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Landscape Online | Volume 97 | 2022 | Article 1101

Submitted: 24 December 2021 | Accepted in revised version: 16 June 2022 | Published: 31 July 2022

# Landscape Metrics Explain the Ecological Susceptibility of Terrestrial Ecosystems

## Abstract

This study examines the effects of the change in the shape of landscape patches, known as landscape structure, on ecological susceptibility, which is defined using the object-oriented method. The aim is to determine whether ecological susceptibility is influenced by the shape of the landscape patches in the southern basin of the Caspian Sea. The multivariate linear regression approach is applied to discover the extent to which the mean, median, and weighted average of the landscape structure metrics can explain the total variations of the ecological susceptibility. To determine the optimal models, an inter-model comparison is conducted using the Akaike information criterion. Sensitivity and uncertainty analyses were performed to determine how sensitive ecological susceptibility is to changes in the variables of the models and how they behave under varying conditions. The models ( $0.64 \geq r^2 \geq 0.27$ ,  $p \leq 0.05$ ) indicate that the landscape structure metrics can be applied to predict ecological susceptibility. Examining the mean, median, and weighted average of the landscape metrics in estimating ecological susceptibility also reveals that the models made by the mean and median values have less uncertainty than those developed by the weighted average. The results show that the regularity or irregularity in the shape of the landscape patches and the degree of contiguity of the land use/land cover patches can significantly affect ecological susceptibility. Closed deciduous broad-leaf forest patches, closed mixed forest patches, and open mixed forest patches can be considered crucial land use/land covers to estimate ecological susceptibility.


Mustafa Nur Istanbuly<sup>1</sup>,  
Mohammad Kaboli<sup>1</sup>, Sara Ahmadi<sup>1</sup>,  
Gouhang Tian<sup>2</sup>, Magdalena  
Michalak<sup>3</sup>, Bahman Jabbarian  
Amiri<sup>3\*</sup>

1) University of Tehran, Faculty of  
Natural Resources, Department of  
Environmental Science, Karaj, Iran


2) Henan Agricultural University, College  
of Landscape Architecture and Art,  
Henan, China

3) University of Lodz, Faculty of Econo-  
mics and Sociology, Department of Re-  
gional Economics and the Environment,  
Lodz, Poland

Corresponding author: University of  
Lodz, Faculty of Economics and Sociolo-  
gy, Department of Regional Economics  
and the Environment, Lodz, Poland  
Email: bahman.amiri@uni.lodz.pl

Mustafa Nur Istanbuly  
 <https://orcid.org/0000-0002-9978-855X>

Mohammad Kaboli  
 <https://orcid.org/0000-0002-9203-2346>

Bahman Jabbarian Amiri  
 <https://orcid.org/0000-0003-1382-786X>

Magdalena Michalak  
 <https://orcid.org/0000-0002-5031-9162>

## Keywords:

susceptibility, landscape structure, subjective, objective, modeling,  
sensitivity, uncertainty

<https://doi.org/10.3097/LO.2022.1101>

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## 1 Introduction

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Susceptibility, by definition, refers to the extent to which a system would suffer from an exogenous threatening process or factor in case of exposure, regardless of the probability of exposure (Cardona et al., 2012). The explanation of the term susceptibility proposed in the subject literature differs depending on the context in which it is addressed (Beroya-Eitner, 2016). Cardona et al. (2012) describe susceptibility in conservation biology as the extent of an organism or ecological community's suffering if they are exposed to a threatening process or factor without considering the likelihood of exposure.

Addressing susceptibility in the biological context would provide enormous potential for relevant works due to the significant diversity in study objects and biological levels. Krebs (2009) introduced a hierarchical organizational structure in the shape of a pyramid for the biological system. The biological system is founded on molecules at the base of the pyramid, and the next levels are cellular organs, cells, tissues, organs, individuals, populations, species, communities, ecosystems, and finally, landscapes as the uppermost level on the top of the pyramid. However, each level of the organization, depending on the number of possible ecosystems, can also be horizontally extended. Therefore, the concept of ecological susceptibility, depending on the purpose of the studies, can be applied from both vertical and horizontal perspectives. Most efforts to address ecological susceptibility have focused on the upper half of the hierarchical organization of the biological system, which is bounded by the spectra between individual and landscape levels. Human health (children and adults) and psychology have been the focus of individual-scale susceptibility studies due to their importance (see, e.g., Belsky, 2013; Klimkina, 2013; Belsky & Pluess, 2016).

Studies at the population level can also be differentiated from the point of the view of the objects of the studies, varying from mosquito larvae (Umar et al., 2008) or the population of the Pallas's Cat (Brown et al., 2005) to the susceptibility of local rice cultivars to *sitophilus oryzae*, the most common rice pest (Oguntola et al., 2019). They can also be differentiated by

the scale of the studies, from microscopic (Brown et al., 2005) to plot level (Oguntola et al., 2019). Both animal (see, e.g., Vázquez and Simberloff, 2002; Straub et al., 2015) and plant species (see, e.g., IUCN, 2010; Trouvé et al., 2020) have been the focus of species-level studies to assess their susceptibility to external stresses such as environmental stressors (Straub et al., 2015) and environmental disturbances, including fires and temperature increase related to climate changes (see, e.g., Vázquez & Simberloff, 2002; IUCN, 2010; Trouvé et al., 2020).

Studies at the ecosystem level focus on the susceptibility of aquatic ecosystems to environmental stressors in general and on oceans (Tremblay et al., 2015), lakes (Qamar et al., 2019; Milecka et al., 2020), rivers (Scavia & Liu, 2009; Evans & Scavia, 2013), and gulfs (Brock et al., 2009), in particular. Terrestrial ecosystems have received less attention regarding their ecological susceptibility. Furthermore, this attention has been limited to a certain number of ecosystems, including forest ecosystems (Tybirk et al., 2000; Mélo et al., 2011; Renard et al., 2012; Vogt et al., 2007). For decades, scientists have studied the ecological relevance of spatial patterns at this level, and some have questioned their suitability to measure the performance of a landscape (Frazier & Kedron, 2017). These doubts arise from uncertainties originating from three spatial properties of data, including distribution, resolution, and scale, which can affect the relationship between ecological processes and spatial patterns, but also lead to deviations in managerial decisions (Frazier & Kedron, 2017).

At the landscape level, various environmental stressors have been studied from the point of view of stressors. Studies in this field include environmental impacts (Nascimento et al., 2017), climatic stressors such as temperature and precipitation (Zhang et al., 2009; Knelman et al., 2019), altitude and aspects (Zhang et al., 2009; Batar et al., 2021), ecological processes such as plant invasions (Myers, 1983), and geoenvironmental stressors (Sun et al., 2019 and Ulakpa et al., 2020).

Determining the extent of ecological susceptibility can be considered as one of the managerial alternatives to reduce the negative effects of human activities (Pereira et al., 2022). The susceptibility of an ecological ecosystem is associated with the services

provided by those natural systems. Today, the problem of water pollution and the scarcity of fresh water resources is due to the inability of different ecosystems to provide some ecosystem services, and this is due to the state of the ecosystem and its susceptibility to various environmental problems (van Vliet et al., 2021; Al-Adamat, 2017; Ouma et al., 2022). The relationship between ecological susceptibility and key environmental problems has been investigated in some studies. These crucial environmental problems include, but are not limited to, global warming, a sharp decrease in forest cover, a decline in biological diversity, acid rain pollution, desertification, water pollution, and a shortage of freshwater resources (Jianping et al., 2014).

To be more specific, there is an interaction between ecological susceptibility and global warming, in which the effects of global warming are intensified by increasing the ecological susceptibility of ecosystems, and vice versa (Dinh Van et al., 2013; Destoumieux-Garzón et al., 2022). Although the susceptibility of ecosystems such as forest ecosystems increases due to a sharp decline in forest cover (Bourgoin, 2019; Kupková et al., 2018; Bourgoin et al., 2020) and also biodiversity (Weiskopf et al., 2020; Keesing et al., 2010; Destoumieux-Garzón et al., 2022), the decline in forest cover could derive a process leading to an increase in ecological susceptibility and consequently weakens the ecosystem weaker in the face of destructive processes such as soil erosion (Istanbuly et al., 2021). Acid rain pollution is a very significant challenge, which is related to the susceptibility of ecosystems at different levels so that if acid rain pollution increases in a given area, it becomes a more susceptible area (Grennfelt et al., 2020; Butler et al., 2019; Tao et al., 2002; Wang et al., 2006), while acid rain pollution could have very large effects in susceptible areas. Arid and semi-arid regions are ecologically susceptible due to the conditions of potential ecological factors, so not paying attention to these fragile conditions during human activities accelerates the desertification process (Hu et al., 2020; Djeddaoui et al., 2017; Afzali et al., 2021; Istanbuly et al., 2021).

In recent years, many studies have been conducted to develop methods, approaches, and even frameworks by which ecological susceptibility could be as-

sessed (Beroya-Eitner, 2016). For example, the developed methods can be considered an expert system for evaluating the ecological sensitivity index (ESI), which is based on a scoring approach (see, e.g., Ferrara et al., 1999; Kosmas et al., 1999a, b, c). Accordingly, the higher the index, the higher the ecological susceptibility. Studies also showed that coniferous forest cover is more sensitive than agricultural and broadleaf forest cover (Brandt, 2015). The methodology developed by GIZ (2013) is also based on a scoring approach. These methodologies to determine ecological susceptibility have been widely applied by Özcan et al. (2018), Abdel Kawy and Belal (2011), Salvati et al. (2013), Darwish et al. (2012), and Abuzaid et al. (2021). Their efforts focused on applying an object-oriented method to determine ecological susceptibility, and the object-oriented method has not been applied for modeling ecological susceptibility. Mirghaed et al. (2018) showed that decreases in landscape metric values (the percentage of landscape, the number of patches, the largest patch index, and the landscape shape index) of forest and rangeland land covers are associated with an increase in the rate of soil erosion. O'Neill et al. (1988) indicated that the fractal dimension index can be included as an indicator by which the degree of human manipulation of the landscape can be measured. Studies by De Paola et al. (2013), Cushman and McGarigal (2019), Arora et al. (2021), and Batar et al. (2021) revealed that broadleaf forest cover, coniferous forest cover, and residential land use have moderate ecological susceptibility. However, rangelands and agricultural land covers have high susceptibility values. The values of ecological susceptibility decrease if the percentage of broadleaf forests and residential areas increases, while the values of ecological susceptibility decrease if the percentage of agricultural lands and rangelands decreases.

The essence of these initiatives in estimating ecological susceptibility shows that the assessments presented therein strongly depend on expert judgments (De Lange et al., 2009). This could be considered a disadvantage, as such studies usually do not provide precise clarification on how experts apply standard methods to reach their judgments (De Lange et al., 2010). Subjective judgments are based on values, emotions, beliefs, and prejudices, and they are a reflection of personal background and intentions. If

not made with precision and expressed in a proper value framework, they may reduce the intended impact and the credit of the evaluator (Matthews, 1975).

Due to this inherent weakness of subject-oriented methods, object-oriented assessments are in high demand due to the repeatability of the results obtained. Such an observation seems valid regardless of the field of science in which this issue is addressed. Hence, to avoid overwhelming controversies, it is necessary to apply more object-oriented methods than subjective ones. Object-oriented approaches to assess ecological susceptibility are widely considered when formulating policies to manage natural resources and the environment. However, there are significant challenges when introducing plausible indicators and/or indices, as assessing ecological susceptibility is an overwhelming task due to the nonlinearity, complexity, and hierarchy in natural systems (Beroya-Eitner, 2016).

Landscape ecology, however, provides metrics of varying degree of complexity that can be applied to easily measure the structure, composition, and configuration of the landscape using available data and software (Kupfer, 2012). Ecosystem degradation can be analyzed by interpreting metric values (Kupfer, 2012; Cale & Hobbs, 1994). However, the application of landscape metrics has its own advantages and disadvantages (McGarigal, 2015; Frazier & Kedron, 2017;) that must be considered before using them. Many studies using landscape metrics have applied a scale (between 10 and 1000 sq km), in which pattern-process links have attracted the most managerial interest (Kupfer, 2012; Forman & Godro, 1986). Despite the scale sensitivity of the shape index (Rutledge, 2003), some landscape metrics, such as the proximity index, are sensitive to the resolution of the spatial data used to calculate them. As the resolution of spatial data increases, the costs associated with preparing the required maps increase. However, small patches are subject to elimination due to a decrease in resolution (Weeks et al., 2005), which could also mean the loss of part of the information. Some landscape metrics, such as the parameter-to-area ratio, are sensitive to changes in the area under study (McGarigal, 2015; Weeks et al., 2005), while others, such as proximity index, which are cal-

culated based on cell/ pixel count in the raster maps (O'Neill et al., 1988), are not sensitive to changes in the study area (Cale & Hobbs, 1994; McGarigal, 2015).

There are only a few studies, if any, in which the necessary attention is paid to taking an objective assessment of ecological susceptibility further, where ecological susceptibility could be estimated using probabilistic models. This study seeks answers to two crucial questions: 1) Is there a significant relationship between the landscape structure and the objectively estimated ecological susceptibility? 2) Do probabilistic models bridge the landscape structure and the objectively estimated ecological susceptibility? Such key questions are justified by the fact that landscape metrics are spatially explicit metrics and easily measurable by publicly accessible land use/ land cover maps. They are also spatially able to indicate three significant features of a given landscape, including composition, structure, and configuration. To fill the gap in current studies, this research was carried out to reveal the relationship between landscape structure metrics and ecological susceptibility, which are estimated using an objective method.

## 2 Materials and Methods

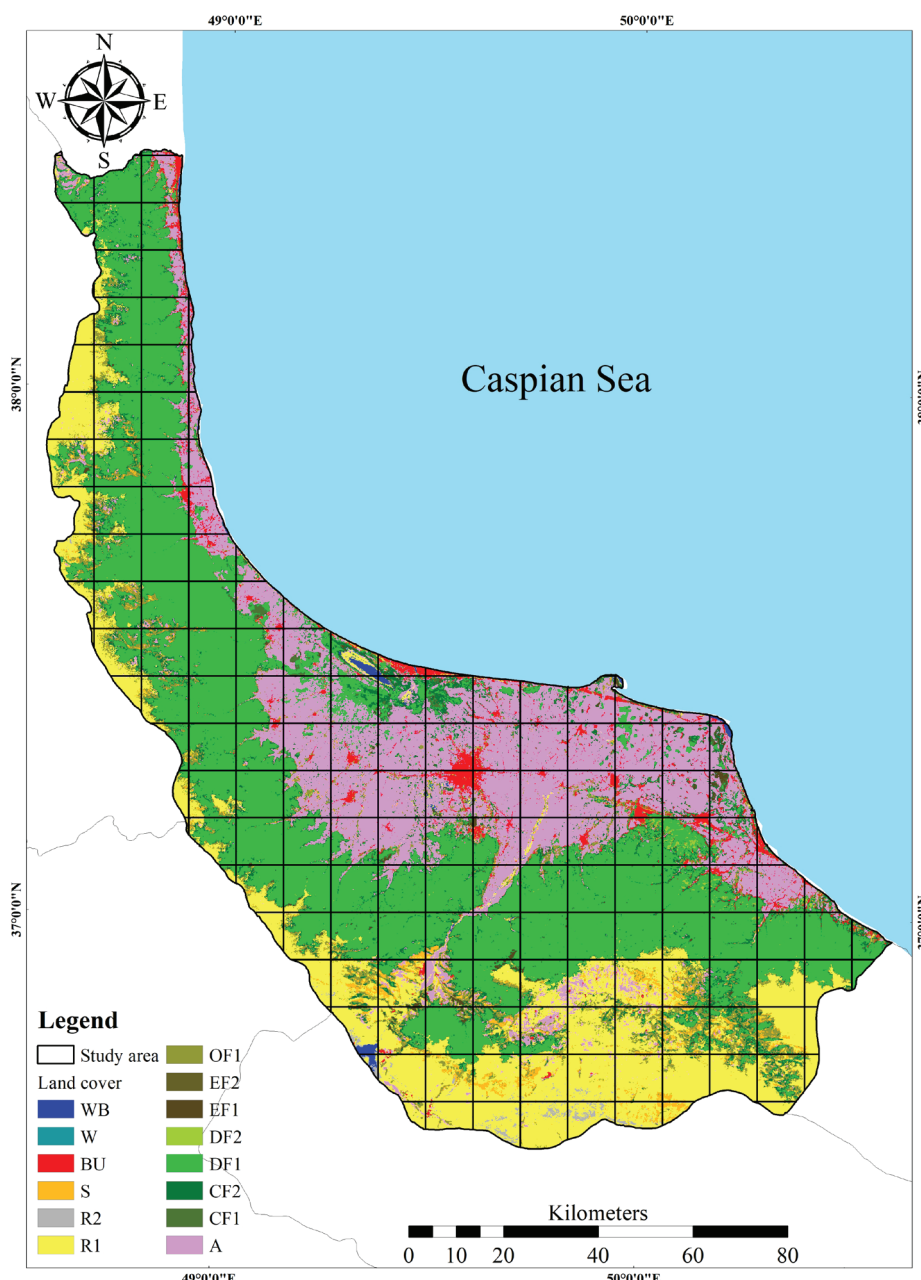
### 2.1. Study Area

The study area (36°33' -38°27' N Lon., 48°32' -50°36' E Lat.) is located in the southern basin of the Caspian Sea, with an area of 14,044 km<sup>2</sup> (Figure 1). The elevation of the area varies between -74 and 3707 (msl). The dominant land covers are forest (53.2%), agricultural land (23.2%), rangeland (48.55%), and others (< 5%). Annual precipitation is 1100 mm, and the annual average temperature is 8.15 °C (Guilan Meteorological Organization, 2019). The primary dominant rocks are travertine sediment rocks (17.5%), low-level piedmont fan and valley terrace deposits (12%), and basaltic volcanic rocks (42.5 %).

### 2.2. Methodology

Figure 2 shows the main stages of the study. The spatial data, as generated and published by different



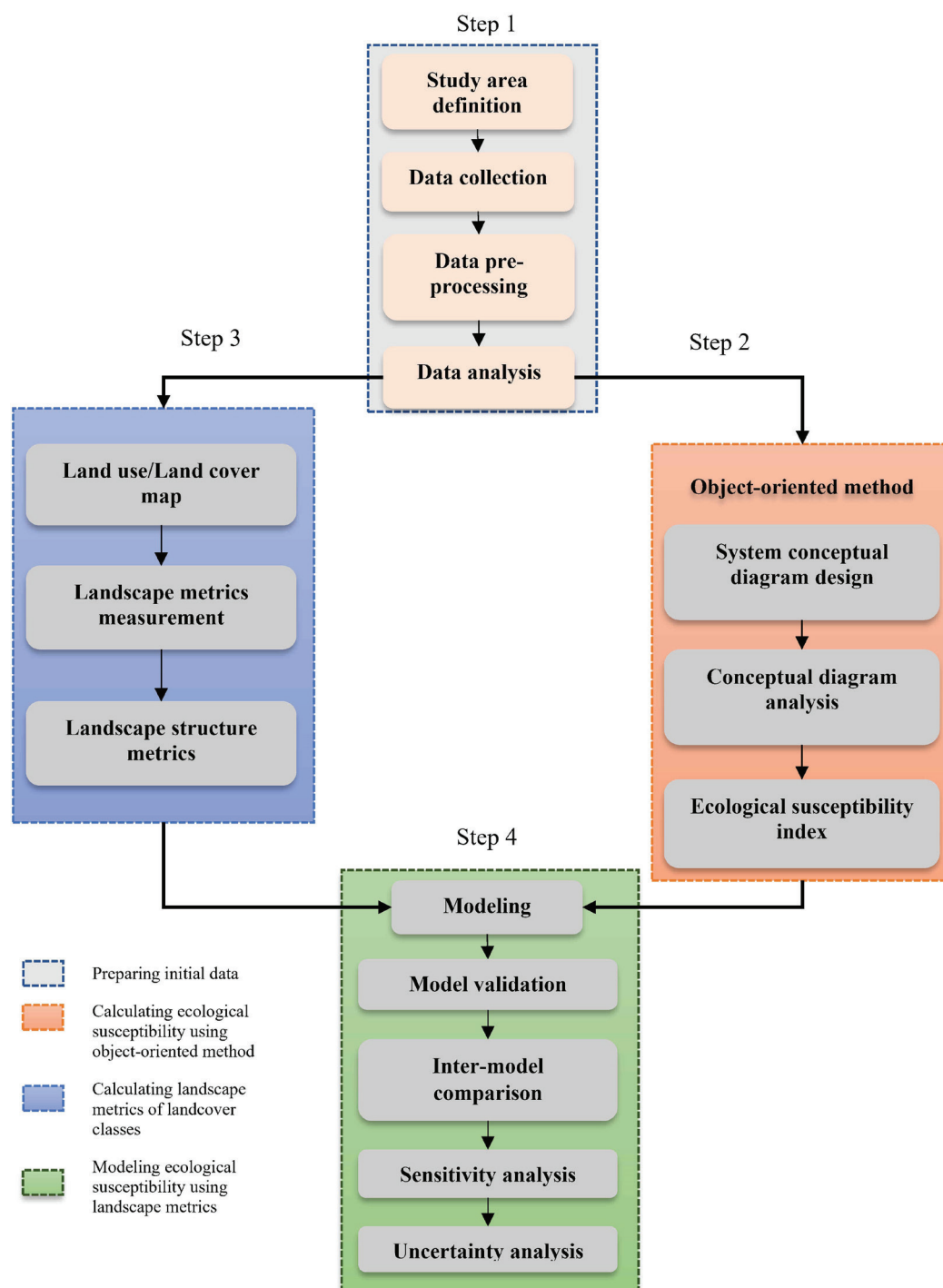


**Figure 1.** The cellular map of the study area and land use/land cover of the study area: (WB) water bodies, (WL) wetland, (DF1) closed deciduous broadleaf forest, (DF2) open deciduous broadleaf forest, (CF1) closed mixed forest, (CF2) closed forest with unknown type, (OF1) open mixed forest, (EF1) closed evergreen needle-leaf forest, (EF2) open evergreen needle-leaf forest, (S) Shrubland, (R1) high-density rangeland, (R2) intermediate density rangeland, (A) agriculture, (BU) Build-up.

administrative authorities, were transformed into a common digital format, then co-registered with the WGS84 source (zone 39n). The study area was divided into 183 cells with a resolution of 10 x 10 km. They were considered study units to determine the measure of ecological susceptibility and also as an arbitrary landscape for which the values of the landscape structure-related metrics were calculated (Fig. 1).

### 2.2.1. Estimation of Ecological Susceptibility

Ecological maps, including slope, geographical aspect, elevation (USGS, 2019), vegetation (Landsat 30 meter), depth of the groundwater table, soil (Soil and Water Research Institute, 1:250,000), climate (Iran Meteorological Organization, 1:50,000), and geology (Iran Geological Survey and Mineral Explorations Organization, 1:250,000) were reclassified in order to present the extent to which each of the eco-



**Figure 2.** The flow diagram of the methodology of the present study

logical factors implies ecological susceptibility. Table 1 shows detailed information on the source data. All pre-processing and analysis of satellite imagery and ecological maps were performed using TerrSet 2020 Geospatial Monitoring and Modeling Software and ArcGIS Desktop 10.5 Software (Gandhi et al., 2015; Purevdorj et al., 1998; Song et al., 2017).

The ecological susceptibility was then estimated by (Eq. 1) where ESI is the ecological susceptibility index,  $K_i$  is the importance of the  $i^{th}$  ecological factor, and  $X_i$  stands for the measure of ecological susceptibility for the  $i^{th}$  cell (Amiri, 2019). Details about the objective estimation of ecological susceptibility can be found in the supplementary section (S).

$$ESI = \sum_{i=1}^{n-1} (K_i X_i) \quad (1)$$

**Table 1.** Detailed information on the source data

Data layer	Format	Scale/Resolution	Year	Source
Digital Elevation Model	Raster	30 meters	2019	<a href="https://www.usgs.gov/">https://www.usgs.gov/</a>
Landsat images	Raster	30 meters	2019	<a href="https://landsat.gsfc.nasa.gov/">https://landsat.gsfc.nasa.gov/</a>
Groundwater table depth	Vector	1:250,000	2019	<a href="http://www.swri.ir/">http://www.swri.ir/</a>
Soil	Vector	1:250,000	2019	<a href="http://www.swri.ir/">http://www.swri.ir/</a>
Climate	Vector	1:50,000	2019	<a href="http://www.irimo.ir/">http://www.irimo.ir/</a>
Geology	Vector	1:250,000	2019	<a href="https://gsi.ir/en">https://gsi.ir/en</a>
Land use / Land cover	Raster	100 meters	2019	(Buchhorn et al., 2019)

### 2.2.2. Measurement of Landscape Metrics

The Land Use/Land Cover (LULC) map (Buchhorn et al., 2019) was applied to calculate the values of the five landscape metrics, which include the perimeter-area ratio, the related circumscribing circle, the fractal dimension index, the shape index, and the contiguity index. The explanation of each of these metrics is provided in Table S5 (McGarigal & Marks, 1995; Rutledge, 2003; Leitão et al., 2012). The LULC map includes water bodies (WB), wetland (WL), closed deciduous broadleaf forest (DF1), open deciduous broadleaf forest (DF2), closed mixed forest (CF1), closed forest with unknown type (CF2), open mixed forest (OF1), closed evergreen needle-leaf forest (EF1), open evergreen needle-leaf forest (EF2), shrubland (S), high-density rangeland (R1), intermediate-density rangeland (R2), agriculture (A), build-up (BU).

### 2.2.3. Modeling

To model the relationship between landscape structure and ecological susceptibility, multiple regression modeling approaches (linear, logarithmic, power, and exponential) were applied to determine which model structure can reveal more reliability for predicting ecological susceptibility by applying landscape metrics (input value  $p < 0.05$  and output value  $p \geq 0.100$ ).

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (2)$$

Where  $Y_i$  is the measure of ecological susceptibility in the  $i^{th}$  cell,  $X_1, \dots, X_n$  are the measures of landscape metrics in the  $i^{th}$  cell,  $\beta_1, \dots, \beta_n$  are coefficients of the model, and  $\beta_0$  is the constant coefficient.

To determine the extent to which the developed models are liable to collinearity issues, variation inflation factors were calculated (Neter et al., 1996; Chatterjee et al., 2000; Daoud, 2017). The goodness of fit was evaluated by plotting the observed versus predicted measures of the models (Ahearn et al., 2005). All statistical analyses and landscape metric calculations were performed applying IBM SPSS for Windows, Release 26, and FRAGSTATS (McGarigal & Marks, 1995; Jaeger, 2000; Vogt et al., 2007).

### 2.2.4. Inter-model comparison

The most appropriate models were then chosen by the Akaike information criterion. The Akaike information criterion was calculated applying Eq. 3 (Burnham & Anderson, 2004; Amiri, 2020) where  $AIC_c$  is the value of Akaike information criterion,  $K$  is the number of variables in the model, including the constant variable, and  $n$  is the number of samples.

$$AIC_c = n \left( \log \frac{RSS}{n} \right) + 2K + \frac{2K(K+1)}{n-K-1} \quad (3)$$

### 2.3.5. Sensitivity and Uncertainty Analyses

The sensitivity analysis of the models could be considered an important step in improving models in general and environmental models in particular (Amiri, 2020), aiming to determine how sensitive the responses of a given model are to a change in the variables. To analyze the sensitivity of the models, conditional SA was applied. Accordingly, the output of the models was examined by changing the values of the variable of interest while adjusting the remaining variables to the mean. The models' outputs were then depicted versus the incremental measures in the variable of interest.

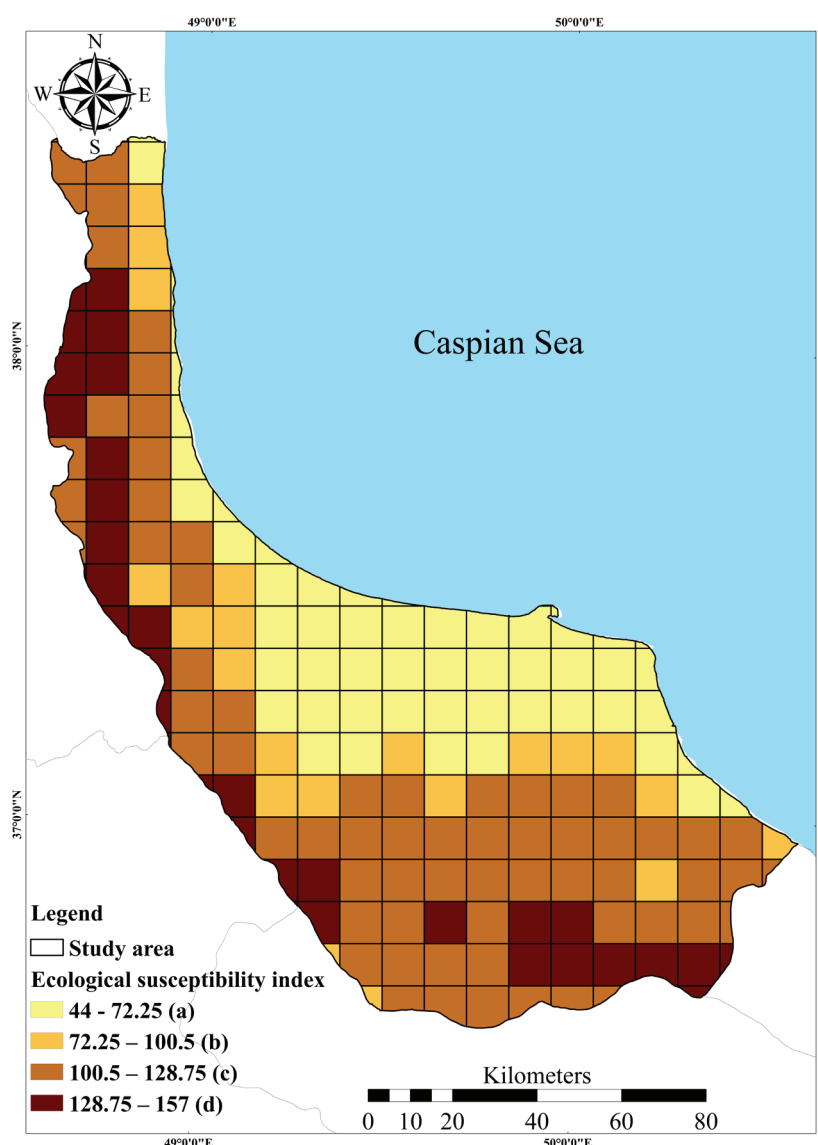


Uncertainty analysis of models is an essential step in any modeling practice. It aims to describe the probability distribution of the model outputs to determine the uncertainty of the predictions made by the model of interest. Monte Carlo simulation was used to analyze the uncertainty of the models. It was carried out by: 1) calculating the central tendency statistics, 2) determining the most fitted statistical distributions to dependent and independent variables, 3) generating random data applying the most fitted statistical distributions for the variables, which is 15,000 in this study, 4) simulating the model outputs using the generated data, and 5) probabilistic analysis of the behaviors of the models. The first step was performed by calculating the cumulative distribution function (CDF) and showing the CDF for the simulated values of the model of interest.

### 3 Results

#### 3.1. Ecological Susceptibility

The ecological susceptibility was calculated using Eq. 1 by reclassifying the spatial data. Ecological susceptibility varies between 44 and 157, where the lower the measure, the more resistant the ecosystem (Table 2). The measures of ecological susceptibility were then reclassified to enhance them into four classes susceptible, semi-susceptible, semi-resistant, and resistant (Table 2 and Figure 3). The results show that only about one-third of the study area (28%) is resistant, although most of the area (58.42%) is considered ecologically semi-susceptible and susceptible.



**Figure 3.** The ecological susceptibility indices of the study area. a: resistant, b: semi resistant, c: semi susceptible, and d: susceptible.

**Table 2.** The distribution statistics of ecological susceptibility in the study area.

Type	Qualitative description	Quantitative ecological susceptibility	Area (km <sup>2</sup> )	%
<b>Ecological susceptibility classification</b>	Resistant	44 – 72.25	3987.09	28.39
	Semi resistant	72.25 – 100.5	1852.40	13.19
	Semi susceptible	100.5 – 128.75	5939.21	42.29
	Susceptible	128.75 – 157	2265.30	16.13
<b>Distribution statistic</b>	Minimum		44	
	Maximum		157	
	Mean		99.74	
	Std. dev		31.60	
	Kurtosis		-1.37	
	Skewness		-0.30	

### 3.2. Landscape Metrics

The results indicated that the most irregular patch shape (shape index = 1.37) was observed in the closed deciduous broadleaf forest, while the open evergreen needle-leaf forest had the most regular shape (shape index = 0.08). From the point of view of the degree of connectivity, the closed deciduous broadleaf forest and the open evergreen needle-leaf forest showed the most connected patches (contiguity index = 0.36) and the most disconnected patches (contiguity index = 0.08) in the landscapes of the study area, respectively. Furthermore, the most extended patches (related circumscribing circle = 0.38) are related to the closed deciduous broadleaf forest, while the shortest patches (related circumscribing circle = 0.22) were observed for the open evergreen needle-leaf forest (Table 3).

### 3.3. Modeling

The four regression models (linear, logarithmic, exponential, and power) were examined using the mean, weighted average, and median values of landscape metrics as independent variables, and the values of ecological susceptibility, which were objectively calculated as the dependent variable (Table S6). The models (Eqs. S2 to S16) were then classified into three groups, which indicate the mean values of the landscape metrics-based models, the weighted average values of the landscape metrics-based models, and the median values of the landscape metrics-based models (Eqs. S2 to S16). The models developed are presented in the Supplementary Materials (S).

### 3.4. Goodness-of-fit test

The goodness of fit of the models (Eqs. S2 to S16) was examined referring to the coefficient of determination, the significance of the model, its coefficients at  $p \leq 0.05$  level, and the multicollinearity of the model variables. The results show that the coefficients of determination of the models based on the mean values of the landscape metrics vary from 0.436 to 0.577, while they change (from 0.396 to 0.590 and 0.264 to 0.641) for the models based on the weighted average and median values of the landscape metrics models, respectively (Table S6) (Figure S3).

### 3.5. Inter-model Comparisons

The inter-model comparisons indicated that the most appropriate model for the mean values of the shape index is Eq. S6, by which 54.65% of all variations in the values of ecological susceptibility can be explained. Eq. S11 was selected as the most appropriate model for the models based on the weighted average landscape metrics, whose coefficient of determination is 0.58. Furthermore, a representative model was developed using the median values of the landscape metrics (Eq. S15). It can explain 58% of the variations in the values of ecological susceptibility (Table S7).

### 3.6. Sensitivity Analysis

The three most appropriate models (Eqs. S6, S11 and S15) were included in the conditional SA (Tables S8 and S9) (Figure S4). For the models based on the mean values of the landscape metrics (Eq. S6), the sensitivity of the model responses to independent variables decreases for the closed deciduous broadleaf forest  $DF1_{shp}$ , the closed mixed forest  $CF1_{shp}$ , the open mixed forest  $OF1_{shp}$ , and the closed evergreen needle-leaf forest  $EF1_{shp}$ . The sensitivity of the model (Eq. S15) increases due to an increase in the slope of the lines for the closed mixed forest  $CF1_{contig}$  (7.46), the open deciduous broad-leaf forest  $DF2_{contig}$  (11.6), the closed deciduous broad-leaf forest  $DF1_{contig}$  (13.23), and the open mixed forest  $OF1_{contig}$  (17.95). The sensitivity of the model (Eq. S11), which is the most appropriate model for the weighted average landscape metrics-based models, decreased, which was related to a change in the values of agriculture  $A_{shp}$  and the closed mixed forest  $CF1_{shp}$ .

**Table 2.** Statistics of the landscape structural metrics in the study area.

Statistics	Landscape metrics	Thematic class, Land use/land cover													
		WB	WL	DF1	DF2	CF1	CF2	OF1	EF1	EF2	S	R1	R2	A	UR
Mean	Related circumscribing circle	0.37 ± 0.22	0.24 ± 0.18	0.44 ± 0.10	0.29 ± 0.20	0.33 ± 0.13	0.42 ± 0.05	0.39 ± 0.05	0.36 ± 0.16	0.22 ± 0.22	0.27 ± 0.11	0.31 ± 0.13	0.39 ± 0.21	0.38 ± 0.08	0.34 ± 0.16
	Contiguity Index	0.19 ± 0.15	0.09 ± 0.07	0.36 ± 0.12	0.12 ± 0.09	0.16 ± 0.08	0.21 ± 0.04	0.19 ± 0.05	0.17 ± 0.10	0.08 ± 0.09	0.12 ± 0.07	0.16 ± 0.09	0.20 ± 0.12	0.24 ± 0.06	0.18 ± 0.10
	Fractal Dimension Index	1.03 ± 0.02	1.01 ± 0.02	1.04 ± 0.01	1.02 ± 0.02	1.03 ± 0.02	1.04 ± 0.01	1.04 ± 0.01	1.02 ± 0.02	1.01 ± 0.02	1.02 ± 0.01	1.02 ± 0.02	1.03 ± 0.02	1.04 ± 0.01	1.03 ± 0.02
	Parameter-Area Ratio	311.26 ± 68.31	355.49 ± 37.10	241.85 ± 49.58	338.91 ± 48.46	325.77 ± 35.10	300.57 ± 16.22	309.57 ± 20.52	316.60 ± 45.46	364.21 ± 46.43	339.70 ± 30.12	322.53 ± 41.79	304.67 ± 55.12	293.11 ± 25.42	313.59 ± 47.98
Weighted Average	Shape Index	0.19 ± 0.15	0.09 ± 0.07	1.37 ± 0.23	1.06 ± 0.09	1.14 ± 0.11	1.29 ± 0.11	1.24 ± 0.11	1.13 ± 0.16	0.08 ± 0.09	1.10 ± 0.11	1.18 ± 0.17	0.20 ± 0.12	1.35 ± 0.17	1.16 ± 0.14
	Related circumscribing circle	0.51 ± 0.25	0.31 ± 0.20	0.60 ± 0.11	0.37 ± 0.22	0.49 ± 0.17	0.67 ± 0.08	0.63 ± 0.08	0.50 ± 0.22	0.28 ± 0.23	0.45 ± 0.18	0.51 ± 0.21	0.49 ± 0.24	0.62 ± 0.11	0.53 ± 0.23
	Contiguity Index	0.34 ± 0.25	0.12 ± 0.09	0.81 ± 0.16	0.18 ± 0.16	0.29 ± 0.14	0.45 ± 0.07	0.43 ± 0.11	0.31 ± 0.21	0.10 ± 0.10	0.27 ± 0.19	0.42 ± 0.28	0.32 ± 0.22	0.70 ± 0.20	0.41 ± 0.23
	Fractal Dimension Index	1.06 ± 0.04	1.02 ± 0.02	1.12 ± 0.05	1.03 ± 0.03	1.05 ± 0.03	1.11 ± 0.04	1.10 ± 0.05	1.05 ± 0.04	1.02 ± 0.02	1.05 ± 0.05	1.08 ± 0.07	1.05 ± 0.04	1.15 ± 0.06	1.07 ± 0.05
Median	Parameter-Area Ratio	251.10 ± 102.89	339.28 ± 43.38	67.55 ± 58.92	312.40 ± 70.81	267.44 ± 60.50	204.16 ± 26.72	212.49 ± 44.82	260.70 ± 85.22	352.08 ± 52.80	276.70 ± 75.62	217.20 ± 109.52	245.85 ± 92.08	111.10 ± 75.82	222.67 ± 92.40
	Shape Index	1.43 ± 0.47	1.07 ± 0.13	3.07 ± 1.41	1.14 ± 0.29	1.35 ± 0.35	2.31 ± 0.83	2.43 ± 1.66	1.34 ± 0.40	1.06 ± 0.10	1.48 ± 0.87	2.27 ± 1.63	1.39 ± 0.54	4.04 ± 2.47	1.82 ± 0.84
	Related circumscribing circle	0.36 ± 0.27	0.19 ± 0.23	0.50 ± 0.14	0.29 ± 0.25	0.33 ± 0.23	0.50 ± 0.09	0.47 ± 0.12	0.40 ± 0.21	0.20 ± 0.26	0.24 ± 0.24	0.32 ± 0.22	0.42 ± 0.24	0.45 ± 0.16	0.39 ± 0.21
	Contiguity Index	0.16 ± 0.16	0.06 ± 0.08	0.31 ± 0.17	0.11 ± 0.10	0.12 ± 0.09	0.18 ± 0.04	0.16 ± 0.05	0.15 ± 0.11	0.06 ± 0.09	0.07 ± 0.08	0.12 ± 0.10	0.18 ± 0.12	0.18 ± 0.08	0.16 ± 0.11
Median	Fractal Dimension Index	1.02 ± 0.03	1.01 ± 0.01	1.03 ± 0.02	1.01 ± 0.01	1.01 ± 0.02	1.02 ± 0.01	1.02 ± 0.01	1.02 ± 0.02	1.01 ± 0.02	1.01 ± 0.01	1.01 ± 0.02	1.02 ± 0.02	1.02 ± 0.01	1.01 ± 0.02
	Parameter-Area Ratio	321.44 ± 75.29	366.94 ± 44.23	251.35 ± 72.34	342.87 ± 55.61	342.96 ± 50.73	301.58 ± 27.53	312.05 ± 31.22	322.29 ± 56.59	373.07 ± 49.97	362.56 ± 47.47	336.68 ± 54.52	307.26 ± 56.69	306.80 ± 42.12	315.07 ± 55.05
	Shape Index	1.11 ± 0.22	1.00 ± 0.02	1.11 ± 0.17	1.02 ± 0.07	1.03 ± 0.08	1.01 ± 0.04	1.01 ± 0.05	1.04 ± 0.12	1.03 ± 0.09	1.00 ± 0.00	1.03 ± 0.10	1.06 ± 0.16	1.02 ± 0.07	1.03 ± 0.10

### 3.7. Uncertainty Analysis

The cumulative density function was applied to analyze the behavior of the three representative models (Tables S8, S9, and S10). As a result, Figure S5 shows that for the models based on the mean values of the landscape metrics (Eq. S6) and those of the median values (Eq. S15), the output  $pr < 0$  is zero. Meanwhile, the model is based on the weighted mean of the landscape metrics (Eq. S11) showed a very low probability, in which the output  $pr < 0$  is not zero.

## 4 Discussion

### 4.1. Landscape Metrics and Ecological Susceptibility

The results show that 6 of the 14 LULC classes were entered into the selected models based on the stepwise approach, that is, the closed deciduous broad-leaf forest, the open deciduous broad-leaf forest, the closed mixed forest, the closed evergreen needle-leaf forest, agriculture, and the open mixed forest. They were selected by the Akaike information criterion as the most appropriate.

Equation S15 revealed direct associations between the ecological susceptibility values and the contiguity indices of the closed deciduous broad-leaf forest ( $DF1_{contig}$ ) and the open mixed forest ( $OF1_{contig}$ ). Meanwhile, the values are inversely associated with the contiguity indices of the open deciduous broad-leaf forest ( $DF2_{contig}$ ) and the closed mixed forest ( $CF1_{contig}$ ). They equal 0 for one-pixel patches and increase to a limit of 1 for a fully connected patch. Consequently, it implies that the higher the contiguity indices of the closed deciduous broad-leaf forest ( $DF1_{contig}$ ) and open mixed forest patches ( $OF1_{contig}$ ), the higher the value of ecological susceptibility.

Table S6 and Equations S6 and S11 showed a significant relationship between the value of ecological susceptibility and the shape index of the closed deciduous broad-leaf forest ( $DF1_{shp}$ ), the closed mixed forest ( $CF1_{shp}$ ), the closed evergreen needle-leaf forest ( $EF1_{shp}$ ), the open mixed forest ( $OF1_{shp}$ ), and agriculture ( $A_{shp}$ ). Accordingly, an increase in the shape index of  $DF1_{shp}$ ,  $EF1_{shp}$ , and  $OF1_{shp}$  is directly related

to the value of ecological susceptibility, while an increase in the shape index of  $CF1_{shp}$  is inversely associated with a decrease in ecological susceptibility.

The functioning of the shape index of agriculture patches ( $A_{shp}$ ) regarding the value of ecological susceptibility changed depending on the model groups. More specifically, the shape index of agriculture patches showed an indirect relationship with the values of ecological susceptibility for the models based on weighted average landscape metrics. Meanwhile, unlike the function it played for the weighted average landscape metrics-based models, the shape index of agriculture patches ( $A_{shp}$ ) revealed a direct association with the ecological susceptibility values for the median landscape metrics-based model. The shape index varies between 1 and infinity, implying that the further away from 1 the index is, the more irregular the shape of the patch. Consequently, our findings suggest that in the median landscape metrics-based model, increasing irregularity in the shape of  $DF1_{shp}$ ,  $EF1_{shp}$ ,  $OF1_{shp}$ , and  $A_{shp}$  is directly associated with an increase in the values of ecological susceptibility. For models based on the weighted average of landscape metrics,  $A_{shp}$  and  $CF1_{shp}$  showed direct relationships with the values of ecological susceptibility.

Our study suggests that the susceptibility of ecosystem can be estimated using landscape metrics. The shape index and the contiguity index of different forest classes can express the state of ecological susceptibility, so they are in line with the findings of Tejaswi (2007). It shows that the shape and contiguity indices of forest patches can indicate the state of the ecological system in general and forest ecosystem in particular, based on which forest can be managed. The relationship between shape and contiguity indices with landscape susceptibility to degradation was addressed by Halbac-Cotoara-Zamfir et al. (2022) and Mohammadi et al. (2021). They found that quantifying landscape metrics can help assess human impacts on ecosystems and then help with monitoring and restoration practices.

Our findings show that the susceptibility of the landscape decreases if the regularity of the forest patches, including the closed deciduous broad-leaf forest, the closed evergreen needle-leaf forest, and the open mixed forest, increases by approaching a square shape. Moreover, if the irregularity of the

closed mixed forest and that of agricultural patches increase, the ecological susceptibility of the landscape decreases in the study area.

Moser et al. (2002) showed that the species richness of vascular plants and bryophytes is associated with changes in the mean shape index of the landscape. Consequently, increasing the metric is inversely associated with a decrease in the species diversity of vascular plants and bryophytes, bearing in mind that the greater the species diversity, the less ecologically susceptible a given landscape is. The relationship between living and non-living factors and ecological resilience was addressed by Cushman and McGarigal (2019). The values of the shape index were modeled as an indicator to determine the resilience of the system. They found that combining landscape shapes is an effective factor in its resilience against destructive factors. However, our findings indicated that the susceptibility of the ecosystem will increase by decreasing the shape index of forest patches (closed deciduous broad-leaf forest, closed evergreen needle-leaf forest, and open mixed forest). Our findings are in line with those of Mirghaied et al. (2018). They showed that the landscape susceptibility to soil erosion is significantly associated with the shape regularity of the forest patches. They found that soil erosion is inversely related to the irregular shape of agriculture patches.

We found that landscape susceptibility decreases if the degree of connectivity between the closed deciduous broad-leaf forest and the open mixed forest decreases and when it increases between the closed mixed forest and the open deciduous broad-leaf forest. It is in line with Huang et al. (2022) for closed mixed forests. They indicated that the discontinuity of forest patches and being close to a square shape can be considered the worst state for a forest landscape, implying the degradation of the landscape. Our study shows that the degree of discontinuity of closed mixed forests and open deciduous broad-leaf forests is associated with an increase in landscape susceptibility, as discontinuity of forest patches is a sign of landscape degradation (Kun et al., 2019; Huang et al., 2022). The landscape becomes weaker and more susceptible (Kun et al., 2019) when the degree of discontinuity of forest patches increases. The findings of this study confirm the direct rela-

tionship between the continuity of closed deciduous broadleaf forests and open mixed forests. This could change due to a change in other environmental conditions (Moser et al., 2002).

McGarigal et al. (2009) and Wang et al. (2014) showed that the mean and weighted average values of the contiguity and the shape indices could indicate the state of a given surface landscape, implying direct relationships between the shape index and the digital elevation model. However, there was an indirect relationship between the shape index and the normalized difference vegetation index. Our findings show that in addition to the mean and weighted average values, the median values of the contiguity index can be used as an indicator of the state of a landscape and thus show its susceptibility.

#### *4.2. Implications*

Subject-oriented approaches are considered difficult, time-consuming, and controversial methods. However, in the present study, the object-oriented method of estimating ecological susceptibility has been taken further so that it can be predicted by probabilistic models. Landscape structure metrics were applied to estimate ecological susceptibility using probabilistic models to provide a bridge between changes in landscape ecology and ecological susceptibility. One of the main strengths of our approach is the availability of LULC maps as the required information layer for calculating the landscape metrics. In regions where land-use planning has not been prepared or has not even begun to be implemented, determining the degree of ecological susceptibility for them, in the absence of land use planning documents, can be considered a roadmap that facilitates the site selection of projects.

#### *4.3. Limitations*

Area-specific properties are a significant drawback of regression models, although the sensitivity and uncertainty analyses performed for the models developed in this study could indicate how they behave under varying conditions. Using landscape metrics, which are inherently dependent on scale, to develop regression models can be considered a limitation when applying these models in other regions.



## 5. Conclusions

In the present study, a fast and straightforward approach was developed to model the relationship between ecological susceptibility and landscape structure-related metrics, which mainly indicates the shape of landscape patches. The regression models constructed in the study show that the metrics of landscape structure could provide considerable reliability in measuring ecological susceptibility. Examining three statistics (the average, weighted average, and median) of landscape metrics in modeling ecological susceptibility also suggests that mean and median landscape metric-based models could provide us with an estimation of ecological susceptibility with less uncertainty compared to weighted average landscape metric-based models. The shape of closed deciduous broad-leaf forest patches and those of open mixed forest, closed mixed forest patches, and their degree of connectivity are very significant when estimating ecological susceptibility. Ecological susceptibility increases with an increase in the degree of connectivity of the closed deciduous broad-leaf forest patches and open mixed forest patches, while an increase in the degree of connectivity of the closed mixed forest patches and open deciduous broad-leaf forest patches is associated with decreased ecological susceptibility.

Based on our findings, the degree of shape irregularity could play different roles in ecological susceptibility. Increasing the shape irregularity of the closed deciduous broad-leaf forest and the open mixed forest increased the ecological susceptibility, while it decreased when the shape irregularity of the closed mixed forest increased. The findings of the present study also revealed that among the LULC classes, in three model groups, the closed deciduous broad-leaf forest patches, the closed mixed forest, and the open mixed forest are the most significant explanatory variables. Therefore, these types of LULC might be considered more in land use planning, as they affect the measures of ecological susceptibility.

## Acknowledgements

The first author (M.N.I.) acknowledges that this study has partly been supported by the Guilans Elite Foundation under Professor Hassan Ebrahimzadeh Mabood Research Grant in 2020.

## Conflicts of interest/Competing interests

The authors report no potential conflict of interest.

## Availability of data and material

The data applied to conduct the present study is available upon written request.

## Supplementary Material

More detailed methods, extended data analysis, equations, results, tables, and additional figures are available in the supplemental material file (S).

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