

Evaluating the desertification vulnerability of a semiarid landscape under different land uses with the environmental sensitivity index^{*}

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Abstract

The objective of this study was to evaluate the desertification vulnerability of an approximately 1,000-ha area in Anatolia, Turkey, comprising semiarid oak (*Quercus* spp.) and pine (*Pinus* spp.) forests and the adjacent cultivated lands by using the environmental sensitivity index (ESI). We calculated the ESI values for 632 randomly selected sites in the study area by entering the desertification indicators vegetation cover, plant type, soil depth, rock fragments, soil texture, slope gradient, drainage, parent material, mean annual precipitation, slope aspect, aridity index, land use intensity, and policy enforcement into the web-based model Desertification Indicator System for Mediterranean Europe. The spatial structure of the ESI values was then evaluated using semivariograms and kriging-interpolated surface maps. The mean ESI value was significantly greater in the cultivated areas (1.47; range = 1.25–1.61) than in the pine (1.32; 1.03–1.45) and oak (1.28; 1.18–1.57) forests ($P < 0.01$). The ESI was moderately spatially dependent in the oak forests and cultivated areas and strongly spatially dependent in the pine forests, as evidenced by the corresponding semivariograms. The ordinary kriging-interpolated maps showed that most of the cultivated areas were critically vulnerable to desertification, whereas the majority of the forested areas were moderately vulnerable. We examined how the ESI values varied with soil organic matter (OM) content as an independent variable and found that the OM content was significantly moderately correlated with the ESI ($n = 632$, $r = -0.51$, $P < 0.01$), suggesting that the ESI could be used to evaluate the desertification vulnerability of similar landscapes across Turkey.

KEYWORDS

cultivated land, DIS4ME, geostatistics, oak forest, pine forest

1 | INTRODUCTION

There are many different definitions of desertification, but the official definition of the United Nations is the 'diminution or destruction of the biological potential of the land [which] can lead ultimately to desert-like conditions' (see Nicholson, Tucker, & Ba, 1998). Drylands

are considered desertification-prone areas (Nicholson et al., 1998), and large areas in the Mediterranean region that include Greece, Italy, Portugal, Spain, and Turkey are at high risk of desertification (Baartman, Van Lynden, Reed, Ritsema, & Hessel, 2007). There has been ongoing debate about the determination of desertification indicators for over 40 years. An appropriate indicator does not necessarily need to meet the strict scientific demands of having full details of causal chains but must meet state-of-the-art scientific know-how

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(Sommer et al., 2011). Whereas some experts argue that the use of the physical indicators of soil degradation and vegetation degradation is sufficient, others claim that only soil degradation can show a long-term decline in potential land productivity, as vegetation degradation is easily reversed (Grainger, Smith, Squires, & Glenn, 2000). It has also been suggested that physical indicators should be complemented by socioeconomic and agricultural indicators. As Berry and Ford (1977) proposed the first desertification indicators, attempts have been made to describe a set that is universally applicable. For example, Helmut and Lambin (2004) grouped the causes of desertification into 10 categories, whereas Prince, De Colstoun, and Kravitz (1998) listed only two indicators, namely, water use efficiency and rain use efficiency. To further complicate this issue, desertification layers and indicators may vary at different geographical scales and between different geographical locations and landscape conditions.

The environmental sensitivity index (ESI) is one of the most widely used methods for mapping regions due to its simplicity and flexibility (Dharumarajan, Bishop, Hegde, & Singh, 2018; Salvati & Bajocco, 2011). The ESI has been evaluated at different scales across Europe (Basso et al., 2000; Contador, Schnabel, Gutiérrez, & Fernández, 2009; Salvati & Bajocco, 2011) and elsewhere (Ali & El Baroudy, 2008), and Salvati and Bajocco (2011) suggested that it can be used as an early warning indicator for identifying desertification vulnerability and monitoring changes in the vulnerability of a landscape over time.

Geostatistics (i.e., semivariograms and cross-semivariograms) is one of the most widely applied tools for evaluating the spatial structure of a variable (Corwin & Vaughan, 1997) and the relationships among the spatial structures of different variables (Isaaks & Srivastava, 1989). A typical geostatistical analysis comprises exploratory statistics, semivariogram analysis, and geostatistical interpolation (kriging; Isaaks & Srivastava, 1989). A semivariogram, which summarizes the variance in a dependent variable as a function of distance, is the key to geostatistics (Palmer, 1988). The parameters (nugget, sill, and range) along with the shape of a semivariogram provide considerable information on the spatial structure of a corresponding variable (Palmer, 1988; Isaaks & Srivastava, 1989). Geostatistical interpolation techniques (i.e., kriging) can be used along with the corresponding semivariogram for spatial interpolation. Li and Heap (2011) compared 72 spatial interpolation methods used in environmental science and concluded that ordinary kriging and inverse distance weighting were the most frequently and widely used methods. The kriging technique has several advantages over its counterparts, as it incorporates the spatial structure of the data into the interpolation through semivariogram modeling and predicts the same known values for the data points where measured data are available (Isaaks & Srivastava, 1989).

Quantification of environmental heterogeneity is important in evaluating relationships between ecological patterns and ecological functions and processes (Gustafson, 1998). Lin, Han, Zhao, and Chang (2010) concluded from their field study, conducted in Inner Mongolia, that vegetation spatial pattern and desertification were associated and that future studies should incorporate spatial information of vegetation spatial pattern in monitoring desertification. Temporal differences between the spatial structures of ESIs can show the dynamics of the distributional patterns of corresponding functions and processes of desertification over time, as results from previous studies have indicated. Ryel, Caldwell,

and Manwaring (1996) reported large temporal changes in the spatial variability of soil moisture and N as shown by temporal differences in their corresponding semivariograms, and Alexandra, Jorge, Fernandez-Palacios, and Gallardo (2009) confirmed changes in the spatial structure of soil variables with fire as evidenced by increased spatial dependence and the geostatistical range of the variables after fire.

We propose that a geostatistical evaluation of the ESI provides opportunities for probing more deeply into understanding land use–desertification linkages. The nugget from the autocorrelation of the ESI can represent small-scale spatial variability (Brownstein et al., 2012), whereas the geostatistical range can represent moderate-to-large-scale spatial variability in the ESI. On-the-other-hand, the type (linear, exponential, Gaussian, or spherical) and shape of the semivariogram of the ESI may provide important information on the spatial pattern of desertification vulnerability that could not be obtained otherwise. In addition, the shape of a semivariogram may provide important information on the spatial structure of the target variable and likely the sources of variability across scales (Trangmar et al., 1985). To our knowledge, the literature on the geostatistical analysis of the ESI on landscapes is sparse, and only a few studies have been conducted to date (e.g., Gaafar, Morsy, and Yehia (2017).

Desertification is one of the main public concerns in Turkey, and thus, studies are needed for developing sound government policies to mitigate desertification across the nation. Recently, a desertification map of Turkey was made using 47 indicators and 37 subindicators grouped under eight desertification categories (TUBITAK, 2015). However, there is currently a lack of data on the desertification vulnerability of landforms and the critical factors that cause desertification on the landscape scale in Turkey. Literature quantifying to what extent land use contributes to desertification is limited, and the delineation of the desertification vulnerability of landforms and the identification of the critical factors causing desertification are lacking in Turkey. Therefore, the objectives of this study were (a) to evaluate the performance of the ESI for identifying critical desertification drivers and calculating desertification vulnerability and (b) to characterize and compare the spatial structures of the ESI in agriculture and forestland uses.

2 | MATERIAL AND METHODS

2.1 | Study area

The study area is located in north-central Anatolia (40°51'38"–40°33'15"N and 33°49'18"–34°06'54"E; Figure 1). It covers 1,000 ha with an elevation ranging from 950 to 1,550 m above mean tide level. The topography of this region comprises hills and steep landforms, with complex slopes adjoining base slopes and microfeatures running up and down in different directions alongside the slopes and hills.

There are three principal land uses in this region: cultivated land, oak (*Quercus* spp.) forests, and pine (*Pinus* spp.) forests. Cereals (particularly wheat, *Triticum aestivum*) are the principal crops, but some vegetables and fruits are also produced for local consumption. Land cultivation is mainly practiced on colluvial aprons and colluvial areas located on footslopes. The drainage pattern is mainly dendritic and rectangular, and all of the soils in the study area are well drained (with the exception of a

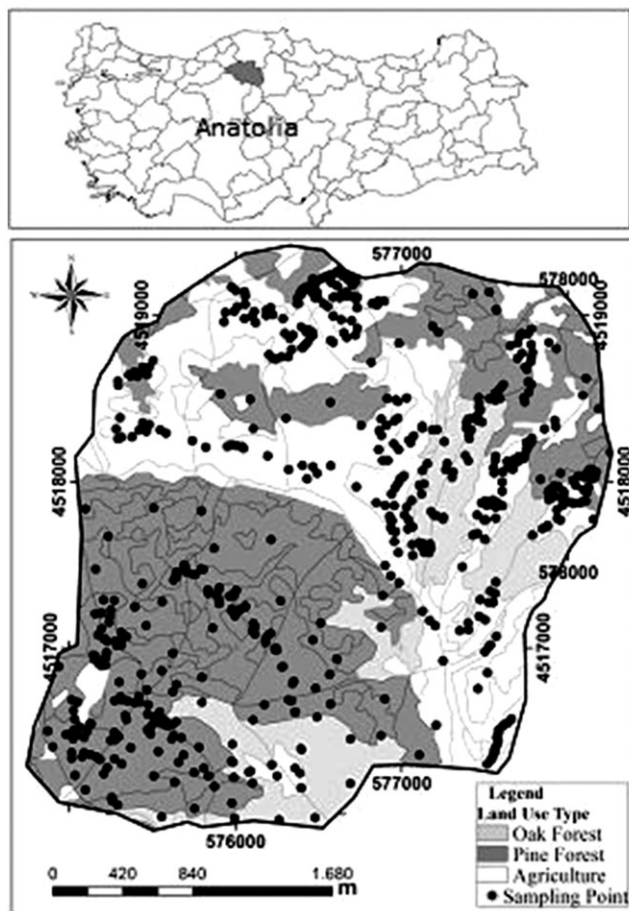


FIGURE 1 Location of the study area, observation sites (dots), and land use types in the study area (produced from the 1:25,000 map using ArcGIS 10.3)

small marshland located in a pine forest). The forested parts are covered by conifers and hardwoods (mainly oaks) that intermix at transition zones. The hardwood forests have been grazed by local growers, and thus, <25% of them are covered by grasses, herbaceous cover, and shrubs.

The local climate is dry-subhumid/semi-arid continental Anatolian (Iyigun et al., 2013), with a mean annual precipitation of 406–538 mm, a mean annual temperature of 9.1–11.1°C, and a mean relative humidity of 61–66%. The long-term mean minimum temperature ranges from −5.0°C to −2.7°C in January, with the lowest temperature on record being −24.0°C, whereas the long-term mean maximum temperature ranges from 26.4°C to 30.9°C in July, with the highest temperature on record being 42.0°C. Flooding occurs occasionally (five to 50 times in 100 years) according to the criteria given in Schoeneberger et al. (2012).

Entisols and Inceptisols are the main soils in this region. The parent materials, that is, limestone, red limestone, sandstone, shale, and colluvial debris, were observed in the oak forests; chalk, sandstone, shale, limestone, and conglomerate were observed in the pine forests; and chalk, sandstone, and shale were observed in the cultivated areas.

2.2 | Determination of the number of observation sites

We determined the necessary number of independent observation sites according to Ott (1993) and Crepin and Johnson (1993). Our

calculations showed that 490 independent observation sites were required to predict the organic matter (OM) content in the study area at a significance level of 0.05. We used variance in the OM content in this calculation because it is one of the key indicators of desertification, and it was also used as an independent variable to validate the ESI in the study area. We increased this sample size by 30% for convenience to capture the spatial structure of the OM in the study area, giving a total of 632 observation sites. We distributed the sample sites across the cultivated land, hardwood (oak) forest, and pine forest areas according to their percentage cover. Thus, 252 observation sites were located in cultivated areas, 122 were in the oak forests, and 258 were in the pine forests. No samples were taken from the patches of grasslands, bushes, and meadows, resulting in the sampling points being clustered in the cultivated, oak forest, and pine forest sites (Figure 1).

2.3 | Soil sampling and laboratory analysis

We obtained soil samples from the topsoil (depth of 0–20 cm) at 252 points in the cultivated areas, 122 points in the oak forests, and 258 points in the pine forests. We then transported these samples to a laboratory at the Department of Forestry at Çankırı Karatekin University, prepared them for analysis, and stored the samples at room temperature until analysis. We measured the particle size distribution (Gee & Bauder, 1986), aggregate stability index (ASI; Kemper & Rosenau, 1986), field capacity and wilting point (Klute & Dirksen, 1986), pH and electrical conductivity (McLean, 1982), soil OM content (Nelson & Sommers, 1982), cation exchange capacity (Rhoades, 1982), and CaCO₃ content (Nelson, 1982) of each sample.

2.4 | Modeling the ESI

Several models have been developed for delineating lands vulnerable to desertification, and the Desertification Indicator System for Mediterranean Europe (DIS4ME) is one of the widely used one among these systems (Dharumarajan et al., 2018). The DIS4ME was developed by Jane Brandt and Nichola Geeson in coordination with Anton Imeson as an extension of the MEDALUS and DESERTLINKS projects to predict the desertification risk in Mediterranean Europe (Greece, Italy, France, Portugal, and Spain). In the DIS4ME framework, the desertification indicators are selected on the basis of three criteria: (a) the correlation between the indicator and the stage of desertification; (b) the correlations within the data matrix; and (c) the contribution of each indicator to the prediction of land sensitivity to desertification (see Salvati & Bajocco, 2011, and references therein). The DIS4ME explains the major desertification-related issues that are occurring across semi-arid Europe and gives examples of how they are manifested locally at study sites in Portugal, Spain, Italy, and Greece. It includes full descriptions of some of the 150 desertification-relevant indicators and comprises a web-based program for calculating the desertification risk under different land uses. In addition, it comprises an expert online tool for evaluating the ESI using a much smaller subset of indicators, which has been used widely

for mapping desertification at local, national, and Mediterranean-wide scales.

Based on the calculated ESI value, the vulnerability of land to desertification is categorized as follows: $ESI \leq 1.17$, unaffected; $1.17 < ESI \leq 1.225$, potentially affected; $1.225 < ESI \leq 1.375$, fragile; and $1.375 < ESI$, critical (Basso et al., 2000; Salvati & Bajocco, 2011). Here, we calculated the ESI values for 252 sites in cultivated areas, 122 sites in oak forests, and 258 sites in pine forests. The desertification categories and indicators that were used in the calculations are given in Table 1. Further details on the desertification criteria and indicators, algorithms for the calculations, and scoring of the desertification indicators can be found in the corresponding references given in Table 1.

2.5 | Validation of the DIS4ME-calculated ESI values

ESI values should be validated using independently measured variables that reflect the state of desertification. Soil OM content is a key indicator of soil quality and is not used as a predictor in the ESI, making it suitable for the validation of the ESI: An adequately negative correlation between the ESI values and the OM content would suggest that the ESI could be used as a quantitative measure of desertification vulnerability. Therefore, we correlated our ESI values with the OM values at the 632 observation sites to evaluate the validity of using the ESI to evaluate desertification vulnerability of the lands in the study area. Similarly, Basso et al. (2000) validated the ability of the ESI to predict different levels of environmental sensitivity at the basin scale using independently measured values of microbial biomass C, microbial biomass N, soil OM content, and soil respiration.

2.6 | Statistical analysis

An exploratory data analysis was conducted on the basic soil property data and the DIS4ME-calculated ESI values. We calculated the mean, standard deviation, coefficient of variation (CV), skewness, and kurtosis for each dataset. In addition, we analyzed whether there were any significant differences between the mean ESI values in the cultivated areas, oak forests, and pine forests using analysis of variance and Fisher's least significant difference test with a significance level of 0.05.

We used the geostatistical software GS+ (Gamma Design, St. Plainwell, MI) to model the spatial structure of the ESI in the study area. We calculated experimental semivariograms and fitted them with spherical, Gaussian, exponential, linear, and nugget models. We then conducted ordinary point kriging (OK) interpolations using the range, sill, and nugget variance of theoretical semivariograms using at least 10 lags while paying attention to the minimum requirement of 30 data pairs in each lag in the OK interpolations. We first conducted a semivariogram analysis of the ESI values separately for each land use type and then conducted an analysis across the entire study area. Half of the shortest axis of the study area was used as the maximum lag distance of the semivariogram in the OK interpolations (Sauer & Meek, 2003). We calculated directional semivariograms along azimuth angles of 0° , 45° , 90° , and 135° with an angle tolerance of 22.5° to ensure that anisotropy did not exist (Sauer & Meek, 2003). A minimum of

10 and a maximum of 15 neighbors within the geostatistical range were used in the OK interpolations. Webster (2001) suggested that data with a skewness of $>|1.0|$ should be considered highly skewed, and therefore, log transformation may be required to fit the data to a normal distribution; data with a skewness of $|0.5|$ to $|1.0|$ should be considered moderately skewed, and thus, a square-root transformation may be required; and data with a skewness of $<|0.5|$ should be considered slightly skewed and can be deemed normally distributed. Therefore, in all cases, we checked the normality of the ESI data before conducting the geostatistical analysis and transformed the data when required.

3 | RESULTS

3.1 | Soil properties and the ESI in the study area

The mean soil OM content, which is an important soil quality indicator, was highest in the pine forests and lowest in the cultivated soils and more variable in the oak and pine forest soils than in the cultivated soils. The mean clay content was highest in the cultivated soils, followed by the oak forest soils and pine forest soils, whereas the reverse was true for the sand content (Table 2). The cultivated soils in this region are mainly located on gently to moderately sloping topographies (footslopes and toeslopes) where downward-transported materials accumulate, whereas the pine forests are located on moderately to steeply sloping land. The field capacity and wilting point showed similar distributions across the land uses (Table 2). The mean soil pH was greatest in the cultivated soils, followed by the oak forest and then the pine forest soils, but the soil pH was more variable in the pine forests than in the oak forests and cultivated soils. The mean CaCO_3 content was two times greater in the oak forest soils and three times greater in the cultivated soils than in the pine forest soils, whereas its variability showed the reverse order. In contrast, the mean ASI was greatest in the pine forest soils and lowest in the cultivated soils and was most variable in the cultivated soils followed by the oak and pine forest soils (Table 2). The majority of the soil properties we studied were moderately variable according to Webster (2001).

The mean ESI was greatest on the cultivated land, followed by the pine forests and then the oak forests (Table 3). In general, the ESI values were moderately variable across the three land uses (Table 3). The results of the analysis of variance and least significant difference tests showed that the mean of ESI values significantly higher in the cultivated areas (ESI_c) than in the oak forests (ESI_o) and pine forests (ESI_p), but there was no significant difference between the ESI_o and ESI_p . The ESI_o was strongly right skewed according to Webster (2001), indicating that a few localities with high desertification vulnerability exist in the oak forests. In contrast, the skewness of the ESI_p indicated that a few localities had very low desertification vulnerability in the pine forests (Table 3). When the data for the ESI_c , ESI_o , and ESI_p were combined (total area, ESI_t), the strong skewness vanished as the high extreme values counterbalanced the low extreme values.

TABLE 1 Desertification categories and indicators used in calculating the environmental sensitivity index in the pine forest, oak forest, and cultivated areas

Category	DI	Description	Threshold	Modifier	Rationale	Method of obtaining the data in this study	Reference
Vegetation	Vegetation cover	Ratio of land covered with vegetation to total land surface area	>40% 10–40% <10%	High Moderate Low	Reduction in vegetation is regarded as an important indicator of desertification	Field survey	Enne and Zucca (2000), Sepehr, Hassanli, Ekhtesasi, and Jamali (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
Soil	Drought resistance	Capacity of vegetation species to resist serious or moderate water stress	Evergreen forests Mediterranean macchia Conifers, deciduous, olives Perennial agricultural trees Perennial grasslands Annual agricultural crops, annual grasslands, bare land	High Moderate Low to moderate Low Very low	It addresses resilience of vegetation to desertification	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
	Fire risk	Composition and flammability of vegetation and its capacity to recover after fire	Orchards Grasslands, broadleaf forests, bushes Mediterranean macchia Coniferous forests	Low Moderate High Very high	It is a measure of vulnerability of vegetation to fire-related changes in the forcing variables (i.e., climate)	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015)
	Soil erosion protection	The degree of protection of soil erosion by vegetation	Evergreen forest Deciduous forests Mediterranean macchia, grasslands, bushes Orchards, annual crops Very sparse vegetation, bare soil	High Moderate Low to moderate Low Very low	It addresses the vegetation capacity to prevent soil degradation by erosion	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
	Soil depth	Depth of the profile from the soil surface to the lithic or paralithic contact	>75 cm 30–75 cm 15–29 cm <15 cm	Deep Moderate Shallow Very shallow	It controls growth of plants via controlling soil water holding capacity, nutrient capacity, and rooting depth	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
Rock	Rock fragments	Percent of surface covered by rocks and cobbles	>60 20–60% <20	High Medium Low	It has a strong control on soil water conservation and soil erosion	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
	Soil texture	It is an indicator of how soil is composed of fine and coarse material	L, SCL, SL, LS, CL SC, SIL, SiCL Si, C, SiC S	Good Medium to good Poor to medium Poor	It is a chief property controlling soil functioning	Determined in the laboratory	Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)

(Continues)

TABLE 1 (Continued)

Category	DI	Description	Threshold	Modifier	Rationale	Method of obtaining the data in this study	Reference
	Slope gradient (%)	Degree of deviation from horizontal between two points on the land surface	<6 6–18 18–35 >35	Gentle Moderate Steep Very steep	It is a fundamental variable controlling soil erosion	Field survey	Enne and Zucca (2000), Sepehr et al. (2007), TUBITAK (2015), Gaafar et al. (2017)
	Drainage	Removal of the excess water from the surface or root zone of the land	Water is removed from the soil readily to rapidly Water is removed from the soil somewhat slowly during some periods of the year Water is removed from the soil slowly	Well drained Imperfectly drained Poorly drained	It has strong control on soil salinization and alkalization	Field survey	Sepehr et al. (2007), Salvati and Bajocco (2011), Schoeneberger et al. (2012), TUBITAK (2015)
	Parent material	The material from which the soil has been derived	Shale, schist, marl, basic, ultrabasic, Conglomerates unconsolidated Limestone, marble, granite, rhyolite, ignimbrite Gneiss, siltstone, sandstone, pyroclastics	Good Moderate Poor	It is a fundamental property affecting soil fertility and the sensitivity of soils to erosion	Field survey	Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
Climate	Mean annual precipitation	Total amount of rain + snow precipitate in a year	<280 mm 280–650 mm >650 mm	Low Moderate High	It is a fundamental variable controlling both soil erosion and the development of vegetation	Obtained from a nearby meteorology station	Enne and Zucca (2000), TUBITAK (2015), Gaafar et al. (2017)
	Aridity index	The Bagnouls–Gausson aridity index is defined according to the formula $BGI = \sum_{i=1}^{12} (2t_i - P_i) / K_i$, where t_i is the average air temperature during month i in °C, P_i is the total monthly rainfall during month i in mm, and K represents the percentage of months in which $2t_i - P_i > 0$	<50 50–75 75–100 10–125 125–150 >150	Humid Subhumid Dry-subhumid Semiarid Arid Hyperarid	It compares the annual temperature regime with that of rainfall and contributes to forming a scale of climate quality	Obtained from a nearby meteorology station	Enne and Zucca (2000), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
Slope aspect	The compass direction that a slope faces		North, north-west, north-east, level	Good	It influences the distribution of energy, meteoric water, vegetation, and soil resources	Field survey	Sepehr et al. (2007), Schoeneberger et al. (2012), TUBITAK (2015)
			South, south-west, south-east	Poor			

(Continues)

TABLE 1 (Continued)

Category	DI	Description	Threshold	Modifier	Rationale	Method of obtaining the data in this study	Reference
Management	Land use intensity (agricultural)	Extent to which the land is used for crop production	Low	Sustainable	It is related to desertification processes such as soil erosion, salinization, soil structure degradation, and the decline in soil organic matter content	Obtained from a local agriculture agency	Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)
			Moderate	Not sustainable			
			High	Not sustainable			
	Policy enforcement	Degree of implementation of environmental protection policies	>75% 25–75% <25%	Complete Partial Incomplete	It specifies application of measures for protection of the land from desertification	Obtained from a local agriculture/forestry agency	Sepehr et al. (2007), Salvati and Bajocco (2011), TUBITAK (2015), Gaafar et al. (2017)

Note. DI: desertification index; L: loam; SCL: sandy clay loam; SL: sandy loam; LS: loamy sand; CL: clay loam; SC: sandy clay; SiL: silty loam; SiCL: silty clay loam; Si: silty; C: clay; SiC: silty clay; S: sand.

3.2 | Geostatistical analysis of the ESI

We modeled the spatial structures of the ESI_a , ESI_o , ESI_p , and ESI_t with semivariograms. The values for the ESI_c and ESI_t were moderately spatially dependent, whereas the ESI_o and ESI_p were strongly spatially dependent according to Cambardella et al. (1994) (Table 4). The ESI_c , ESI_o , and ESI_t were described by a spherical model, whereas the ESI_p was described by an exponential model (Table 4 and Figure 2). The greatest geostatistical range occurred for the ESI_c , followed by the ESI_o and ESI_p (Table 4 and Figure 2). We verified the semivariograms by cross-validation, which showed that the ESI_t had the greatest r value.

We interpolated the ESI_c , ESI_o , ESI_p , and ESI_t by OK using the corresponding semivariogram parameters given in Table 4. OK perfectly predicted the mean ESI in all cases, but the CV, skewness, and kurtosis of the interpolated data diverged from the measured data in the majority of the cases (Table 5). In particular, the CV of the interpolated ESI values was always lower than that of the measured ESI values because OK inherently overpredicts lower values and underpredicts higher values.

4 | DISCUSSION

Land use was the principal driver of desertification in the study area. The cultivated lands were more vulnerable to desertification than were the pine and oak forests, as reflected by the mean ESI value for cultivated areas (ESI_c) being significantly greater than the mean ESI for the oak forests (ESI_o) and the mean ESI for the pine forests (ESI_p ; $P < 0.01$). Within the cultivated areas, low vegetation cover (see Table 1, modifiers; as the soil surface is unprotected most of the year due to conventional tillage), very low erosion protection, shallow soils, heavy soil texture (Table 2), and incomplete enforcement of the existing policy on environmental protection were the most critical agents of desertification. Similarly, these agents are also among the main soil degradation processes on agricultural lands across Europe (Imbrenda, D'Emilio, Lanfredi, Ragosta, & Simoniello, 2013). The main causes of the high desertification risk in the cultivated lands were deteriorated soil structure (as indicated by the low ASI; Table 2) and degraded soil hydraulic properties (e.g., decreased water storage) due to a shallow eroded topsoil coupled with weak soil structure.

The ASI was greatest in the pine forests followed by the oak forests and cultivated soils (Table 2). The ASI is an important indicator of soil structure quality, which affects the soil air–water relationship, and soil OM is an important soil aggregate-stabilizing agent. However, the greater mean ESI for the pine forests than for the oak forests (Table 3) indicates that the pine forests are more vulnerable to desertification than are the oak forests (although the difference between the means of the ESI_o and ESI_p was not significant at the significance level of 0.05). Similarly, Ersahin, Bilgili, Dikmen, and Ercanlı (2016) recently found that pine forests are more vulnerable to climate variations than are broadleaf forests across Anatolia.

Topography is another major factor that affects desertification in the study area, as evidenced by the serious water erosion we observed on uneven relief with steep slopes, especially in the forested

TABLE 2 Descriptive statistics for some soil properties in three land uses

Variables	Min	Max	Mean	SD	Skewness	Kurtosis	CV (%)
Cultivated (n = 252)							
BD (g cm ⁻³)	0.86	1.81	1.40	0.17	-0.34	-0.12	12.33
Sand (%)	2.00	59.00	24.49	11.31	0.26	-0.67	46.17
Clay (%)	23.00	71.00	50.00	8.69	-0.20	-0.40	17.39
Silt (%)	10.00	50.00	25.75	6.31	0.40	0.77	24.48
pH	6.25	8.28	7.24	0.28	-0.98	1.84	3.91
EC (dS m ⁻¹)	0.02	1.10	0.12	0.11	7.20	53.78	95.00
OM (%)	0.10	3.65	1.76	0.63	0.22	-0.18	35.82
ASI (%)	15.16	80.78	55.66	13.89	-0.52	-0.22	24.95
FC (%)	15.48	41.70	27.77	4.36	0.36	0.58	15.72
WP (%)	8.85	29.53	18.19	3.71	0.39	0.19	20.40
CaCO ₃ (%)	0.44	46.68	16.42	12.04	0.24	-1.14	73.34
Oak forest (n = 122)							
BD (g cm ⁻³)	0.72	1.87	1.14	0.20	0.38	1.20	17.72
Sand (%)	5.00	57.00	32.97	12.07	-0.37	-0.62	36.63
Clay (%)	23.00	71.00	44.33	11.18	0.42	-0.38	25.23
Silt (%)	13.00	43.00	22.96	5.48	1.07	2.16	23.86
pH	5.35	7.56	6.37	0.58	-0.24	-1.18	9.14
EC (dS m ⁻¹)	0.02	0.20	0.11	0.04	-0.01	-0.76	40.29
OM (%)	0.60	16.84	4.07	3.03	1.86	4.42	74.41
ASI (%)	30.65	88.51	66.90	10.49	-0.97	1.21	15.67
FC (%)	12.75	44.97	29.29	5.58	0.32	0.41	19.06
WP (%)	8.03	35.50	19.62	5.17	0.64	0.07	26.38
CaCO ₃ (%)	0.58	48.72	10.75	12.74	1.29	0.46	118.46
Pine forest (n = 258)							
BD (g cm ⁻³)	0.76	1.67	1.17	0.25	-0.15	-0.28	21.04
Sand (%)	14.00	69.00	37.51	9.27	0.27	0.43	24.73
Clay (%)	21.00	61.00	38.42	7.55	0.42	0.21	19.65
Silt (%)	7.00	42.00	24.30	5.80	0.14	0.07	23.87
pH	4.54	7.69	5.84	0.70	0.93	-0.18	11.90
EC (dS m ⁻¹)	0.00	0.84	0.10	0.09	5.64	39.05	91.53
OM (%)	0.08	21.65	6.27	4.21	0.90	0.47	67.12
ASI (%)	13.57	94.31	70.92	10.20	-0.99	3.76	14.38
FC (%)	14.55	45.26	28.95	5.11	0.65	0.58	17.64
WP (%)	7.13	34.83	16.75	3.89	0.66	1.43	23.25
CaCO ₃ (%)	0.88	57.06	5.01	9.68	3.31	10.60	193.35

Note. BD: bulk density; EC: electrical conductivity; OM: organic matter; ASI: aggregate stability index; FC: field capacity; WP: wilting point; SD: standard deviation; CV: coefficient of variation.

TABLE 3 Exploratory statistics for ESI in cultivated (ESI_c), oak forest (ESI_o), pine forest (ESI_p), and total area (ESI_t)

Variable	n	Mean	Max	Min	SD	CV (%)	Skewness	Kurtosis
ESI _c	252	1.47	1.61	1.25	0.060	4.12	-0.188	-0.234
ESI _o	122	1.28	1.57	1.18	0.054	4.28	1.36	5.97
ESI _p	258	1.32	1.45	1.03	0.076	5.68	-1.42	4.63
ESI _t	632	1.37	1.61	1.03	0.096	7.02	-0.015	-0.142

Note. n: number of observation sites; SD: standard deviation; CV: coefficient of variation; ESI: environmental sensitivity index.

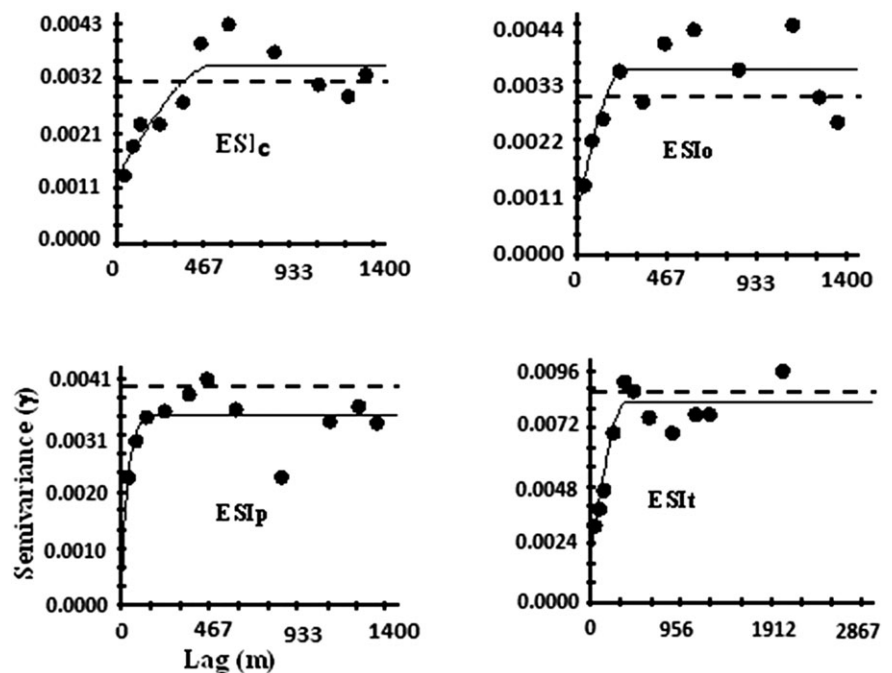
areas with low vegetation cover. Furthermore, the shallow soil depth at these localities is not adequate for supporting plants for preventing water erosion. Vegetation cover is also low at the accumulation sites on the foothills due to the continuous accumulation of colluvial debris

from the sideslopes. In addition, very erodible soils derived from sandstones and chalks are highly prone to desertification at many of the sloping localities in the study area; these soils are also quite poor in OM.

TABLE 4 The parameters for isotropic semivariograms of ESI values for cultivated (ESI_c), oak forest (ESI_o), pine forest (ESI_p), and total area (ESI_t)

Variable	Model	C _o	C _s	C _o /C _s × 100	A (m)	RSS	Spatial dependency	R ²	r
ESI _c	Spherical	0.0013	0.0034	38.23	526.0	3.76 × 10 ⁻⁵	Moderate	0.72	0.63
ESI _o	Spherical	0.0008	0.0035	22.85	244.0	3.25 × 10 ⁻⁶	Strong	0.63	0.36
ESI _p	Exponential	0.0003	0.0034	8.82	102.0	1.92 × 10 ⁻⁶	Strong	0.39	0.68
ESI _t	Spherical	0.0021	0.0082	25.61	374.0	5.82 × 10 ⁻⁶	Moderate	0.88	0.79

Note. C_o: nugget variance; C_s: sill; A: geostatistical range; RSS: residual sum of squares; R²: coefficient of determination; r: correlation coefficient for cross-validation; ESI: environmental sensitivity index.

**FIGURE 2** Experimental (spheres) and theoretical (lines) semivariograms for environmental sensitivity index (ESI) in cultivated (ESI_c), oak forest (ESI_o), pine forest (ESI_p), and total area (ESI_t). The dashed lines represent general variance**TABLE 5** Results of ordinary kriging (OK) interpolations

Variable	n	Mean		Variance		CV (%)		Skewness		Kurtosis		MAPE	
		M	I	M	I	M	I	M	I	M	I	r	
ESI _c	252	1.467	1.469	0.0032	0.0013	4.61	2.98	-0.17	-0.32	0.13	-0.12	3.26	0.63
ESI _o	122	1.28	1.27	0.0023	0.00063	4.27	2.18	0.36	-0.77	1.07	0.94	2.29	0.46
ESI _p	258	1.33	1.33	0.0040	0.0018	4.72	3.21	-1.33	-0.18	6.36	2.26	2.74	0.62
ESI _t	632	1.38	1.38	0.0086	0.0059	6.74	5.60	0.24	0.40	-0.88	-1.14	3.08	0.79

Note. n: sample size; M: measured; I: interpolated; CV: coefficient of variation; MAPE: mean absolute percentage error; r: cross-validation correlation coefficient; ESI: environmental sensitivity index; ESI_c: cultivated areas; ESI_o: oak forests; ESI_p: pine forests; ESI_t: total study area.

4.1 | Spatial structure of the ESI

We evaluated the spatial structures of the ESI_c, ESI_o, ESI_p, and ESI_t using semivariograms (Table 4 and Figure 2), which showed that the ESI_p was approximated by an exponential model, whereas the other parameters could be explained by spherical models. The ESI_c was moderately spatially dependent, whereas the ESI_o and ESI_p were strongly spatially dependent (Table 4) according to Cambardella et al. (1994), who proposed that if the nugget ratio is <25%, the variable is deemed strongly spatially dependent; a nugget ratio between 25%

and 75% is moderately spatially dependent; and a nugget ratio > 75% is weakly spatially dependent. The strong spatial dependency of the ESI in the oak and pine forests (Table 4) suggests that the ESI values were spatially autocorrelated more strongly than those in the cultivated areas, as interpreted elsewhere (Buenemann et al., 2011). Spatial autocorrelation refers to the tendency of nearby sites to be similar to each other in the target variable (Buenemann et al., 2011). In the context of land degradation, the moderate spatial dependency of the ESI_c values indicates that high-vulnerable and low-vulnerable sites tended to coexist in cultivated areas. However, the exploratory

statistics analysis (Table 3) resulted in greater CV values for the ESI in the forested areas than in the cultivated areas, suggesting a more heterogeneous distribution of ESI values in the pine and oak sites. This inconsistency between traditional statistics and geostatistics may be attributed to the fact that when autocorrelation occurs, it may violate key assumptions of conventional statistics, such as the stationarity and independence of samples, potentially leading to inadequate parameter estimation, as suggested by Buenemann et al. (2011). For example, any samples separated with a distance shorter than the geostatistical range cannot be considered independent according to traditional statistics, as noted by Campbell (1978).

The semivariogram of the ESI_o attains its maximum distance of influence, geostatistical range (A), at 244 m; the ESI_p attains its A at 102 m, the ESI_c attains its A at 526 m, and the ESI_t attains its A at 374 m (Table 4). The geostatistical range (A) is the distance within which the ESI values are autocorrelated. The geostatistical ranges for all four of the ESIs are shorter than half of the shortest axis of the study area, revealing that, as suggested elsewhere (Campbell, 1978), the study area is large enough to evaluate the spatial structure of the ESI by geostatistics in individual land uses as well as in total area at the current sampling scheme. The ESI_c exhibited the greatest nugget effect, the percent variance not explained by distance (Isaaks & Srivastava, 1989), whereas the greatest structural variance occurred for the ESI_p , for which the structural variance attributed approximately 92% of the total variance within a range of 102 m. The nugget variance is related to several factors such as small-scale patterns that cannot be detected by the sampling scheme used, errors in laboratory analysis, and errors in the accuracy of the sampling locations recorded by the Global Positioning System (Ersahin et al., 2017; Gregory, Grunwald, Osborne, Reddy, & Newman, 2006). A small-scale pattern is mainly attributed to the existence of short-range variation that is not detected by the corresponding scheme of sampling. A significant portion of nugget variance corresponds to the small-scale variability caused by small patches of vegetation resulting from a nonuniform distribution of resources such as soil water content, soil nutrients, and soil physical properties (Ryel et al., 1996). In our case, the greater nugget effects in the ESI_c and ESI_a than in the ESI_p can be attributed to small-scale (within distances shorter than the distance between the closest samples) localization of some of the desertification indicators (i.e., soil depth and vegetation cover) that we used to calculate the ESI.

4.2 | Kriging interpolation of the ESI

We evaluated the spatial pattern of the ESI across the land uses by interpolating the ESI_c , ESI_o , and ESI_p separately using the parameters (nugget, range, and sill) of their corresponding semivariograms with OK (Table 5). In each case, the interpolation was made for the entire study area because each land use type was represented by isolated pockets dispersed in the study area (Figure 1). We also interpolated the ESI of the total study area (ESI_t) using the parameters of a combined semivariogram for the ESI_c , ESI_o , and ESI_p . The variable ESI was successfully interpolated by OK, as indicated by the adequately low mean percent absolute error (MAPE; Table 5). Ideally, a MAPE < 0.1 indicates a good performance of the subject model (Armstrong &

Collopy, 1992). However, although the values of the MAPE were below 0.1 in all cases with little variation, the values of the cross-validation coefficient (r) were highly different and even low for the ESI_o according to Agunbiade and Ogunyinka (2013), who noted that a correlation coefficient between absolute 0.30 and 0.5 is considered low (it is considered negligible when $r < \text{absolute } 0.3$). When the MAPE and r are considered together, the results suggest that the interpolation quality was higher for the ESI_t than for the ESI_a , ESI_o , and ESI_p (Table 5). Kravchenko (2003) stressed that the resolution and scheme of sampling and the strength of spatial dependency are the main factors affecting the performance of kriging interpolation. Table 4 shows that the ESI_t was moderately spatially dependent while the ESI_o and ESI_p were strongly spatially dependent. On the other hand, the ESI_t has the greatest r , indicating that the OK interpolation of the ESI_t outperformed that of the ESI_p and ESI_o . Although the reason for the greater performance of the ESI_t is not clear, one explanation would be that the far denser resolution of the ESI_t (122 for the ESI_o and 252 for the ESI_p vs. 632 for the ESI_t) would surpass the effect of stronger spatial dependency for the ESI_o and ESI_p in affecting kriging performance. We decided that the combined semivariogram (ESI_t) of the individual ESIs (ESI_c , ESI_p , and ESI_o) represented the desertification vulnerability better than did the individual semivariograms. Therefore, only the ESI_t was mapped and interpreted (Figure 3).

Figures 1 and 3 show that the majority of the cultivated areas in this region are critically vulnerable to desertification according to Basso et al. (2000) and Salvati and Bajocco (2011), who reported that the vulnerability of land to desertification is categorized as follows: $ESI \leq 1.17$, unaffected; $1.17 < ESI \leq 1.225$, potentially affected; $1.225 < ESI \leq 1.375$, fragile; and $1.375 < ESI$, critical. Sites with ESI values > 1.37 were generally located in the cultivated areas (Figures 1 and 3), whereas those with ESI values < 1.37 were mainly distributed in the forested areas, indicating that the primary spatial pattern of the ESI was controlled by land use. The spatial pattern of the ESI_t also showed that there are several 'patches of fertile islands' in the forested areas and 'degraded islands' in the cultivated areas. We observed that the south-facing, steep slopes comprised highly degraded localities in the cultivated areas. Measures should be taken

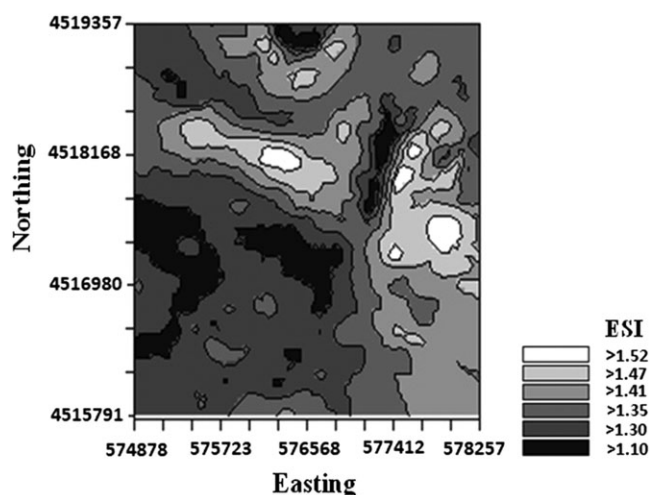


FIGURE 3 Spatial pattern of kriging-interpolated values of environmental sensitivity index (ESI) in the study area

to mitigate desertification while allowing for sustainable farming in cultivated areas, which will require management practices that increase the OM content and decrease soil erosion. This may include the use of organic fertilizers, such as farmyard manure, composts, and green fertilizers, and the adaptation of conservation tillage with proper residue management.

The fragile ($1.225 < \text{ESI} \leq 1.375$) and potentially affected ($1.17 < \text{ESI} \leq 1.225$) areas were mainly located in the oak and pine forests (Figures 1 and 3). These areas comprise very steep, eroded, south-facing slopes, very shallow to shallow soil depths, and low vegetation cover (Table 1); therefore, these factors are the common desertification drivers here. Therefore, to rehabilitate these localities, grazing and wood collecting should be avoided for the purpose of lessening the severe erosion evidenced by the removal of eroded material from steep slopes and its accumulation at the depressions of side slopes. In contrast, the unaffected ($\text{ESI} \leq 1.17$) areas in the forests were mainly located on slopes lower than approximately 10% that are relatively protected from erosion and thus are high in plant cover and have deep soils (Figures 1 and 3). For example, we observed that the ESI was lower in depressions than on adjacent eroded, steep slopes. It is important that the fertility of these areas is maintained in the future by protecting the plant cover from high-intensity grazing and/or improper forestry activities.

4.3 | Rationality of the ESI concept for delineating desertification vulnerability

It is important that we assess the validity of the desertification indicators across different spatial and temporal scales when conducting desertification studies. Here, we validated the use of the ESI as an indicator of desertification by using the OM content of the soils as an independent variable. We found that the OM content was significantly moderately negatively correlated with the ESI ($n = 632$, $r = -0.51$, $P < 0.01$), suggesting that ESI may successfully quantify the desertification vulnerability of lands in the study area. Furthermore, our ESI values were mostly consistent with the desertification risk values shown on a desertification risk map of Turkey (TUBITAK, 2015), with greater ESI values falling in areas with greater desertification risk values and vice versa.

In this study, we evaluated the desertification vulnerability of our study area at the landscape scale, which may be considered a 'process (operational) scale' according to Zhank, Drake, and Wainwright (2004). These authors stated that an environmental phenomenon can be best observed at this scale, and thus, these results can be used as an early warning for policy makers that the necessary measures need to be taken to prevent further degradation of the study area.

The ESI is conceptualized adequately in the DIS4ME framework; as the key variables are identified, the related indicators are clustered, the interconnections among the indicators are described, and the methodologies for synthesizing the information obtained from the indicators are defined. However, these indicators should not be considered final because advancing scientific knowledge and changing policy concerns will result in the indicator sets evolving constantly (Sommer et al., 2011). Furthermore, it should be noted that the

DIS4ME gives equal weights to all of the indicators, which is its greatest disadvantage.

Semiarid ecosystems are highly vulnerable to desertification, with changes in the vegetation characteristics potentially leading to substantial degradation of their landscapes (Puttock et al., 2013). In particular, climate change may lead to anomalies in the vegetation characteristics, feedbacks between the landscape and vegetation, and socioeconomic variables. Irregularities in the total annual precipitation, extreme temperatures, humidity, interannual differences in annual precipitation, and the aridity index may have important consequences for the spatial pattern and overall changes in the ESI across the study area.

5 | CONCLUSIONS

In this study, we used the ESI to evaluate the desertification vulnerability of 1,000 ha of land in Anatolia that has a complex topography and comprises different land uses. We found that land use was the main desertification driver in this region, with the cultivated lands having a significantly greater mean ESI value than have the forested lands ($P < 0.01$). We were unable to link climate to desertification vulnerability because the range of entries for the climate variables that are accepted in the DIS4ME (e.g., <280 , $280\text{--}650$, and >650 mm for annual precipitation) is larger than the range observed in the study area. Therefore, we had to assume that the climate variables were identical across the study area despite this not being the case.

Our results demonstrated that the ESI is useful for delineating the desertification vulnerability of cultivated areas, oak forests, and pine forests at the landscape scale, which was evidenced by the significant moderate negative correlation ($n = 632$, $r = -0.51$, $P < 0.01$) between the ESI and the soil OM content. These results showed that the ESI conceptualization and the indicators that were used to calculate the ESI were valid for quantifying the desertification vulnerability of the lands in the study area.

Geostatistical analysis was shown to be useful in delineating the ESI and evaluating the spatial structure and pattern of the ESI in individual land uses as well as in total area. A moderate nugget effect, calculated for the cultivated areas and oak forests, evidenced that the short-scale variability was greater in these land uses than in the pine forests. Temporal and spatial changes in the ESI should be monitored, and human–environment interactions should be considered when developing adaptive management practices to mitigate desertification. In this regard, geostatistics can aid the evaluation of changes in the spatial structure of the ESI using semivariograms and the identification of areas that are vulnerable to desertification using kriging-interpolated maps of the ESI.

The lessons learned from this study can be used in future studies that aim to evaluate the desertification vulnerability of various dryland types, and the resulting information can be compiled into spatial maps not only in similar geographic regions in Turkey but also under similar ecological conditions across the world. However, these indicators should not be considered final because the indicator set should be improved with advancing scientific knowledge and changing policy

concerns. In addition, the indicators should be tested at different scales to assess their adaptability.

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