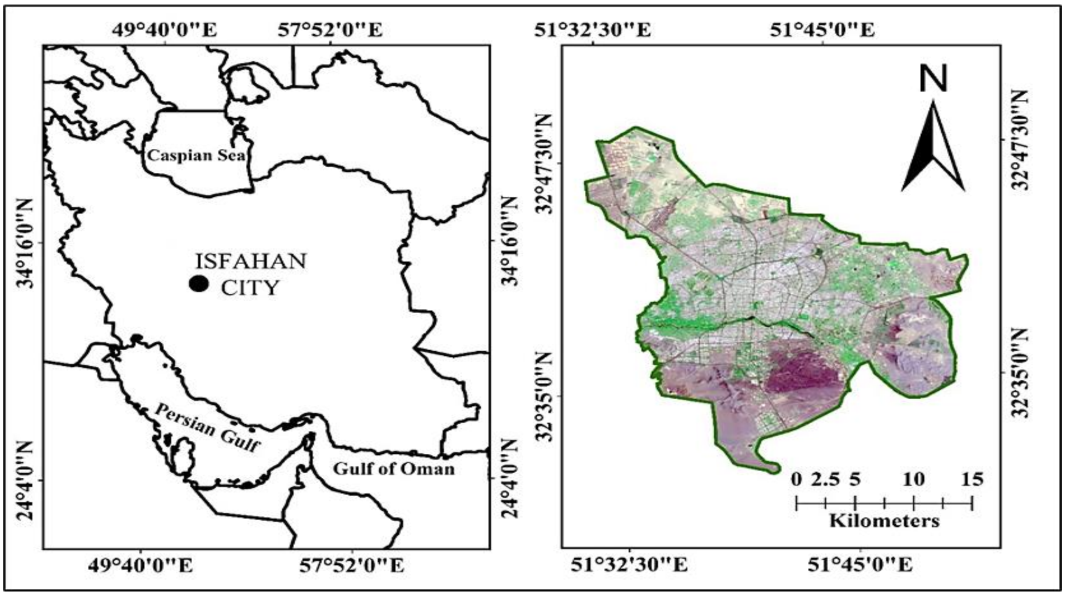


Fig. 1. Location of the Isfahan City in central Iran (left) Landsat 8 satellite image of Isfahan City (right).

Table 1. Characteristics of satellite images applied in this study

Satellite	Sensor	Spatial Resolution (m)	Imaging Date	Path	Row
Landsat5	TM	30	2002/07/06	37	164
Landsat5	TM	30	2011/07/09	37	164
Landsat8	OLI	30	2020/07/01	37	164

Table 2. Kappa coefficient and overall accuracy resulting from the classification

Classification Type	Year	Kappa Coefficient	Overall Accuracy
	2002	0.92	89.76
Maximum likelihood algorithm	2011	0.94	90.91
	2020	0.96	92.84

2.3. Improved remote sensing ecological index

The environmental quality assessment method proposed in this study is based on remote sensing techniques. The environmental quality in semi-arid areas, as a comprehensive qualitative assessment, is shown through five Remote Sensing Ecological Indicators. These indicators include vegetation, humidity, dryness, heat and soil salinity.

2.3.1. Normalized difference vegetation index

In the framework of IRSEI; vegetation index is an important indicator of the environmental quality. Normalized Difference Vegetation Index (NDVI) was used to describe vegetation of the study area. Vegetation, as a vital component of ecosystems, plays an essential role in the earth's carbon cycle and climate dynamics. The range of this indicator varies between -1 and +1. Values closer to +1 indicate areas with thicker vegetation, while values closer to -1 indicate areas with higher quality vegetation (Karbalaei Saleh et al., 2021). Eq. 1 was applied to calculate NDVI.

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}) \quad (1)$$

Where ρ_{NIR} is the near infrared band and ρ_{Red} is the red band.

2.3.2. Land surface moisture index

Due to the direct relationship between conversion of the components of the tasseled cap such as brightness, humidity and vegetation with the characteristics of the surface of the land the Land Surface Moisture (LSM) index is usually used to determine the environmental quality (Zawadzki et al., 2016). The LSM index for Landsat 5 (TM) and Landsat 8 (OLI) was calculated using Eqs. 2 and 3, respectively:

$$LSM_{TM} = 0.03151\rho_{Blue} + 0.2021\rho_{Green} + 0.3102\rho_{Red} + 0.1594\rho_{NIR} - 0.6806\rho_{SWIR1} - 0.6109\rho_{SWIR2} \quad (2)$$

$$LSM_{OLI} = 0.1511\rho_{Blue} + 0.1973\rho_{Green} + 0.3283\rho_{Red} + 0.3407\rho_{NIR} - 0.7117\rho_{SWIR1} - 0.4559\rho_{SWIR2} \quad (3)$$

Where ρ_{Blue} is the blue band, ρ_{Green} the green band, ρ_{Red} the red band, ρ_{NIR} the near infrared band, ρ_{SWIR1} the first mid-infrared band and ρ_{SWIR2} the second mid-infrared band.

2.3.3. Normalized Differential Build-up and Bar Soil Index

The dryness index was determined using a combination approach of building and bare soil indices due to the existence of human settlements and construction areas in the study area, as well as the existence of bare soil (Eq. 4). Into some extend; these two indicators can reflect the state of soil health, the phenomenon of soil drying, and as a result the environmental quality and its deviations. The dryness index or Normalized Differential Build-up and Bar Soil Index (NDBSI) is the average of the bare soil index (Eq. 5) and the index of built-up area (Eq. 6) quantities (Xu, 2010):

$$NDBSI = (IBI + BI)/2 \quad (4)$$

$$BI = [(\rho_{SWIR1} + \rho_{Red}) - (\rho_{NIR} + \rho_{Blue})]/[(\rho_{SWIR1} + \rho_{Red}) + (\rho_{NIR} + \rho_{Blue})] \quad (5)$$

$$IBI = \frac{\{2\rho_{SWIR1}/(\rho_{SWIR1} + \rho_{NIR}) - [\rho_{NIR}/(\rho_{NIR} + \rho_{Red}) + [\rho_{Green}/\rho_{Green} + \rho_{SWIR1})]\}}{\{2\rho_{SWIR1}/(\rho_{SWIR1} + \rho_{NIR}) + [\rho_{NIR}/(\rho_{NIR} + \rho_{Red}) + [\rho_{Green}/\rho_{Green} + \rho_{SWIR1})]\}} \quad (6)$$

Where IBI and BI are the Index of Build-up Area and the Bare Soil Index, respectively. Also, ρ_{Blue} indicates the blue band, ρ_{Green} the green band, ρ_{Red} the red band, ρ_{NIR} the near infrared band and $\rho_{SWIR1}$the first mid-infrared band.

2.3.4. Land Surface Temperature Index

The land surface temperature is mainly influenced by the surface emissivity, which is dependent on the NDVI index. Hence, the NDVI-based emissivity method was used to extract LST from Landsat TM band 5 and Landsat OLI band 10. For the Landsat thermal band, 5 numbers of each pixel were converted to spectral radiance using Eq. 7 (Zhou et al., 2014):

$$L_\lambda = \frac{L_{max\lambda} - L_{min\lambda}}{QCal_{max} - QCal_{min}} \times (QCal - QCal_{min}) + L_{min} \quad (7)$$

Where L_λ is the top atmospheric radiance (W/m2sr/µm), $L_{max\lambda}$ is the related spectrum radiance to $QCal_{max}$ and $L_{min\lambda}$ is the related spectrum radiance to $QCal_{min}$, $QCal_{max}$ is the maximum quantum calibrated pixel value, $QCal_{min}$ is the minimum quantum calibrated pixel value and QCal is the quantum calibrated pixel value. Eq. 8 was applied to calculate the top atmospheric radiance for Landsat 8 (Barsi et al., 2014):

$$L_\lambda = M_L \times Q_{Cal} + A_L \quad (8)$$

Where L_λ represents the top atmospheric radiance (W/m2sr/µm), M_L is the multiple scaling factor for a band, Q_{Cal} is the quantum calibrated pixel value and A_L is the collective scaling factor for a given band. The brightness temperature was obtained using Eq. 9 (Giannini et al., 2015):

$$T_B = \frac{K_2}{\ln\left[\frac{K_1}{L_\lambda} + 1\right]} - 273.15 \quad (9)$$

Where K_1 and K_2 are the calibration constants that can be obtained from the metadata file belong to the image and 273.15 to convert the brightness temperature from Kelvin to Celsius. Vegetation ratio was calculated using Eq. 10:

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad (10)$$

To calculate land surface emissivity in Landsat 5 and 8 satellites, Eqs. 11 and 12 were used, respectively:

$$\varepsilon = \begin{cases} \varepsilon_w = 0.985 & NDVI \leq 0 \\ \varepsilon_s = 0.97 & 0 < NDVI < 0.2 \\ 0.004 \times P_v + 0.986 & 0.2 \leq NDVI \leq 0.5 \\ \varepsilon_v = 0.99 & NDVI > 0.5 \end{cases} \quad (11)$$

$$\varepsilon = \begin{cases} \varepsilon_w = 0.991 & NDVI \leq 0 \\ \varepsilon_s = 0.966 & 0 < NDVI < 0.2 \\ \varepsilon_v P_v + \varepsilon_s (1 - P_v) + C_\lambda & 0.2 \leq NDVI \leq 0.5 \\ \varepsilon_v = 0.973 & NDVI > 0.5 \end{cases} \quad (12)$$

Where ε_s, ε_v and ε_w are the emissivity of soil, vegetation and water body, respectively, and C_λ is the height and depression of the surface, which is considered equal to zero on a flat surface. Eq. 13 was used to convert the brightness temperature to the land surface temperature:

$$LST = \frac{T_B}{1 + \left[\frac{\lambda * T_B}{\rho}\right] * \ln(\varepsilon)} \quad (13)$$

Where λ is the wavelength of emitted radiation, ρ is obtained through the equation $\rho = h \times c/b$ whereas h is Planck constant, c is the speed of light, and b is Boltzmann constant (Orhan and Yakar, 2016).

2.3.5. Normalized differential salinity index

Considering that soil salinity can have a significant relationship to drought and that the red and near-infrared spectral bands show specific reactions to soil salinity; Soil salinity information can be estimated through remote sensing techniques based on Eq. 14 (Azabdaftari and Sunar, 2016):

$$NDSI = (\rho_{Red} - \rho_{NIR})/(\rho_{Red} + \rho_{NIR}) \quad (14)$$

Where NDSI is Normalized Differential Salinity Index ρ_{NIR} is the near infrared band and ρ_{Red} is the red band.

In order to determine the relative importance of variables and produce an IRSEI map following calculation of the indicators; principal component analysis was used in the ArcGIS software. Principal component analysis by compressing multidimensional data can help eliminate the effect of collinearity between variables (Mishra et al., 2017). Since the range of values is different for various indicators; all indicators should be normalized before applying principal component analysis so that the number range fluctuates between 0 and 1 (Jolliffe and Cadima, 2016). Normalization of indices carried out using Terrset2020 software. The IRSEI values were classified into five classes with 0.2 intervals named with descriptions: very poor, poor, moderate, good and excellent to show the environmental quality of Isfahan City in more details. In order to extract the IRSEI index; the first component of PCA was applied which has the highest percentage of changes (Eq. 15):

$$IRSEI_0 = PC1[f(NDVI; LSM; NDBSI; LST; NDSI)] \quad (15)$$

In cases where the map of positive indicators (vegetation and Land surface moisture) in the first component is negative; the IRSEI index is modified using equation (16) so that higher values indicate a better environmental condition (Hu and Xu, 2018):

$$IRSEI = 1 - IRSEI_0 = 1 - PC1[f(NDVI; LSM; NDBSI; LST; NDSI)] \quad (16)$$

Pearson's correlation test was used to quantitatively analyze the relation between IRSEI and Remote Sensing Ecological Indicators. Pearson's correlation, which varies between +1 and -1, is a classic approach for calculating correlation coefficients and is primarily used to describe linear correlations and works with the assumption that the two variables in question are normally distributed and have a non-zero standard deviation.

2.3.6. IRSEI Accuracy Assessment

The accuracy and reliability of the IRSEI index were qualitatively evaluated using an image comparison approach (Philip et al., 2024). Three land use change events occurring in vegetation, built-up areas and bare lands were used for validation. In order to further validate the results of IRSEI, a total of 150,000 random sample points were extracted for each index and processed for correlation analysis.

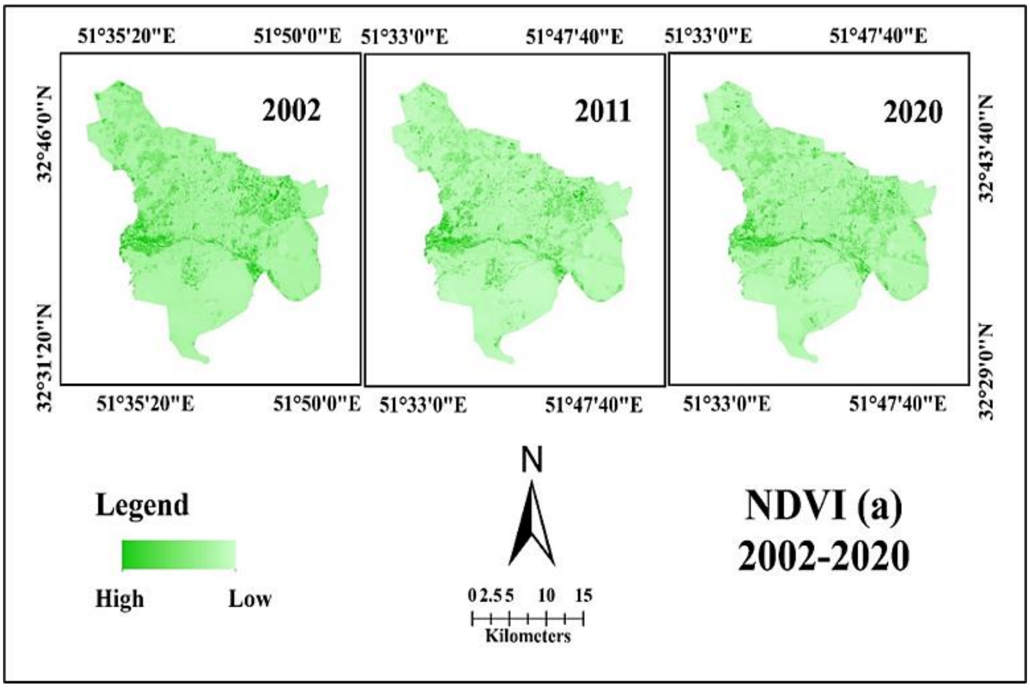
3. Results and discussion

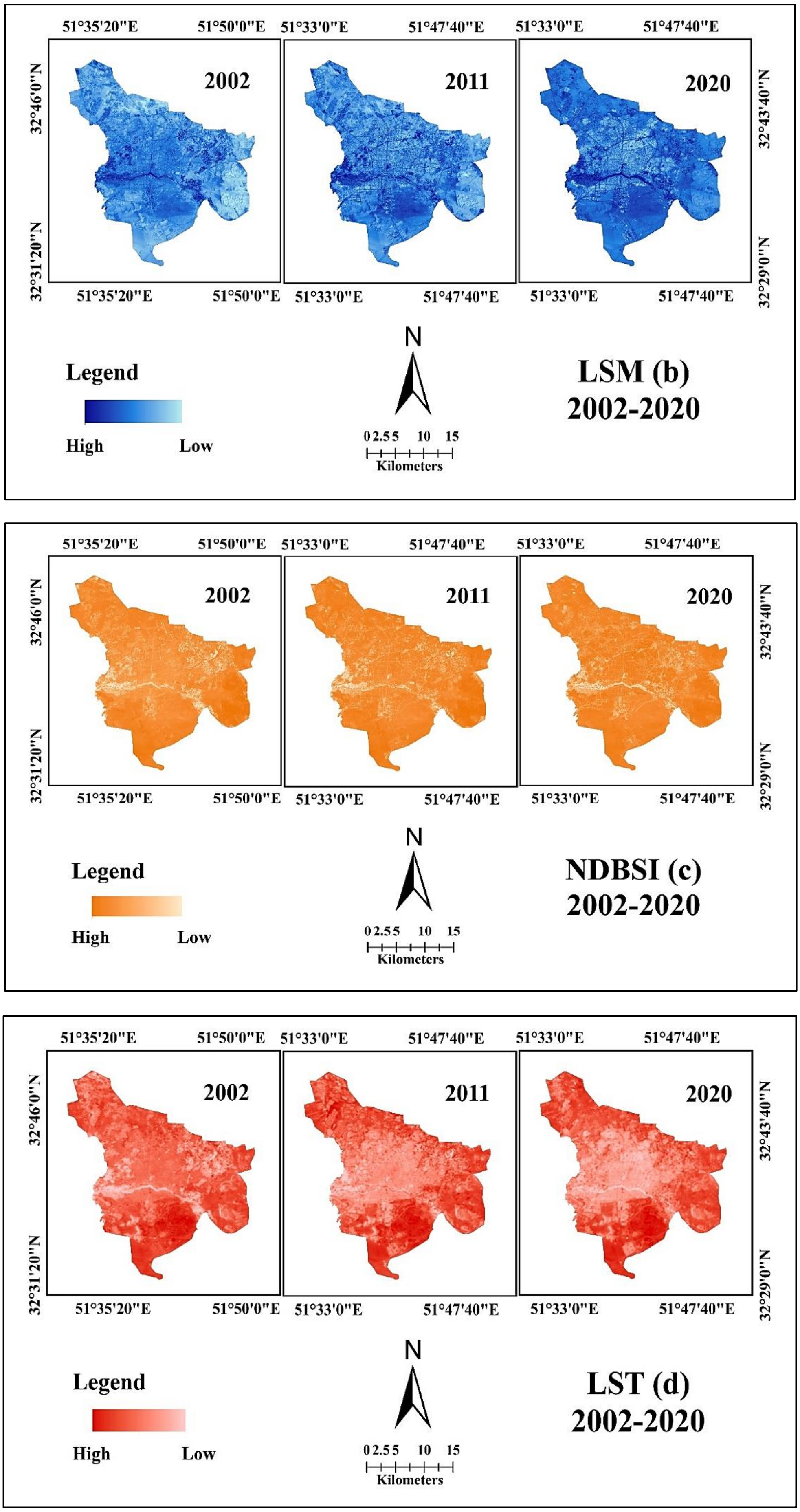
3.1. Spatial and temporal changes in the environmental quality

The mean values and standard deviation of the ecological indices during the 18 years period studied are presented in table 3 emphasizing on that the vegetation index (NDVI) and the humidity index (LSM) have similar trends as they have increased from 0.38 to 0.46 and from 0.65 to 0.76, respectively, during 2002-2020 when the NDVI index in Isfahan City has been relatively favorable (Fig. 2).

Although there was some decrease in 2011; the vegetation index remained relatively high during the study period. This confirms that the vegetation in the studied area has maintained a positive status for a long period of time. The LSM index shows a relatively stable performance and indicates that the vegetation has preserved satisfactory levels of humidity. Heat index (LST) and dryness index (NDBSI) have been on the rise and elevated from 0.82 to 0.88 and from 0.58 to 0.67, respectively, while the salinity index (NDSI) has had a downward trend from 0.61 to 0.53 (Table 3) during 2002 to 2020. The NDBSI index reflects some changes for the studied period duration as it had a low value in 2002 but has increased in 2020. From the theoretical point of view; NDBSI has a negative effect on ecosystems. But the comprehensive reflection of the IRSEI index can only be determined through an integrated analysis in connection with other ecological indicators (Wang et al., 2024). In fact, the drought reduction mainly was observed in the areas that the vegetation index increased confirming its opposite trend compared to the vegetation index. The LST index decreased around Zayandeh-Roud river and patches of land with vegetation, but it increased in the areas under construction and barren lands. Dry areas (bare lands) in Isfahan city experienced a significant NDSI index (Fig. 2).

It is worth mentioning that there is little vegetation and topographic diversity, which facilitate the accumulation of salt and leads to a high degree of soil salinity (Hou and Rusuli, 2022). Previous studies showed that vegetation indices (NDVI) and humidity (LSM) have a positive effect while the dryness indices (NDBSI), heat (LST) and salinity (NDSI) have a negative effect on the quality of the environment since vegetation and humidity are directly related to vegetation but dryness and soil salinity are more related to the heat of the earth (Karbalaei Saleh et al., 2021; Shan et al., 2019; Xu, 2013).

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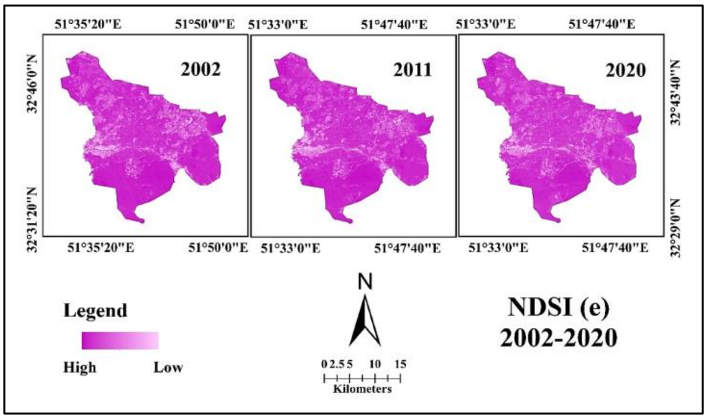

Fig. 2. Map of NDVI (a), LSM (b), NDBSI (c), LST (d), and NDSI (e) indices in 2002, 2011 and 2020.

Table 3. Mean and standard deviation of Remote Sensing Ecological Indicators (2002, 2011 and 2020).

Year	Index	NDVI	LSM	NDBSI	LST	NDSI
2002	Mean	0.38	0.65	0.58	0.82	0.61
	Standard deviation	0.10	0.07	0.08	0.04	0.10
2011	Mean	0.33	0.66	0.62	0.87	0.66
	Standard deviation	0.11	0.08	0.09	0.05	0.11
2020	Mean	0.46	0.76	0.67	0.88	0.53
	Standard deviation	0.08	0.05	0.10	0.05	0.08

As shown in Table 4, in the First Principal Component (PC1), NDVI and LSM values were negative and NDBSI, LST and NDSI values remained positive during the 18 years period of this study. The specific values of PC1 in 2002, 2011 and 2020 were 76.23, 72.34 and 68.47%, respectively. Meanwhile, the share of PC1 has exceeded 68%. PC1 has collected most of the information of all five indicators and this corresponds to the actual situation of the studied area. As a result; the produced IRSEI properly shows the changes of the environmental quality of Isfahan city. The mean and standard deviation of IRSEI for the study area confirm that the overall value of IRSEI is not favorable (Table 5). Significant stability in standard deviation values was obtained during 18 years of the studied period as the average value of IRSEI reached its peak in 2002, while the lowest value was seen in 2020. This shows that the environmental quality of the Isfahan city experienced a downward trend from 2002 to 2020, which could be due to the increase of construction and heat. Li et al. (2021) evaluated the quality of the urban environment and spatial heterogeneity in the City of Wuhan, and their results indicated that from 1995 to 2015, the average IRSEI of the City of Wuhan decreased from 0.60 to 0.47 and worsened. The environment has overwhelmed the improvements. For further analyze of the differences in the spatial distribution of the IRSEI results; they were divided into five categories including very poor, poor, moderate, good and excellent with a distance of 0.2. Figure 3 clearly illustrates that the numerical changes and the distribution of IRSEI classes in Isfahan city were different during 2002-2020.

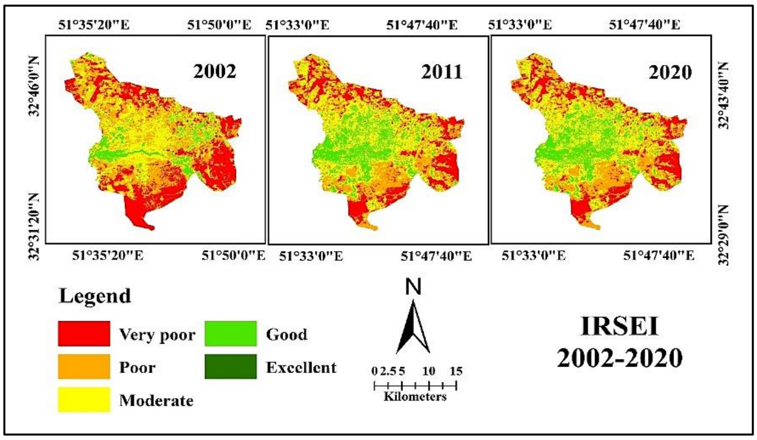

Fig. 3. IRSEI classification map of Isfahan City (2002, 2011, and 2020).

This variety can be attributed to the different effects of various ecological indicators in each year. The classification of IRSEI results in the studied years is presented in table 6. The IRSEI of Isfahan city with very poor environmental quality first decreased and then increased, which confirmed the overall decreasing trend from 16512.66 hectares in 2002 to 12302.73 hectares in 2020. The area with poor and moderate environmental quality increased from 19372.77 and 14363.46 hectares in 2002 to 16527.51 and 12141.63 hectares in 2020, respectively.

In the City of Isfahan; the area with good environmental quality was 14024.70 hectares in 2020, which showed an increase of 9277.02 hectares compared to 2002. In addition, the area transferred to excellent environmental quality was almost unchanged during the studied years. However, areas with poor and moderate environmental quality were still found in the study area most of them exposed to frequent human activities especially construction.

The results of IRSEI within the scope of this study showed that this index has the ability to evaluate the environmental quality in semi-arid areas. Wang et al. (2021) presented a drought remote sensing index for environmental quality monitoring in the Aral Lake Basin in Central Asia using the combination of land degradation indicators. Bai et al. (2021) also proposed an advanced ecological index for remote sensing applications in arid regions by integrating desertification and salinity indices. These studies approved that the improved remote sensing ecological index (IRSEI) is more applicable in arid regions. Researchers tend to suggest improvements for the RSEI index based on practical necessities to meet the actual needs of its practical use.

Table 4. Contribution of five indicators in the First Principal Component (PC1).

Index/PC1	2002	2011	2020
NDVI	-0.473	-0.496	-0.517
LSM	-0.393	-0.385	-0.374
NDBSI	0.491	0.512	0.525
LST	0.395	0.315	0.218
NDSI	0.473	0.496	0.517
Eigenvalue (%)	76.23	72.34	68.47

Table 5. Changes in mean and standard deviation of IRSEI.

Year	2002	2011	2020
Mean	0.32	0.21	0.11
Standard deviation	0.05	0.04	0.05

Table 6. Classification of Isfahan City during the studied period of 2002-2020 based on IRSEI.

Year	Area	Very poor	Poor	Moderate	Good	Excellent
2002	ha	16512.66	19372.77	14363.46	4747.68	27.54
	%	30.00	35.20	26.10	8.62	0.05
2011	ha	10481.76	17416.44	16647.39	10450.89	27.63
	%	19.04	31.65	30.25	18.99	0.05
2020	ha	12302.73	16527.51	12141.63	14024.70	27.54
	%	22.35	30.03	22.06	25.48	0.05

3.2. Correlation Between IRSEI and RSEI

In order to ensure the quality of data; a correlation analysis was performed for NDVI, LSM, NDBSI, LST and NDSI indices with IRSEI (Table 7). The results of the analysis showed a positive correlation between the indices of greenery and humidity and IRSEI and a negative correlation between the indices of dryness, heat and salinity and IRSEI. These results are compatible with the effects of environmental factors and help to validate the integrity of data quality. Wang et al. (2024) found that the correlation coefficients between ecological indicators and IRSEI followed a recognizable pattern. In their research a positive correlation was observed between NDVI and LSM with IRSEI, but a negative correlation was observed between NDBSI, LST and Integrated Salinity Index (ISI) with IRSEI. It is worth mentioning that ecological indicators for 2002 showed the strongest average correlation with IRSEI, which reached 0.820. This is while relatively high average correlation values were observed in other years as well. The values of five indicators in different years also maintained high levels, and the highest correlation coefficient during the 18 years of the period studied was related to LST (0.985) and NDBSI (0.946), respectively. These findings show that heat and drought have a significant effect on the quality of ecosystems, while other indicators such as vegetation, humidity and salinity are similarly related to the environmental quality. Jing et al. (2020) obtained the negative correlations of RSEI to dryness and heat indices as 0.821 and 0.800, respectively.

Table 7. Correlation analysis between IRSEI and Remote Sensing Ecological Indicators.

Year	NDVI	LSM	NDBSI	LST	NDSI	Average Correlation
2002	0.732	0.835	-0.946	-0.856	-0.732	0.820
2011	0.440	0.569	-0.626	-0.914	-0.440	0.598
2020	0.256	0.370	-0.279	-0.985	-0.265	0.433
Mean value	0.476	0.591	-0.617	-0.918	-0.479	-

3.3. Comparison of land use map with RSEI

Different land uses often show distinct ecological characteristics; and a meaningful and accurate environmental quality assessment must be aligned with the specific characteristics of these land uses. For the studied area; five classes were considered including built-up areas, bare lands, agricultural lands, water and vegetation (Fig. 4). The land use pattern of Isfahan city for 2001, 2011 and 2021 was combined with the distribution pattern of ecological indicators to investigate the relationship between land use types and environmental quality. The results showed that the types of land use and the values of ecological indicators have good compatibility in different years. In fact, the most decreasing trend is related to agricultural lands as their area in 2020 decreased by 4.25% compared to 2002 (Table 8).

In agricultural lands, factors such as land degradation, irrigation, fertilization, and artificial planting may lead to salinity changes in them, resulting in a decrease in environmental quality. The average NDVI index that represents vegetation in 2002, 2011 and 2020 was 0.38, 0.33 and 0.46 respectively. There was a direct relationship between the percentage of vegetation and agricultural land in some years of the studied period with the NDVI index. The average values of IRSEI in the category of vegetation shows a decreasing trend from 0.38 in 2002 to 0.33 in 2011 and has slightly increased to 0.46 in 2020. Vegetation areas that tend to have a lower IRSEI value show a decreasing trend of environmental quality.

According to Lin et al. (2020); the decreasing trend of environmental quality in the coastal City of Pingtan in China is mainly related to the decrease of vegetation and cultivated lands. The average NDBSI index in the City of Isfahan showed that human activities in 2002, 2011 and 2020 were 0.58, 0.62 and 0.67, respectively, and there is a direct relationship between this index and the constructed area. On the other hand, the constructed area has an inverse relationship to the environmental quality as its changes from 2002 to 2020 were about 5.64%. Zhu et al. (2020) also introduced land use changes as the main cause of deterioration of the environmental quality of Zhengzhou City in China due to urban area expansion. The lowest environmental quality in the studied area is related to barren lands. NDSI values for 2002, 2011 and 2020 were 0.61, 0.66 and 0.53 respectively. In the current study, barren lands showed a direct relationship with the NDSI index during the study period, so that both had a decreasing trend during the years 2002 to 2020.

Based on the research of Ye and Kuang (2022), the variables of altitude, slope, average monthly rainfall and land use pattern were among the main factors affecting the environmental quality in the southeast of Chongqing. The reduction of vegetation, the increase in surface temperature, the exposure of bare soil and the increase of impervious surfaces have led to the deterioration of the quality of the area. Economic areas with small green spaces characterized by high rates of urbanization and human activities record low ecological quality (Philip et al., 2024).

Therefore, to improve the quality of the environment; more reasonable use of land resources in urban planning and construction must be considered to accelerate the construction of urban parks and other facilities, expand the urban green area, and reduce human activities that disrupt the environment.

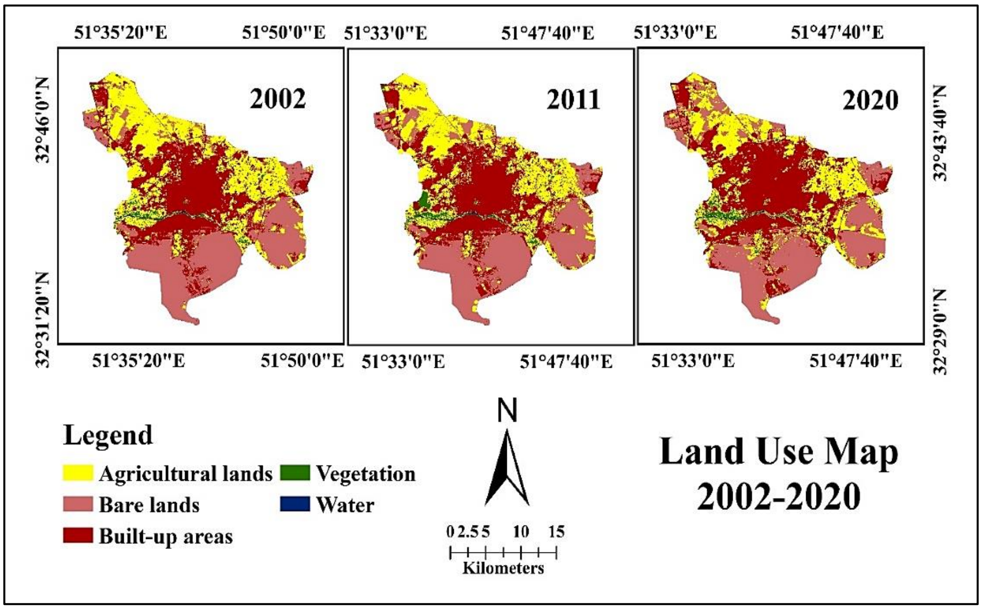

Fig. 4. Land use map of Isfahan City (2002, 2011 and 2020).

Table 8. Land use changes of Isfahan City during 2002 to 2020.

Year/Land Use	Built-up		Bare Land		Agricultural Land		Vegetation		Water	
	ha	%	ha	%	ha	%	ha	%	ha	%
2002	18859.20	34.27	18186.10	33.05	16700.30	30.35	1069.64	1.94	208.82	0.37
Changes (2002 to 2011)	539.76	0.98	-179.79	-0.33	-834.77	-1.52	481.55	0.87	-11.40	-0.02
2011	19398.96	35.25	18006.31	32.72	15865.53	28.83	1551.19	2.81	197.42	0.35
Changes (2011 to 2020)	2562.54	4.66	732.51	-1.33	-1501.23	-2.73	-264.02	-0.49	-51.45	-0.09
2020	21961.50	39.91	17273.80	31.39	14364.30	26.10	1278.17	2.32	145.97	0.26
Changes (2002 to 2020)	3102.30	5.64	-912.30	-1.66	-2336.00	-4.25	208.53	0.38	-62.85	-0.11

4. Conclusion

The environmental quality of the City of Isfahan was investigated and an IRSEI was proposed and the spatial and temporal analyzes of the environmental quality of this City were carried out using remote sensing data. Based on the obtained results; The negative effect of heat, dryness and salinity indicators was significantly more than the positive effect of vegetation and humidity indicators on the environmental quality of the studied area. The proposed IRSEI also indicated the decreasing trend of environmental quality in different areas in Isfahan City during the 18 years of the study period. The average values of IRSEI indicated a decrease in the environmental quality of Isfahan City. The area with poor and moderate environmental quality increased from 19372.77 and 14363.46 hectares in 2002 to 16527.51 and 12141.63 hectares in 2020, respectively. Excellent and good qualities were mainly observed in the vegetation around Zayandeh-Rud River. Moreover, there are still areas with poor environmental quality in the City of Isfahan, most of which are located in the vicinity of constructed areas, which show the deterioration of the environmental quality due to urban expansion. This study also showed a strong correlation between IRSEI and NDVI, LSM, NDBSI, LST and NDSI indices in the study area. Finally, it can be said that during 2002 to 2020; the land use changes were one of the main factors of reducing the environmental quality of Isfahan City although the increase in vegetation cover and the imposition of restrictions on human activities was significantly considered. It is suggested that factors such as meteorological conditions, biodiversity, airborne particles, and other human activities that may affect the environmental quality in semi-arid regions should be applied in future studies to conduct a more comprehensive assessment of the environmental quality.

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