Environ Monit Assess (2023) 195:208
https://doi.org/10.1007/s10661-022-10814-1

Useful indicators and models for assessing erosion control ecosystem service in a semi-arid forest landscape

Can Vatandaşlar · Mehmet Yavuz

Received: 4 August 2022 / Accepted: 6 December 2022

Abstract Forests provide a large array of ecosystem services (ESs) such as wood supply, extreme natural event prevention, and ecotourism opportunities. The quantitative characterization of ESs is a crucial but costly task for environmental managers. The aim of this study was to develop easily applicable models and indicators for assessing erosion control ES in a semi-arid landscape. In order to accomplish this, 107 randomly selected plots were visited for field measurements and topsoil sampling. Several parametric tests were then used to analyze the field data. The findings revealed that (i) normalized difference vegetation index (NDVI), (ii) cover management (C) factor of the Revised Universal Soil Loss Equation (RUSLE), (iii) soil organic matter content, (iv) canopy cover ratio, and (v) land use/land cover (LULC) types could be used as useful performance indicators of erosion control ES. Two regression models were developed based on these indicators and compared to RUSLE results for the study area. Using the first model, we were able to estimate the soil protection performance of different LULC types by NDVI at the pixel level ($R^2_{adj} = 0.90$, $p < 0.05$). The second model estimated annual potential soil loss using NDVI and ground slope values ($R^2_{adj} = 0.57$, $p < 0.05$). Based on the ES indicators framework, a practical approach was proposed in this study for rapid assessment of the soil erosion problem without running RUSLE. Thus, environmental managers are expected to make well-informed landscape planning decisions and improve their ES provision application capabilities at a reduced cost.

Keywords Forest management planning · Landscape ecology · Revised Universal Soil Loss Equation (RUSLE) · Biophysical indicators · Soil protection performance index (SPPI)

C. Vatandaşlar (✉) · M. Yavuz
Dept. of Forest Engineering, Faculty of Forestry, Artvin Çoruh University, 08100 Artvin, Turkey
e-mail: canvatandaslar@artvin.edu.tr

M. Yavuz
e-mail: myavuz32@gmail.com

Introduction

Every year, 642 million tons of sediment are washed into the seas in Turkey as a result of water-borne soil erosion (Erpul et al., 2018). With a better understanding of the role of forest cover in protecting soil against erosion, research in this field has increased over the last century on a global scale. Indeed, when compared to bareland conditions in the same climatic gradient, forest cover can reduce surface runoff by 15–20 times and soil loss by up to 350 times (GDF, 2014). Therefore, erosion control is regarded as an essential ecosystem service (ES), particularly in erosion-prone countries (Akgöz et al., 2022; Aytop & Şenol, 2022).

ESs can be briefly defined as "the benefits that humans derive from nature" (TEEB, 2010). Based on the latest version of the Common International Classification of Ecosystem Services (CICES), ESs are grouped into three main sections: (i) provisioning, (ii) regulating and maintenance, and (iii) cultural (Burkhard et al., 2012; CICES, 2018; Tokgöz & Say, 2021). In this classification scheme, the erosion control ES is listed under the regulating and maintenance section and it is defined as "regulation of baseline flows and extreme events."

The quantification of ESs is crucial for operationalizing the ES concept within the context of management planning (Baskent, 2020; Caglayan et al., 2021; Tiemann & Ring, 2022). It is often performed by direct measurements on the ground, indirect measurements via remote sensing, and/or modeling tools (Burkhard & Maes, 2017; Knoke et al., 2021). Whatever method is chosen, robust indicators are needed for them to be effectively used in practice.

The indicators are used to spatially assess the supply, flow, and demand of a given ES over a specific time frame (Tiemann & Ring, 2022; Vihervaara et al., 2017). The volume of harvested wood, for instance, is a useful indicator of well-managed forests. Utilizing solid wood units such as cubic meters, cubic feet, or cords can aid in easily tracking, quantifying, and assessing the flow of wood production. For regulating and cultural forest ESs, however, the quantification step is often challenging (Knoke et al., 2021). Taking erosion control ES, for instance, it is hard to model how much soil loss is being prevented each year by specific land use/land covers (LULCs) in an investigated area. Although many erosion prediction models are used worldwide, they only provide potential soil loss and its spatial distribution throughout the area. Thus, additional indicators or proxies are often used to reveal the erosion control ES supplied by each LULC type (Egoh et al., 2012; Oudenhoven et al., 2015; Tokgöz & Say, 2021).

The adaptation of indicators for erosion control ES varies by country. In Turkey, for example, if the slope rate in forested land is greater than 60%, the land is assigned to the erosion control ES (aka soil protection function) in forest management plans (GDF, 2017). Despite its limitations, such as the lack of other factors contributing to soil loss, the ground slope is used as a practical indicator for forest planners. In Germany, on the other hand, Koschke et al. (2012) used the runoff coefficient as a proxy indicator for quantifying the same ES in a landscape planning framework. The altitude, soil type, soil loss, bulk density, and the ratio of forested lands are other indicators used to approximate soil-related ESs worldwide (Oudenhoven et al., 2015). However, when used alone, these indicators are incapable of grasping such complex ESs (Egoh et al., 2012; Vatandaşlar et al., 2020).

To overcome these limitations, Guerra et al. (2014) developed a conceptual framework to distinguish the capacity of erosion control ES (supply) and its actual provision (flow). They first quantified the structural impact of soil erosion without service provisioning (i.e., bareland condition). Then, the researchers calculated the mitigated impact of erosion using the Revised Universal Soil Loss Equation (RUSLE) model. Finally, a fraction of the structural impact was determined as the actual ES provision. Although scientifically sound, the framework is ineffective for incorporating erosion control ES into forest management plans. The framework is challenging to realize on the ground due to a lack of knowledge and expertise among forest planners and land managers in integrating erosion models into management plans. Because of their intensive fieldwork and limited time, they can barely implement erosion models like those proposed by Guerra et al. (2014). Thus, considerably more practical—but still quantitative—models or indicators are desperately needed in this discipline.

The present study aims to develop useful models and indicators for assessing the erosion control ES of forested lands. Individual tree parameters (tree age, tree height, diameter at breast height (DBH), annual growth ring width), stand parameters (basal area, stand age, stand height, stand origin, canopy cover ratio, regeneration status, health status, stand vertical layering, stand form, silvicultural status), forest floor parameters (litter thickness, litter depth, ground closure of undergrowth vegetation, surface roughness, surface stoniness), deadwood parameters (number of fallen deadwood, number of stumps, number of standing deadwood and their DBHs), topographical parameters (slope, aspect), soil parameters (silt, clay, sand content, soil type, organic matter (OM)), and soil erosion parameters (vegetation cover, rainfall erosivity, soil erodibility, slope length and steepness, conservation support practices) were used as useful indicators to achieve our objectives. To estimate the surface soil loss by water erosion, the RUSLE model was used. The sediment delivery ratio (SDR) and sediment yield (SY) to the river systems were also estimated.

To this end, an intensive timber survey and soil sampling were performed in 107 randomly selected plots in Olur Forest Enterprise, northeastern Turkey. After analyzing data sets collected from the field, relationships among ES indicators, soil properties, and other forest-related parameters were investigated. Moreover, two regression models and several performance indicators are proposed for the management planning context. The findings of this study are expected to be used in forest and land management plans to allocate different landscape units to the appropriate ES (Caglayan et al., 2021) and for forest function mapping, a common management tool in European forestry (Tiemann & Ring, 2022). They can also be utilized by erosion modelers and other resource managers who work with or are interested in ES assessments.

Materials and methods

Study area

Olur Forest Enterprise is the study area located between 40°14′18″ – 40°58′45″N and 41°49′55″ – 42°19′59″E in Erzurum Province (Fig. 1). Its total area coverage is 80,864 ha, and only 9.2% of it is forested. The rest of the study area is composed of unproductive grassland (54.2%), degraded lands/forest openings (26.3%), agriculture (9.4%), and other LULCs. Sparsely vegetated areas prevail in the landscape, as adverse climate conditions (i.e., low annual precipitation total) limit plant growth in this sub-region (Yener, 2022). According to Erinç's Aridity Index (Erinç, 1965), the semi-arid climate type is dominant in Olur Forest Enterprise, with an annual average total precipitation of 430 mm (Duman, 2017; TMS, 2018). The climate data observed between 1990 and 2018 shows that the annual average air

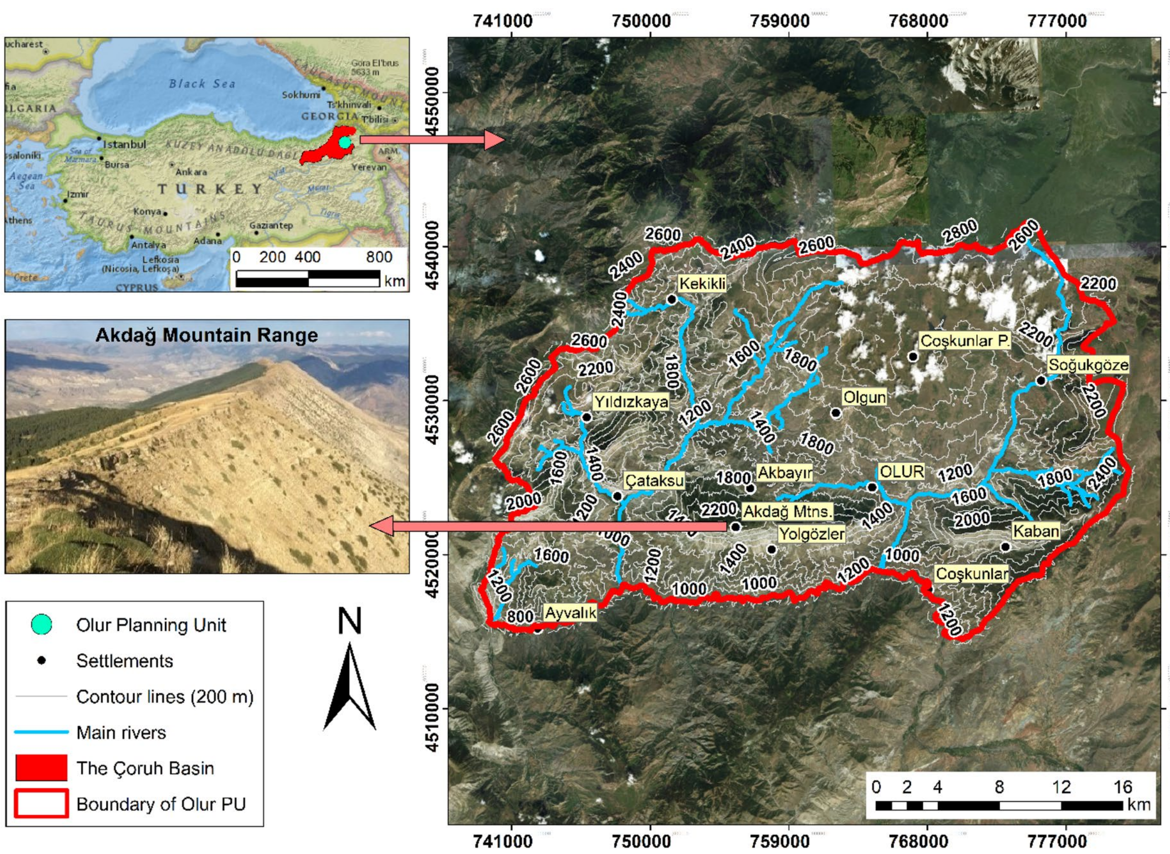

Fig. 1 Location of Olur Forest Enterprise

temperature is approximately 10 °C. Moreover, the study area has a harsh topography ranging from 830 to 2840 m with an average slope of 42% (Fig. 1). Thus, shallow soils prevail in the area, mainly in the sandy loam texture. Regarding forest ecosystems, pure and even-aged stands exist in the productive forests of the enterprise. In Turkish forestry, productive forest refers to any forested land with a tree canopy cover of more than 10% (FAO, 2000; GDF, 2017). The main tree species is Scots pine (*Pinus sylvestris* L.), where juniper (*Juniper* sp.) and poplar (*Populus* sp.) trees are also found individually in degraded lands. Land degradation is one of the most critical problems in the study area, as noted in the current forest management plan (GDF, 2015).

Field sampling

In order to represent the variation in different vegetation types, slope groups, and bedrock formations, we sampled 107 randomly selected plots from several LULC classes during the summer of 2018. The number of samples was determined in such a way that each stand type would have at least one sample, while main LULC classes (e.g., forest, grassland, agriculture) would still have at least 30 samples. Following the national forest management guideline (GDF, 2017), we installed circular plots of 400, 600, and 800 m^2 in forest stands with full, medium, and loose canopy cover, respectively. The non-forest plots, on the other hand, were 20 × 20 m square shaped. Since the plots differed in size, we standardized all the parameters measured in the field per hectare (ha) unit so that they could be compared to each other. The field sampling procedure consists of three distinct stages, as explained below;

1. *Traditional timber survey:* DBH of all trees above 8 cm, the height of the dominant trees (m), canopy cover ratio (%), stand age (year), and thickness of the annual growth rings of each species (mm) were measured in the first stage. Moreover, stem quality, stand origin (from high forest or coppice), regeneration status, health status (infested by insects, fungi, or not infested), number of tree layers (one-, two-, or multiple-layered), forest form (even-aged or uneven-aged), silvicultural status, and expected ESs (provisioning, regulating, or cultural) were observed and recorded in inventory sheets. Further information on the measurements and sampling design can be found in the GDF (2017).
2. *Additional measurements and field observations:* in this stage, the thickness of the litter layer (cm), height (cm) and ground closure (%) of undergrowth vegetation, stand basal area (m^2 ha^{-1}), surface stoniness (%), surface roughness (unitless), number of fallen deadwood (#), number of stumps (#) and their DBHs (cm), aspect (sunny or shady), and observed erosion type (e.g., rill, gully, sheet) were measured.
3. *Soil sampling*: disturbed topsoil samples (0–15 cm in depth) were collected after the litter and humus layers were removed. They were placed in plastic bags, labeled, and taken to the soil laboratory of Artvin Coruh University (ACU) for analysis. Furthermore, soil moisture was determined in the field and recorded as five broad classes, from very dry to very wet.

Soil analyses

Collected soil samples were subjected to physical (texture) and chemical (organic matter) analyses in the soil laboratory. Soil samples were air-dried, cleaned of woody debris, and grounded before texture analysis. The Bouyoucos hydrometer method (Bouyoucos, 1962) was used to determine the percentage of silt, clay, and sand fractions of each sampled soil. Subsequently, soil type was assigned using the USDA's soil classification system.

Schumacher's (2002) procedure was followed to determine the OM content in percent using the Walkley–Black wet oxidation method (Walkley & Black, 1934). Then, titration values were assessed using an Excel-based program.

Erosion prediction model

RUSLE model was used for estimating surface soil loss caused by water erosion processes such as sheet, rill, and interrill on the ground. The model uses five factors to quantify the annual surface soil loss, as Renard et al. (1997) formulated in Eq. 1.

$$A = R \times K \times LS \times C \times P \tag{1}$$

where A is the average annual soil loss (t ha^{-1} year^{-1}), R is the rainfall-runoff erosivity factor (MJ mm ha^{-1} h^{-1} year^{-1}), K is the soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}), LS is the slope length and steepness factor (unitless), C is the cover management factor (unitless), and P is the conservation support practices factor (unitless).

Rainfall-runoff erosivity (R) factor

The R factor is the erosivity capacity of the kinetic energy of raindrops to the soil. Observed precipitation data and digital elevation models (DEM) are utilized for calculating R factor. Its value can be computed using Eq. 2, proposed by Arnoldus (1977) and Wischmeier and Smith (1978). However, this value is only valid for the weather station from which the precipitation data was collected, and therefore, it should be distributed to the case study area. To that end, the Olur weather station's data (elevation of 1395 m) and Eq. 3 by Renard and Foster (1998) were used to calculate new precipitation amounts for the entire study area using the Spatial Analyst Tool within the ArcGIS and Eq. 4 to interpolate altitude differences on precipitation (Erinç, 1996; Tüfekçioğlu & Yavuz, 2016). Equation 4 assumes that every 100-m increase in altitude results in a 54-mm increase in annual total precipitation and vice versa (Erinç, 1996).

$$R = \sum_{k=1}^{12} 1.735 \times 10^{(1.5log10(Pi^2/P)-0.08188)} \tag{2}$$

$$Rnew = Rstation\ (Pnew/Pstation)\ 1.75 \tag{3}$$

$$Pnew = Pstation \pm 54h \tag{4}$$

In Eqs. 2–4, P_i is the mean monthly precipitation amount for the ith month (mm), P is the mean annual total precipitation amount (mm), R_{new} is the new R factor value for a given pixel (MJ mm ha^{-1} h^{-1} year^{-1}), R_{station} is the original R factor value for the weather station (MJ mm ha^{-1} h^{-1} year^{-1}), P_{new} is the amount of new calculated mean annual total precipitation amount (mm), P_{station} is the original mean annual total precipitation amount recorded by the station (mm), and h is the altitude difference between the station and a given pixel (hm).

Soil erodibility (K) factor

When all other erosion factors are held constant, some soil types more readily erode than others. The main reason for this difference is the properties of the soil itself which can be defined as soil erodibility, also known as the K factor in RUSLE (Wischmeier & Smith, 1978). K factor can be calculated using a nomograph proposed by Wischmeier and Smith (1978) or other methods in the soil literature (i.a., Deviren Saygın et al., 2011; Schmidt et al., 2018a). Whichever method is chosen, they often use soil properties including structure, texture, permeability, and organic matter content in their formulizations. In this study, Torri et al. (1997) and Torri et al. (2002)'s formulas (Eqs. 5–6) were preferred to calculate K factor values.

$$K = 0.0293\left(0.65 - D_G + 0.24{D_G}^2\right)exp\left[-0.0021\left(\frac{OM}{f_{clay}}\right) -0.00037\left(\frac{OM}{f_{clay}}\right)^2 - 4.02f_{clay} + 1.72{f_{clay}}^2\right] \tag{5}$$

$$D_G = \sum f_i \log_{10}(\sqrt{d_i d_{i-1}}) \tag{6}$$

where K is the soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}), OM is the organic matter content in soil (%), f_{clay} is the clay content in soil (%), D_g is the decimal logarithm of the geometric mean of particle size distribution, f_i is the mass fraction of the related size class, d_i is the maximum diameter of the ith class (mm), and d_{i-1} is the minimum diameter of the ith class (mm). Finally, K factor values calculated for each sample plot were interpolated to the entire study area using the inverse distance weighting (IDW) method in ArcGIS.

Slope length and steepness (LS) factor

In theory, slope length (L) and land steepness (S) separately affect soil erosion processes. In practice, however, they are lumped together and incorporated into RUSLE as a single topographic factor—LS (Wischmeier & Smith, 1978). Because of rapid advancement in remote sensing and geospatial technologies, it is much easier to calculate and map the LS factor in GIS, even for broad areas through DEM data. In a GIS environment, L refers to flow accumulation times pixel size, whereas S refers to the surface slope rate of each pixel in slope maps (Kinnell, 2001; Schmidt et al., 2019). Hence, the LS factor was calculated using Eq. 7 in the present study.

$$LS = [(Flow\ accumulation \times Cell\ size)/22.13]0.4 \times [Sin(Slope)/0.0896]1.3 \quad (7)$$

where flow accumulation is the accumulated upslope contributing area for each pixel (m^2), cell size is the pixel size of the raster surface in GIS (m), and sin(slope) is the sinus of the surface slope rate (°). Here, it should be noted that the surface slope in degree units must be converted to radiance units by multiplying with a 0.01745 coefficient.

Cover management (C) factor

The effect of vegetation cover is represented by *C* factor (aka soil loss ratio) in RUSLE. It comprises five sub-factors which can be formulated as in Eq. 8 (Renard et al., 1997).

$$C - factor = PLU \times CC \times SC \times SR \times SM \quad (8)$$

where PLU is the previous land use, CC is the crown closure, SC is the surface cover, SR is the surface roughness, and SM is the soil moisture. Each sub-factor depends on several biophysical variables on the ground. The term PLU describes the relationship between previous tillage practices' impact on soil consolidation and the influence of previous crops' sub-surface residual effects on erosion (Renard et al., 1997). PLU values of 0.5 and 1 were provided for the land use classes classified as forests and other land uses, respectively, as used in the study by Suriyaprasit and Shrestha (2008). Using the equations given by Renard et al. (1997), the CC sub-factor was calculated within the 107 sample plots in the study area. For this, information on the average tree height at which raindrops land after touching the canopy and the percentage of the land area that the canopy covers are needed. They were measured and parameterized for each sample plot, as explained in detail by Vatandaşlar and Yavuz (2017).

C factor is one of the most critical factors in the RUSLE model (Akgöz et al., 2022; Koralay & Kara, 2022; Vatandaşlar & Yavuz, 2017). Unlike other factors, it is the unique one that may be rapidly changed by human intervention. Thus, all practitioners and decision-makers can readily affect it without even realize. Therefore, spatial modeling of the *C* factor as accurately as possible is crucial, particularly in large heterogeneous landscapes such as Olur's mountainous watershed. To this end, erosion modelers from different parts of the world are continuously paying enormous efforts. They usually focus on developing robust models to estimate *C* factor values based on remote sensing indices, such as Fraction of Green Vegetation Cover (FGVC) or NDVI (de Jong, 1994; Schmidt et al., 2018b; van der Knijff et al., 1999; Vatandaşlar & Yavuz, 2017). NDVI is a well-known indicator for quantifying living vegetation's health, distribution, and vigor. It uses the spectral difference between red and near-infrared bands of optical images, as formulated in Eq. 9 (Tucker, 1979).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (9)$$

where NIR is the digital number (DN) for a given pixel of the near-infrared band, and Red is the DN for a given pixel of the red band in multispectral imagery.

Following the NDVI-based modeling approach (Vatandaşlar & Yavuz, 2017), Pearson's correlation analysis was first performed to examine possible relationships between ground-measured *C* factor values of each plot and their mean NDVIs derived from multispectral imagery (35-cm-resolution aerial photos) by pixel basis. The correlation analysis was used to show potential relationships between the field-measured *C* factor and NDVI values ($r = -0.80$, $p < 0.01$). The adjusted coefficient of determination (R^2_{adj}), root-mean-squared error (RMSE), and residual analysis were used to determine the best-fit model. Then, using the best-fit model, the *C* factor values were obtained for the whole study area. The correlation analysis showed a strong, negative, and non-linear relationship between *C* factor and NDVI ($r = -0.80$, $p < 0.01$). The developed regression models are shown in Fig. 2. Among them, the best one was the *logistic model* (Eq. 10) with an R^2_{adj} and RMSE of 0.87 and 0.065, respectively (Vatandaşlar, 2020).

$$c = 1/(\frac{1}{u} + (3,003 \times \left(1623,312^{NDVI}\right)) \quad (10)$$

where NDVI is the normalized difference vegetation index value in a given pixel on the NDVI map (unitless) and *u* is the upper prediction limit of the logistic

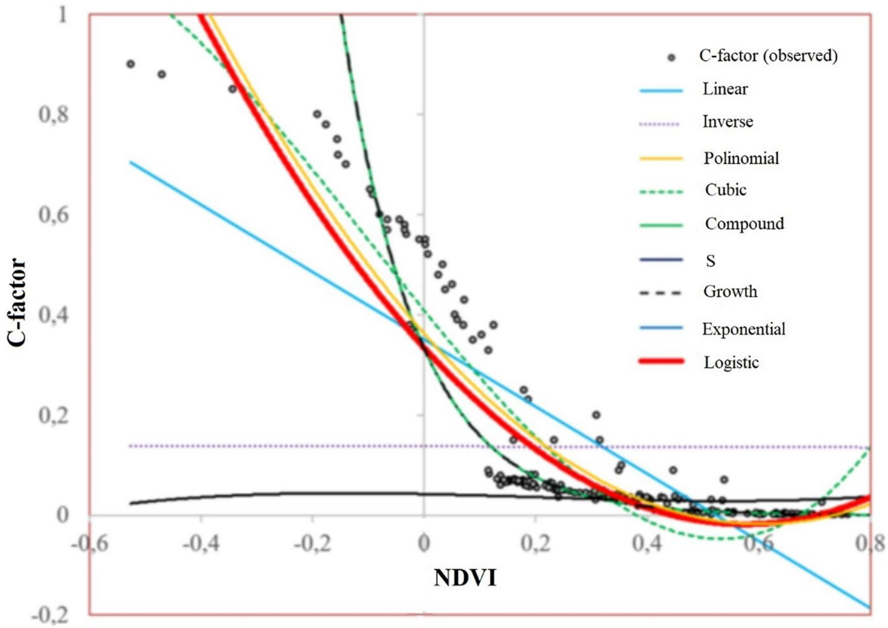

Fig. 2 Regression relationship between NDVI and *C* factor values

model. Since *C* factor ranges from 0 to 1, *u* equals 1 in the equation.

Conservation support practices (P) factor

P factor refers to human-made soil protection measures such as terrace systems, strip-cropping on the contour, and contour tillage. They are able to control soil erosion loss to a certain extent by slowing runoff water and thus reducing the amount of soil it can carry (Wischmeier & Smith, 1978). In this study, a value of "one (1)" was assigned to each pixel of the *P* factor map, assuming no conservation practice in the study area.

Sediment delivery ratio (SDR) and sediment yield (SY)

The average annual soil loss (A) calculated by RUSLE estimates surface soil transported within the study area which may not be totally carried away from the watershed. Therefore, SDR was first calculated to determine how much of the transported soil left the watershed. In the next step, the average annual soil loss was multiplied by the SDR to determine SY, defined as the amount of soil having left the watershed (Tüfekçioğlu & Yavuz, 2016). In the present study, Eqs. 11–12 were used for calculating SDR and SY, respectively (Boyce, 1975; USDA, 1983).

$$SDR = 0.5656 \times B^{-0.11} \quad (11)$$

$$SY = SDR \times A \quad (12)$$

where SDR is the sediment delivery ratio of a given watershed (%), *B* is the total area of the watershed (km^2), SY is the sediment yield of the watershed (t ha^{-1} year^{-1}), and *A* is the average annual soil loss estimated by RUSLE (t ha^{-1} year^{-1}).

Statistical tests

A series of statistical analyses were performed using the field data, to examine the possible relationships among the forest-related parameters, soil properties, and quantity of erosion control ES. The Kolmogorov–Smirnov test was used to control the "normal distribution" of data sets. If the data were normally distributed, Pearson's correlation analysis was performed to understand the magnitude and nature of the correlative relationship among the measured data sets (e.g., growing stock and OM content). The *Log* transformation of non-normal data was performed before performing a parametric test. On the other hand, independent samples *t* test and analysis of variance (one-way ANOVA) were used for categorical data such as forest form (even- or uneven-aged) and soil moisture classes (i.e., dry, wet). Finally, regression analysis was employed to model the relationships among some measured variables. All the tests were performed at a minimum 5% significance level ($p < 0.05$) using SPSS 20.0 statistical software (SPSS, 2012).

Results and discussion

Forest-related parameters

Descriptive statistics for the structural parameters measured in the field are presented in Table 1. Accordingly, an average stand age of nearly 90 indicates that Olur's forests are generally mature and in their advanced developmental stages. The Scots pine forest stands in the study area have almost reached their rotation age, which was set at 100 years within the management plan (GDF, 2015). Except for forest compartments designated for non-provisional ESs (e.g., habitat protection and recreation), they must therefore be restored as soon as possible.

Table 1 also shows that the forests were not fully stocked in Olur Forest Enterprise. The mean growing stock and basal area values were only 162.4 m^3 ha^{-1} and 19.1 m^2 ha^{-1}, respectively, while the number of trees and canopy cover were approximately 432 # ha^{-1} and 50%, respectively. A cover ratio of 50% refers to medium-covered forests closing half of the ground with their tree crowns (GDF, 2017). This means that the rest of the ground is unprotected from the erosive effects of raindrops, which are critical for most water-borne soil erosion processes. In another study by Vatandaşlar and Zeybek (2020) in Turkey, growing stock, basal area, and the number of tree parameters were reported to be as high as 690 m^3 ha^{-1}, 62 m^2 ha^{-1}, and 1200 # ha^{-1}. Although the two study areas were dissimilar in tree species and forest structure, the vast difference among the values implied that Olur's forests were in quite poor condition in terms of wood stock. The high quantity of deadwood also supports this implication. Based on the timber survey, standing and lying deadwood averages were 20.2 # ha^{-1} and 14.8 # ha^{-1}, respectively (Table 1). Their sum (35.0 # ha^{-1}) almost made up 10% of the total number of trees (432.6 # ha^{-1} on average). In a semi-arid national park in Turkey, Karahalil et al. (2017) analyzed the deadwood volume in another pine-dominated forest. They suggested that 2–3% of the total growing stock could be left in the forest for biodiversity. Thus, the deadwood quantity in our study area seems too high, even for a protected area. A possible reason for this might be the severe mistletoe (*Viscum album* ssp. *austriacum*) infestations observed in pure Scots pine stands, located at relatively low altitude belts (appr. 1400 m in Olur). Yavuz and Alkan (2016) investigated the effects of mechanically removing mistletoe species on Scots pine radial growth in the same region and found that 15% of radial growth was lost. Scots pine stands experienced growth losses of up to 67% prior to dieback, according to another study by Bilgili et al.

Table 1 Descriptive statistics for stand parameters measured in the forest sample plots

Stand parameters	Descriptive statistics			
	Min	Mean	Max	S.D
Stand age (year)	23.0	88.8	152.0	28.7
Annual increment in DBH (mm)	1.0	2.8	8.0	1.7
Basal area (m^2 ha^{-1})	0.0	19.1	47.0	12.3
Growing stock (m^3 ha^{-1})	1.0	162.4	448.0	119.0
Stand top height (m)	4.0	11.7	24.0	7.2
Canopy cover (%)	4.0	50.9	85.0	22.6
Number of trees (# ha^{-1})	50.0	432.6	950.0	212.6
Number of standing deadwoods (# ha^{-1})	0.0	20.2	250.0	43.8
Number of fallen deadwoods (# ha^{-1})	0.0	14.8	300.0	42.8
Number of stumps (# ha^{-1})	0.0	70.8	399.0	88.9
Thickness of litter layer (cm)	0.0	3.1	7.0	2.3
Height of undergrowth vegetation (cm)	1.0	32.8	100.0	26.1
Closure of undergrowth vegetation (%)	3.0	43.1	80.0	21.7

(2018). According to Duman (2017), the semi-arid climate in Olur is thought to be another factor contributing to the poor wood stock. Given the observed meteorological data (TMS, 2018) and climate modeling studies (i.a., Yener, 2022), the annual average precipitation totals in that sub-region decreased well below 400 mm owing to climatic variations. Such an amount of precipitation is insufficient for well natural forest development. Descriptive statistics for other stand parameters are shown in Table 1.

Soil properties

Descriptive statistics for the soil samples collected from the study area are shown in Table 2. The averages for the sand, clay, and silt fractions in the soil were 62.0%, 13.5%, and 24.5%, respectively. Thus, the soil texture of the general area showed a sandy loam characteristic according to the USDA's soil classification system. These results align with those previously reported by Yavuz and Tufekcioglu (2019) and Duman (2017). Specifically, Duman (2017) studied nearby watersheds and reported average values of 66.7%, 13.2%, and 20.1% for sand, clay, and silt fractions in the soil. In this respect, Olur Forest Enterprise has no distinctive soil texture structure from its surroundings. On the other hand, an average OM content of 5.8% was found in the soil samples collected. It might appear slightly high at first glance for an uncovered semi-arid region, but soil samples were mainly collected from the forest, the richest LULC regarding OM content. In another study, Yilmaz et al. (2015) collected soil samples from forest, agriculture, and grassland LULCs and found that soil OM content changed between 4.83% and 6.52% in Trabzon (NE Turkey). Thus, it was seen that the results obtained by the present study were in synergy with those of others in the region.

Table 2 Descriptive statistics for soil analysis results

Soil parameters	Descriptive statistics			
	Min	Mean	Max	S.D
Sand fraction (%)	38.4	62.0	84.4	9.8
Clay fraction (%)	3.6	13.5	31.7	6.4
Silt fraction (%)	11.9	24.5	40.8	5.9
OM content (%)	0.6	5.8	10.0	2.4
Soil erodibility (*K* factor) (t ha h ha^{-1} MJ^{-1} mm^{-1})	0.032	0.040	0.048	0.004

Regarding soil erodibility, the average *K* factor value was 0.040 t ha h ha^{-1} MJ^{-1} mm^{-1} (Table 2). It ranged from 0.032 t ha h ha^{-1} MJ^{-1} mm^{-1} in clay-dominated forest soils to 0.048 t ha h ha^{-1} MJ^{-1} mm^{-1} in the sand- and silt-dominated open lands. Our results showed less soil erodibility rate than Yavuz and Tufekcioglu's (2019) findings (0.13 t ha h ha^{-1} MJ^{-1} mm^{-1}) for the Uzundere sub-watershed located in northeastern Turkey. These were expected findings because clay soils are more resistant to erosional processes. In contrast, sandy and silt soils show little or no resistance to detachment (Renard et al., 1997; Torri et al., 1997). Duman (2017) conducted a study analyzing the soil properties in the Coruh River Basin, including the Olur sub-watershed. For Olur, the researcher calculated average *K* factor values of 0.050 t ha h ha^{-1} MJ^{-1} mm^{-1} and 0.052 t ha h ha^{-1} MJ^{-1} mm^{-1} for degraded forests and grasslands, respectively. The slight differences between his and our values are attributable to the sampling design. Since it was an erosion project, the researcher mostly sampled soils from productive and degraded forestlands. In the present study, however, the focus was on productive forests to assess their erosion control capacities. Here, it should be noted that the *K* factor statistics presented in Table 2 come from the collected soil samples. If they were interpolated to the entire study area, the *zonal statistics* results might show slight differences in the *K* factor map.

Environmental factors

Surface stoniness (%), slope length (m), slope rate (%), altitude above sea level (m), and surface roughness (unitless) were chosen as the environmental factors and their descriptive statistics are shown in Table 3. Based on the field survey, the average surface stoniness was calculated to be 20%, and it changed considerably from 0 to 95%. This indicates a heterogenic landscape structure in terms of topsoil. Additionally, a mean stoniness ratio of 20% is an indicator of a shallow soil layer, resulting in limited plant growth. In terms of erosion control, however, the stone layer may contribute to the ES provision capacity of some LULC classes. Stones may play a significant role in protecting soil resources against raindrops' erosive effect (i.e., splash erosion). Thus, the

Table 3 Descriptive statistics for environmental parameters measured in the sample plots

Environmental parameters	Descriptive statistics			
	Min	Mean	Max	S.D
Surface stoniness (%)	0	20.0	95	24.6
Slope length (m)	22	171.0	1300	212.9
Slope rate (%)	0	34.1	94	24.4
Altitude above sea level (m)	776	1721.5	2446	412.6
Surface roughness (unitless)	0	5.93	30	5.41

surface stoniness parameter should also be considered in erosion modeling and ES studies, as Panagos et al. (2014) noted.

As for surface roughness, an average value of 5.93 was found in Olur Forest Enterprise (Table 3). This was relatively high compared to other studies that used the same method (Vatandaşlar et al., 2020). One reason for this may be the harsh topographic condition at the landscape scale. As shown in Fig. 3, the extreme geomorphology of the study area should lead to high surface roughness values. Another possible reason could be surface stoniness at the small (plot) scale. Stones and small rocks on the soil surface might have affected the smoothness. Thus, the surface roughness increased on the slopes, as reported in another study by Thomsen et al. (2015). In fact, a rough slope is desired at a small scale because it reduces the velocity of surface runoff. On the other hand, it limits plant growth in most cases, as well. Therefore, the surface roughness should also be studied further in erosion modeling studies which will be conducted in the future.

RUSLE outputs

Table 4 shows the values for individual RUSLE factors as well as the total amount of soil loss in the study area. Based on Boyce (1975)'s formula, the SDR for the study area was 0.271, suggesting that almost one-third of the transported soil carries away from the Olur watershed. By multiplying SDR with RUSLE's A, the area-specific SY for the Olur Forest Enterprise was estimated to be an average of 15.8 t ha^{-1} year^{-1} (Table 4). It ranged from zero to 639.2 t ha^{-1} year^{-1} across the watershed. Erpul et al. (2018) published a national erosion atlas containing all the major basins of Turkey. The Olur watershed is located in the Coruh

Fig. 3 An overview of geomorphological formations from the study area (photo: C. Vatandaşlar)

Table 4 RUSLE outputs with soil loss amounts for the study area

RUSLE factors	Descriptive statistics			
	Min	Mean	Max	S.D
Rainfall-runoff erosivity (R) factor (MJ mm ha^{-1} h^{-1} year^{-1})	7	324	925	139
Soil erodibility (K) factor (t ha h ha^{-1} MJ^{-1} mm^{-1})	0.0315	0.0398	0.0479	0.0017
Slope length and steepness (LS) factor (unitless)	0	9	7286	20
Cover management (C) factor (unitless)	0	0.091	0.999	0.089
Average annual soil loss (A) (t ha^{-1} year^{-1}) [a]	0	58.3	2358.7	84.1
Sediment yield (SY) (t ha^{-1} year^{-1}) [b]	0	15.8	639.2	22.8

[a] *A* refers to the topsoil amount transported within the watershed

[b] SY refers to the soil losses washed away from the watershed

River Basin in this atlas. While there was no specific estimation for our study area, the researchers estimated an average soil loss of 26 t ha^{-1} year^{-1} for the whole basin. Thus, the Olur Forest Enterprise can be considered one of the sheltered watersheds in the Coruh River Basin. It can be attributed to this sub-region's low precipitation amounts (< 450 mm in total) throughout the year (TMS, 2018; Yener, 2022). Nevertheless, an average SY of 15.8 t ha^{-1} year^{-1} is still a high amount compared to other sub-regions of the country. Using the RUSLE method, for example, Koralay and Kara (2022) estimated an average SY of 1.46 t ha^{-1} year^{-1} for the Değirmendere watershed in the eastern Black Sea sub-region. The difference in LULC shares of the two study areas may be a reason for the different results. Unlike Olur, almost half of the Değirmendere watershed is covered by dense forests.

In most erosion studies, the *C* factor is regarded as the most important factor in the RUSLE model (Akgöz et al., 2022; Schmidt et al., 2018b; van der Knijff et al., 1999; Vatandaşlar & Yavuz, 2017). In the present study, massive efforts have been put into the *C* factor modeling stage, as mentioned in the methodology section. The residual distributions of several regression models can be visually compared in Fig. 4 together. The *logistic model* appeared to be the best (Fig. 4h), since its deviation from the zero line (normal) was less, and its residuals were more balanced compared to other models. In addition, the R^2 and RMSE values of the *logistic model* were superior to those exhibited by other models (Fig. 2). Thus, the *logistic model* was used to estimate *C* factor values in the RUSLE.

The relationships among soil, environmental, and forest-related parameters

Correlations between continuous data

Statistically significant correlations between the parameters measured in the plots are presented in Table 5. Accordingly, a positive relationship was detected between the *K* factor and the closure of undergrowth vegetation ($r = 0.39$, $p < 0.01$). In other words, soil erodibility increased parallel with the undergrowth vegetation's closure. Similarly, OM content positively correlated with stand top height, canopy cover, litter layer thickness, altitude, and the number of stumps in the Olur Forest Enterprise (Table 5). Among them, canopy cover showed the strongest correlation with the OM content in the soil ($r = 0.66$, $p < 0.01$).

For the clay fraction in the soil, positive correlations were detected with basal area and canopy cover, whereas a negative correlation was observed between the clay fraction and the surface roughness (Table 5). The silt fraction, on the other hand, showed weak positive relationships with the canopy cover and the closure of undergrowth vegetation, i.e., $r = 0.31$ and $r = 0.35$, respectively. However, their confidence levels were relatively high ($p < 0.01$). Similarly, another weak correlation coefficient ($r = -0.34$) was found between the sand fraction and canopy cover (Table 5). Unlike the clay fraction, the direction of this fraction was negative, indicating that canopy cover in sandy soils was lower than that in other soil types. In another study, Yilmaz et al. (2015) found that the sand fraction of soil was higher in broadleaved forests than in

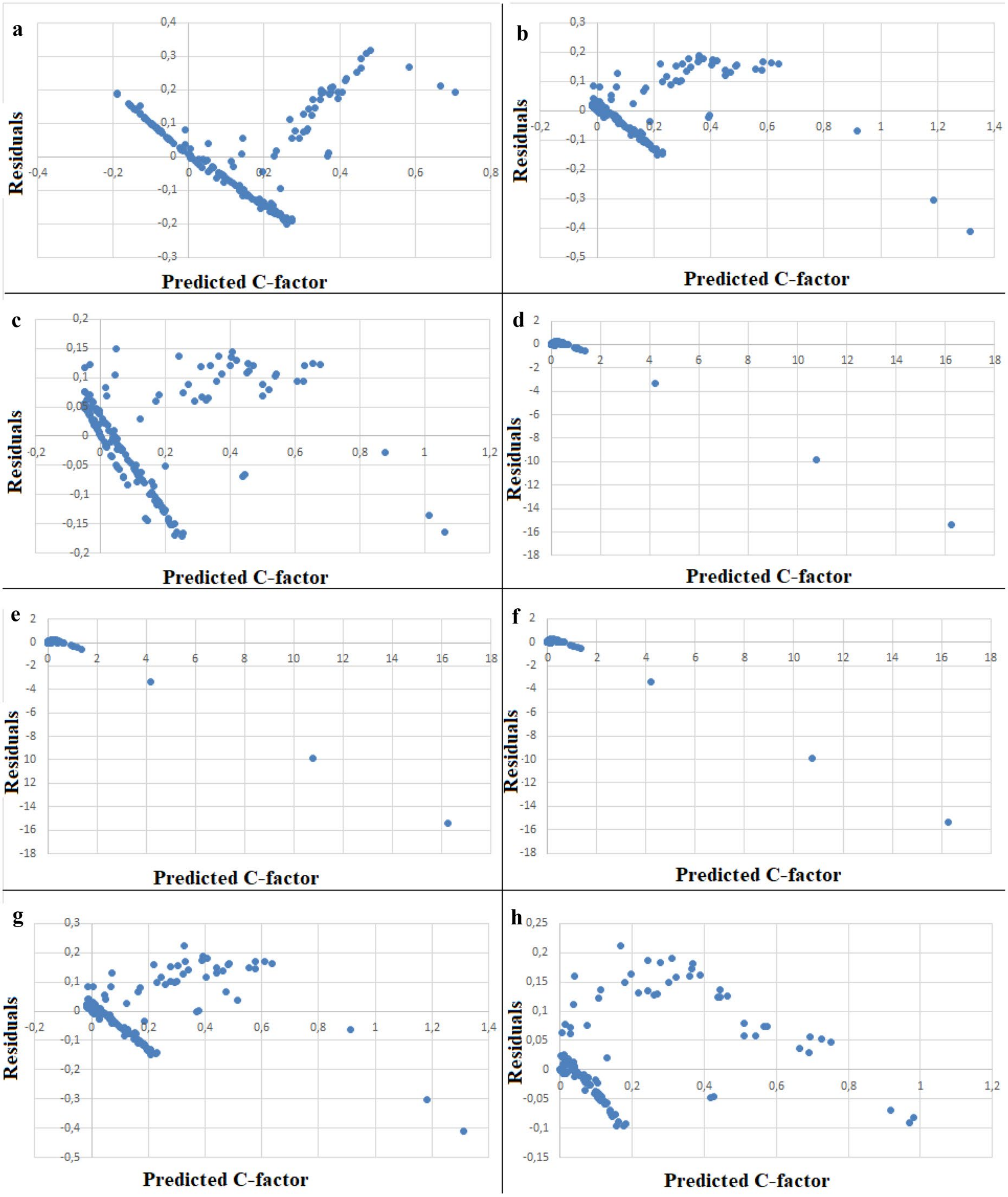

Fig. 4 Distribution of the residuals for each *C* factor model. **a** Linear, **b** polynomial, **c** cubic, **d** compound, **e** exponential, **f** growth, **g** inverse, **h** logistic models

Table 5 Correlations among soil and other parameters measured in the field

Soil parameters	Other parameters	*p*-value (two-tailed)	Pearson's *r*[a]
Soil erodibility (*K* factor) (t ha h ha^{-1} MJ^{-1} mm^{-1})	Closure of undergrowth vegetation	<0.01	0.39
OM content (%)	Stand top height	<0.01	0.43
	Canopy cover	<0.01	0.66
	Thickness of litter layer	<0.01	0.46
	Altitude	<0.01	0.38
	Number of stumps	<0.05	0.30
Clay fraction (%)	Basal area	<0.05	0.35
	Canopy cover	<0.01	0.34
	Surface roughness	<0.01	−0.30
Silt fraction (%)	Canopy cover	<0.01	0.31
	Closure of undergrowth vegetation	<0.01	0.35
Sand fraction (%)	Canopy cover	<0.01	−0.34

[a]Only the correlations having *r* coefficients of more than ±0.30 were presented in the table

conifers. Since sandy soils are more susceptible to water-borne erosion processes, these findings suggest that pure conifer stands should be promoted in forests designated for erosion control ES.

As shown in Table 5, there were statistically significant correlations between all soil properties and the canopy cover parameter. Indeed, the canopy cover ratio of forest stands can be a helpful indicator for assessing soil-related ESs. This can be attributed to the ecological processes on the forest floor in fully covered stands. These stands, in particular, have a lot of leaves, needles, and other dry materials on the floor. They form a leaf litter layer, which gives the soil more protection. It also consists of a considerable amount of OM. The litter is decomposed over time, and thus, the chemical structure of the soil is influenced by these ecological processes (Berg & Laskowski, 2006). In contrast, OM content was lower in degraded forests, with a canopy cover of less than 10% (Duman, 2017; GDF, 2017). In line with our findings, Duman's (2017) study indicated that soil stoniness was generally high in these types of lands. Thus, in forests designated for soil protection, canopy cover ratios of stands should be kept as high as possible.

Table 6 *t* test results for soil and other parameters

Soil parameters (continuous)	Other parameters (categorical)	*p*-value (two-tailed)
Soil erodibility (*K* factor) (t ha h ha^{-1} MJ^{-1} mm^{-1})	Rocks on forest floor (present vs. absent)	<0.01
	Lichen or moss (present vs. absent)	<0.05
OM content (%)	Stand mixture (pure vs. mixed)	<0.001
	Regeneration on forest floor (present vs. absent)	<0.01
	Observed erosion (present vs. absent)	<0.05
	Aspect (sunny vs. shadowed)	<0.001
	Anthropogenic pressure (present vs. absent)	<0.001
	Illicit cutting (present vs. absent)	<0.001
	Stumps on forest floor (present vs. absent)	<0.001
Clay fraction (%)	Rocks on forest floor (present vs. absent)	<0.05
Silt fraction (%)	Undergrowth vegetation (present vs. absent)	<0.05
	Lichen or moss (present vs. absent)	<0.05
Sand fraction (%)	Stumps on forest floor (present vs. absent)	<0.05

t test results for categorical data

All soil-related values significantly changed based on the categorical parameters, such as stand mixture and aspect class (Table 6). In the sample plots, the presence of rock, lichen, and moss increased *K* factor values ($p < 0.05$). Similarly, the soil OM content was influenced by many categorical parameters (Table 6). For instance, the sampling plots with regeneration (saplings) had higher OM content, which is attributable to the richness of the growing site conditions. Conversely, the sampling plots with apparent erosion trails, such as rills, sheets, or gullies, had lower OM since they had lost their fertile topsoil due to water-borne erosion.

The clay fraction in the soil differed based only on the presence of rocks on the forest floor (Table 6). As for silt fraction, however, the presence of undergrowth vegetation and lichen/moss richness increased it significantly. Finally, the sand fraction was influenced only by the presence of stumps on the forest floor. If the sampling plots had any stumps, the sand fraction in the soil was higher than in those without stumps.

ANOVA results for categorical data

One-way ANOVA results showed that all soil properties differed depending on categorical variables consisting of more than two sub-groups (Table 7). Accordingly, the types of intervention to forest and rock size significantly changed the *K* factor values in the Olur Forest Enterprise. Unfortunately, no post hoc test was performed because of the lack of plots for each type. Thus, the cause-effect relationship could not be thoroughly examined for the *K* factor. OM content, on the other hand, differed based on eight parameters: LULC, stand type, regeneration status, soil moisture, observed erosion type, aspect class, anthropogenic pressure, and severity of illicit cutting. LULC classes, in particular, significantly changed OM content in the soil. Soils in productive forests were more prosperous than those in other LULC classes in terms of OM. Likewise, the soils of conifer stands had more OM than those of broadleaved and mixed stands. Another significant difference was in the aspect class: north-facing lands had higher OM content than the others.

Table 7 ANOVA results for soil and other parameters

Soil parameters (continuous)	Other parameters (categorical)	ANOVA *p* (two-tailed)	Levene *p*	Post hoc test
Soil erodib. (*K* factor) (t ha h ha^{-1} MJ^{-1} mm^{-1})	Silvicultural intervention (none, tending, thinning, regeneration)	<0.05	>0.05	–
	Rock size (small, medium, large)	<0.01	>0.05	–
OM content (%)	LULC (degraded forest, productive forest, agric., grassland)	<0.001	>0.05	Tukey
	Stand type (broadleaved, conifer, mixed)	<0.001	>0.05	Tukey
	Regeneration status (none, poor, moderate, strong)	<0.05	>0.05	Tukey
	Soil moisture (very dry, dry, cool, moist, wet)	<0.01	>0.05	Tukey
	Observed erosion (none, sheet, rill, gully, landslide, mass mov.)	<0.05	>0.05	Tukey
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	<0.001	>0.05	Tukey
	Ant. pressure (none, ill. cut., settl., grazing, recr., road, multiple)	<0.01	<0.01	–
	Severity of illicit cutting (none, slight, moderate, severe)	<0.05	<0.05	Tamhane
Clay fraction (%)	LULC (degraded forest, productive forest, agric., grassland)	<0.01	>0.05	Tukey
	Silvicultural intervention (none, tending, thinning, regeneration)	<0.05	>0.05	–
	Rock size (small, medium, large)	<0.01	>0.05	–
Silt fraction (%)	LULC (degraded forest, productive forest, agric., grassland)	<0.001	>0.05	Tukey
Sand fraction (%)	LULC (degraded forest, productive forest, agric., grassland)	<0.001	<0.05	Tamhane
	Soil moisture (very dry, dry, cool, moist, wet)	<0.05	>0.05	Tukey
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	<0.05	>0.05	Tukey

In terms of clay, agricultural areas had the highest clay fractions in the soil. Similarly, the types of silvicultural interventions and rock sizes significantly influenced the clay fraction in the Olur Forest Enterprise (Table 7). Regarding the silt fraction, LULC was the only parameter that influenced soil. Namely, soils of productive forests were siltier than those of the other LULC classes. This can be related to the study area's dominant texture class (sandy loam). Finally, LULC, soil moisture, and aspect were found to be the driving factors of the sand fraction in the soil. In this respect, the soils of agricultural lands had less sand than the other LULCs.

In general, OM content in the soil was the most influenced soil property by categorical parameters. Additionally, the difference in LULC classes changed almost all soil properties in the Olur Forest Enterprise (Table 7). Hence, our study showed similar results to the findings of Yilmaz et al. (2015) regarding the effect of LULCs on soil erosion in Trabzon Province (NE Turkey).

The relationships among erosion control ES indicators and other parameters

Correlations between continuous data

The normalized difference vegetation index (NDVI), cover management factor (*C* factor), actual soil loss (i.e., RUSLE-A), maximum soil loss (i.e., bareland condition), prevented soil loss (i.e., soil retention), and soil protection performance index (SPPI) were

Table 8 Correlations among ES indicators and other parameters

Indicators for erosion control ES	Other parameters	*p*-value (two-tailed)	Pearson's *r* [a]
Normalized Difference Vegetation Index (NDVI) (unitless)	Basal area	<0.01	0.62
	Growing stock	<0.01	0.59
	Stand top height	<0.01	0.70
	Canopy cover	<0.01	0.76
	Thickness of litter layer	<0.01	0.65
	Surface stoniness	<0.01	−0.58
	OM content	<0.01	0.67
Cover management factor (*C* factor) (unitless)	Basal area	<0.01	−0.62
	Growing stock	<0.01	−0.54
	Stand top height	<0.01	−0.71
	Canopy cover	<0.01	−0.76
	Thickness of litter layer	<0.01	−0.63
	Surface stoniness	<0.01	0.65
	OM content	<0.01	−0.67
Actual soil loss (t ha^{-1} year^{-1})	Slope length	<0.01	0.69
Maximum soil loss (t ha^{-1} year^{-1})	Thickness of litter layer	<0.01	0.53
	Slope rate	<0.01	0.51
	Prevented soil loss	<0.01	0.99
Prevented soil loss (t ha^{-1} year^{-1})	Thickness of litter layer	<0.01	0.54
	Slope rate	<0.01	0.50
Soil Protection Performance Index (SPPI) (%)	Stand top height	<0.01	0.59
	Canopy cover	<0.01	0.69
	Thickness of litter layer	<0.01	0.59
	Surface stoniness	<0.01	−0.62
	OM content	<0.01	0.63
	NDVI	<0.01	0.82
	C factor	<0.01	−0.93

[a]Only the correlations having r coefficients of more than ± 0.50 were presented in the table

considered as performance indicators for erosion control ES. This sub-section examines the relationships among these indicators and other measured parameters statistically. The significant correlations are shown in Table 8. Accordingly, a negative correlation was observed between NDVI and surface stoniness. In contrast, positive relationships were found between NDVI and basal area, growing stock, stand top height, canopy cover, the thickness of the litter layer, and soil OM. Among them, the stand top height and canopy cover showed relatively strong correlations ($r=0.70$ and $r=0.76$, respectively). This is not surprising because NDVI is a practical remote sensing index, providing quantitative information on the quantity, distribution, and vigor of living vegetation in a given area (Tucker, 1979). Tokgöz and Say (2021) also state that, typically, a positive correlation exists between NDVI and ES value. In this respect, many studies model the structural parameters of forests using NDVI maps derived from remotely sensed images (Bulut et al., 2016; Kayitakire et al., 2006; Yavuz & Hall, 2018). However, the correlation coefficients for the thickness of the litter layer and OM content were lower because they could not be detected by optical remote sensing.

Similar to the NDVI, the same parameters showed significant correlations with the *C* factor, but their directions were opposite (Table 8). The *C* factor considerably shapes the soil loss ratio in the RUSLE erosion prediction model (Renard et al., 1997). As demonstrated by Knijff et al. (1999), it has a strong and inverse relationship with NDVI. When the *C* factor increases, the NDVI generally decreases. Thus, it can be effectively modeled using NDVI, as done in Eq. 10. That is why the same parameters showed similar magnitudes but opposite directions, as shown in Table 8.

The slope length was the only parameter that showed a significant correlation with actual soil loss (Table 8). The correlation coefficient was rather strong ($r=0.69$). This was expected because the actual soil loss was estimated using RUSLE. In RUSLE, the slope length (*L* factor) is an individual parameter in the equation. It is well known that a slope's length significantly affects surface runoff, resulting in accelerated soil erosion (Renard et al., 1997).

Maximum soil loss (i.e., bareland conditions) showed a positive correlation with the thickness of the litter layer, slope rate, and prevented soil loss. The relationship with slope can be attributed to the model structure of RUSLE since it is in RUSLE's equation as *S* factor. In another study, Oudenhoven et al. (2015) obtained similar findings. They found that soil loss increased with an increasing slope in the grassland LULC class. In our case, both maximum and prevented soil losses were derived by RUSLE's A—annual actual soil loss. If the maximum soil loss is high, prevented soil loss will also be high. However, the correlation between maximum soil loss and litter layer thickness cannot be explained by our knowledge. Maybe, it was a random statistical relation.

Since maximum soil loss is highly correlated with prevented soil loss, the same parameters showed similar correlations with it (Table 8). The prevented soil loss increased as the litter cover increased. This is meaningful because the litter layer has a protective function in the topsoil. Chi et al. (2008), for instance, installed erosion plots in fir forests with and without litter. After the field measurements, they calculated that the plots without the litter layer yielded 71 times more soil loss than the other plots. From these findings, along with those presented in Table 8, it is understood that the litter layer on the forest floor is crucial for erosion control ES.

As for SPPI, many parameters showed a positive or negative correlation (Table 8). Except for the surface stoniness and *C* factor parameters, the directions of the correlations were positive. Accordingly, stand top height positively correlated with SPPI ($r=0.59$). It is attributable to the relationship between site quality and top height. Namely, stand top height is higher in good growing sites (Seki & Sakici, 2022), and tally trees typically have larger canopies with lots of branches, leaves, and needles. Thus, they can effectively protect the topsoil against the kinetic energy of raindrops (Barnes et al., 1998). Besides, their large canopies reduce the amount of water reaching the soil surface due to interception. As a result, the soil erosion rate decreases under forest cover. Therefore, SPPI was higher in dense forest stands.

Except for prevented soil loss, the highest correlation coefficient was found between SPPI and *C* factor (Table 8). The NDVI parameter took second place after the *C* factor, with an *r* coefficient of 0.82. These findings indicate that SPPI can be computed using the NDVI. Thus, the SPPI can be spatially estimated based on a NDVI map and an appropriate regression model. Here, NDVI is preferred over the *C* factor as an estimator because field measurement and calculation of the *C* factor have several difficulties, as discussed in Vatandaşlar and Yavuz (2017).

It should also be noted that only the correlations with $r > 0.50$ are presented in Table 8 ($p < 0.05$). Nevertheless, all *p* values are less than 0.01 in the table, which is more than expected for forest research. In many other forestry studies, a *p*-value of 0.05 is considered sufficient for showing a statistically significant difference between the two groups (i.a., Seki & Sakici, 2022).

t test results for categorical data

Independent samples *t* test showed that all indicators of erosion control ES differed significantly depending on some categorical parameters, such as stand mixture and aspect class (Table 9). Accordingly, the average *C* factor was lower in pure stands than in mixed stands. Likewise, it was smaller in infected stands than in healthy ones. The presence of undergrowth vegetation in forest stands also increased *C* factor values. This may be explained by the canopy cover parameter. Indeed, dense undergrowth is generally seen in loosely covered forests due to exposure to excessive sunlight (Barnes et al., 1998). In parallel, the *C* factor increases as the ratio of tree crowns decreases in these forests (Vatandaşlar & Yavuz, 2017).

The forests with multiple layers had lower *C* factor averages than the one-layered forests. This provides support to the general assumption that "multilayered forests are better for soil protection" (GDF, 2017; Kalıpsız, 1982). On the other hand, the *C* factor averages were higher if any erosion trail existed in the plots. Active erosion processes such as sheets, rills, and gullies generally transport productive topsoil with living vegetation. By doing so, it contributes to an increase in *C* factor values. Regarding aspect, the north-facing (shadowed) forest plots had lower *C* factor averages, possibly due to the moist environment, which was favorable for plant growth (Kantarcı, 2000). The other parameters influencing the *C* factor are listed in Table 9.

Actual soil loss (RUSLE-A) was influenced by four parameters, including stand mixture, observed erosion, aspect, and stumps on the forest floor (Table 9). It was significantly lower in the pure stands, dominating the study area. In Olur Forest Enterprise, forestlands mostly consisted of one evergreen species, Scots pine. In contrast, few mixed stands in Olur consisted of broadleaved species, such as poplar and oak. They are generally located in degraded lands or along riparian zones. We believe that this is the main reason for the reduced erosion rates in the pure conifer forests. As expected, erosive sites and south-facing (sunny) aspects increased soil loss. Indeed, field observations clearly showed that more arid and sunny aspects had no or sparse vegetation cover (Fig. 1). Thus, higher soil loss amounts were estimated for this aspect class. Duman (2017) also reported similar findings for accelerated erosion in the Olur Watershed. Finally, the presence of stumps on the forest floor decreased the actual soil loss, possibly by reducing the velocity of runoff on the floor without litter.

As for maximum soil loss, this indicator was significantly influenced by the stand mix and the presence of lichen or moss (Table 9). Specifically, maximum soil loss was higher in pure forest stands than in mixed stands. Similarly, it had a higher average in forests with lichens or moss. However, maximum soil loss should not be considered a real-world problem on the ground. It simulates soil loss in a scenario area without vegetation cover (Vatandaşlar, 2020). In this respect, maximum soil loss may be high on the upper slopes of sub-alpine lands where lichen and moss prevail on tree trunks, as well as on the forest floor. Since these highlands take high amounts of rainfall (i.e., *R* factor in RUSLE), maximum soil loss will also increase (Tüfekçioğlu & Yavuz, 2016).

Three parameters caused significant differences in the amount of prevented soil loss in Olur ($p < 0.05$). They were the stand mixture, the presence of lichen/moss, and the presence of *Astragalus* sp. (Table 9). The difference caused by the stand mixture was the same as that of the maximum soil loss. Prevented soil loss was higher in the forest plots with lichen and/or moss because they provided an additional protection layer to the topsoil. Likewise, the presence of *Astragalus* sp., especially in the degraded and sparsely covered forests, significantly increased the prevented soil loss in Olur. This is expected because it is a well-known species used to combat erosion in the region (Zengin et al., 2009). Thus, the protective effects of these kinds of shrubs or herbaceous vegetation should not be underestimated (Fig. 5). Instead, their distribution may be promoted where woody vegetation cannot grow.

Table 9 *t* test results for ES indicators and other parameters

Indicators for erosion control ES	Other parameters (categorical)	*p*-value (two-tailed)
Cover management factor (*C* factor) (unitless)	Stand mixture (pure vs. mixed)	< 0.001
	Stand health (healthy vs. infected)	< 0.01
	Undergrowth vegetation (present vs. absent)	< 0.05
	Regeneration on forest floor (present vs. absent)	< 0.01
	Stand layerness (one layer vs. multiple layer)	< 0.01
	Silvicultural intervention (present vs. absent)	< 0.001
	Observed erosion (present vs. absent)	< 0.001
	Aspect (sunny vs. shadowed)	< 0.001
	Anthropogenic pressure (present vs. absent)	< 0.001
	Illicit cutting (present vs. absent)	< 0.01
	Standing deadwood (present vs. absent)	< 0.05
	Fallen deadwood (present vs. absent)	< 0.01
	Stumps on forest floor (present vs. absent)	< 0.001
	Residues on forest floor (present vs. absent)	< 0.001
Actual soil loss (t ha^{-1} year^{-1})	Stand mixture (pure vs. mixed)	< 0.05
	Observed erosion (present vs. absent)	< 0.01
	Aspect (sunny vs. shadowed)	< 0.01
	Stumps on forest floor (present vs. absent)	< 0.05
Maximum soil loss(t ha^{-1} year^{-1})	Stand mixture (pure vs. mixed)	< 0.001
	Lichen or moss (present vs. absent)	< 0.001
Prevented soil loss (t ha^{-1} year^{-1})	Stand mixture (pure vs. mixed)	< 0.001
	Lichen or moss (present vs. absent)	< 0.001
	Astragalus sp. (present vs. absent)	< 0.05
Soil Protection Performance Index (SPPI) (%)	Stand mixture (pure vs. mixed)	< 0.01
	Regeneration on forest floor (present vs. absent)	< 0.01
	Stand layerness (one layer vs. multiple layer)	< 0.01
	Silvicultural intervention (present vs. absent)	< 0.001
	Observed erosion (present vs. absent)	< 0.001
	Aspect (sunny vs. shadowed)	< 0.001
	Anthropogenic pressure (present vs. absent)	< 0.001
	Illicit cutting (present vs. absent)	< 0.01
	Fallen deadwood (present vs. absent)	< 0.05
	Stumps on forest floor (present vs. absent)	< 0.01
	Residues on forest floor (present vs. absent)	< 0.001
Normalized Difference Vegetation Index (NDVI) (unitless)	Stand mixture (pure vs. mixed)	< 0.001
	Regeneration on forest floor (present vs. absent)	< 0.05
	Stand layerness (one layer vs. multiple layer)	< 0.05
	Silvicultural intervention (present vs. absent)	< 0.01
	Observed erosion (present vs. absent)	< 0.001
	Aspect (sunny vs. shadowed)	< 0.001
	Anthropogenic pressure (present vs. absent)	< 0.001
	Illicit cutting (present vs. absent)	< 0.01
	Fallen deadwood (present vs. absent)	< 0.05
	Stumps on forest floor (present vs. absent)	< 0.001
	Residues on forest floor (present vs. absent)	< 0.01

Fig. 5 Photographs demonstrating the effect of *Astragalus* sp. on soil protection (left-photo: Aydın Tüfekçioğlu) and a Scots pine tree resisting soil erosion (right-photo: Mehmet Yavuz) in the study area

SPPI was markedly influenced by many parameters in the Olur Forest Enterprise ($p<0.05$). Pure stands, for example, showed superior performance in terms of soil protection. Similarly, stands with regeneration cover on the forest floor showed a higher performance than those of stands without regeneration. This indicates that the regeneration cover provides an additional layer for soil protection, such as litter. The average SPPI of layered stands was higher than that of one-layered stands. It is an already-known forest structure that promotes soil protection (Kalıpsız, 1982; Yavuz & Hall, 2018; Vatandaşlar et al., 2020). As in the *C* factor, north-facing forest plots were better for soil protection due to wetter conditions in shadowed areas (Barnes et al., 1998). More importantly, the plots with stumps and residuals on the forest floor had a higher SPPI than the others. This can be attributed to the reduced velocity of surface runoff, as well as the "mulch effect" of the residuals. Thus, it can be recommended that tree stumps and harvesting residuals should be left on the forest floor.

Finally, NDVI was influenced by 11 parameters measured on the ground (Table 9). Most of their significance values were less than 0.001, indicating that statistically very significant differences existed. The parameters were similar to those of the *C* factor because NDVI is an independent variable in *C* factor models (Vatandaşlar & Yavuz, 2017). Therefore, these parameters are not repeated here.

In brief, (i) *C* factor was the most affected indicator in Table 9; (ii) the parameters influencing the *C* factor also caused differences in the NDVI means; (iii) since actual/maximum/prevented soil losses were mostly shaped by topography and climate, they were less affected by forest structural parameters; (iv) the parameters influencing maximum and prevented soil losses were almost the same for the Olur Forest Enterprise; and (v) the stand mixture caused differences in almost all ES indicators documented in Table 9.

ANOVA results for the categorical data

One-way ANOVA results showed that all ES indicators differed depending on categorical parameters with more than two sub-groups. The average *C* factors, for example, were significantly influenced by nine variables, including LULC, stand type, and regeneration status ($p < 0.05$) (Table 10). Accordingly, the *C* factor was minimal in productive forests, with a canopy cover of more than 10%. It means that the best soil protection is provided by dense forests, as expected. In terms of stand type, there was no significant difference between the broadleaved and mixed forest stands. In conifers, however, the *C* factor was lower than that of the others. As previously seen in the *t* test, shadowed aspects were more sheltered than the sunny ones in the ANOVA results. Regarding soil types, at least one group showed a significant difference, but it could not be detected using a post hoc test due to insufficient sampling data.

The averages for actual soil loss differed depending on LULC, stand type, observed erosion, aspect, and rock size (Table 10). It was statistically lower in productive forests than in degraded forests and grasslands ($p < 0.001$). In terms of the observed erosion types, there was no difference in the averages, except for rill and mass movement. Annual potential soil loss was higher in sampling plots with rills than in those with the mass movement. Similarly, a significant difference was found between the flat and east-facing plots ($p < 0.001$). The erosion rate was minimal in flat areas, as they had no ground slope (Renard et al., 1997).

Maximum and prevented soil losses were only changed by LULC and stand type classes (Table 10). Their averages were lower in productive forests than in degraded forests and agricultural lands. Regarding stand types, the average of coniferous forests was found to be higher than that of both broadleaved and mixed forests. The reason for the similarity of both results was the strong correlation between the maximum and prevented soil losses, as shown in Table 8. In other words, the higher the maximum soil losses, the higher the prevented soil losses.

As for the SPPI, the productive forest was the best LULC class among all. Specifically, the average SPPI for conifers was higher than that for the others. Pure conifer forests again were superior to both broadleaved and mixed forests. Soil protection in the plots without severe erosion hazard was better than that in plots with any observed erosion trails. Regarding aspect class, the forests located in shadowed aspects protect soil better than those found in sunny aspects. The difference between the two aspect classes was observed for many indicators. It is indirectly related to the high cover rates on north-facing slopes in Turkey due to the moister microclimate (GDF, 2015; Kantarcı, 2000). In addition, there were significant differences in the *C* factor averages based on the soil type (Table 10) but, once again, post hoc tests could not be performed because of insufficient soil samples of each type.

Finally, the average NDVI differed almost in all LULCs, except for grassland and degraded forest. Specifically, productive forests had the highest NDVI averages, as expected. The same difference was also observed in the *C* factor (Table 10). As for stand types, pure conifers had the highest average. This can be attributed to their higher total leaf area relative to that of broadleaves (Asan, 2017). In terms of the diameter class of stumps, the only difference was seen between the pole (i.e., I. class: 8–19.9 cm) and other classes (i.e., ≥ 20 cm). The NDVI averages of different classes were higher than those of the thin classes. Since the *C* factor was derived from NDVI, other variables showed similar differences with the *C* factor.

Briefly, (i) NDVI was the most influenced indicator by other parameters; (ii) LULC class and stand type parameters significantly changed the averages of all indicators ($p < 0.01$); (iii) observed erosion and aspect class parameters changed the averages of most indicators; and (iv) the same parameters (i.e., LULC and stand type) had meaningful effects on both maximum and prevented soil losses.

New indicators, study's limitations, and an outlook

As a performance indicator, SPPI provides valuable information on the erosion control ES of forests at the stand level. Thus, it may help quantify and integrate the ES value into forest management and

Table 10 ANOVA results for ES indicators and other parameters

Indicators for erosion control ES (continuous)	Other parameters (categorical)	ANOVA *p*-value	Levene *p*-value	Post hoc test
Cover management factor (*C* factor) (unitless)	LULC (degraded f., productive f., agriculture, grassland)	< 0.001	< 0.001	Tamhane
	Stand type (broadleaved, conifer, mixed)	< 0.001	< 0.01	Tamhane
	Regeneration status (none, poor, moderate, strong)	< 0.01	< 0.001	Tamhane
	Obs. erosion (none, sheet, rill, gully, landslide, mass mov.)	< 0.001	< 0.01	Tamhane
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	< 0.001	< 0.01	Tamhane
	Soil type (scl, cl, sl, l, ls, sc) [a]	< 0.001	< 0.05	–
	Ant. press (none, ill.cut., settl., graz., recr., road, multiple)	< 0.01	< 0.001	–
	Severity of illicit cutting (none, slight, moderate, severe)	< 0.05	< 0.001	Tamhane
	Diameter class of stumps (I, II, III, IV) [b]	< 0.01	< 0.001	Tamhane
Actual soil loss (t ha^{-1} year^{-1})	LULC (degraded f., productive f., agriculture, grassland)	< 0.001	< 0.001	Tamhane
	Stand type (broadleaved, conifer, mixed)	< 0.01	< 0.01	Tamhane
	Obs erosion (none, sheet, rill, gully, landslide, mass mov.)	< 0.001	< 0.001	Tamhane
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	< 0.001	< 0.001	Tamhane
	Rock size (small, medium, large)	< 0.01	> 0.05	–
Maximum soil loss (t ha^{-1} year^{-1})	LULC (degraded f., productive f., agriculture, grassland)	< 0.001	< 0.001	Tamhane
	Stand type (broadleaved, conifer, mixed)	< 0.01	< 0.01	Tamhane
Prevented soil loss (t ha^{-1} year^{-1})	LULC (degraded f., productive f., agriculture, grassland)	< 0.001	< 0.001	Tamhane
	Stand type (broadleaved, conifer, mixed)	< 0.01	< 0.001	Tamhane
Soil Protection Performance Index (SPPI) (%)	LULC (degraded f., productive f., agriculture, grassland)	< 0.001	< 0.001	Tamhane
	Stand type (broadleaved, conifer, mixed)	< 0.001	< 0.01	Tamhane
	Regeneration status (none, poor, moderate, strong)	< 0.01	< 0.001	Tamhane
	Obs. erosion (none, sheet, rill, gully, landslide, mass mov.)	< 0.001	< 0.001	Tamhane
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	< 0.001	< 0.01	Tamhane
	Soil type (scl, cl, sl, l, ls, sc) [a]	< 0.001	< 0.05	–
	Ant. press. (none, ill.cut., settl., graz., recr., road, multiple)	< 0.05	< 0.001	–
	Severity of illicit cutting (none, slight, moderate, severe)	< 0.05	< 0.001	Tamhane

Table 10 (continued)

Indicators for erosion control ES (continuous)	Other parameters (categorical)	ANOVA *p*-value	Levene *p*-value	Post hoc test
Normalized Difference Vegetation Index (NDVI) (unitless)	LULC (degraded f., productive f., agriculture, grassland)	<0.001	<0.01	Tamhane
	Stand type (broadleaved, conifer, mixed)	<0.001	>0.05	Tukey
	Regeneration status (none, poor, moderate, strong)	<0.05	<0.001	Tamhane
	Soil moisture (very dry, dry, cool, moist, wet)	<0.05	<0.05	Tamhane
	Obs. erosion (none, sheet, rill, gully, landslide, mass mov.)	<0.001	<0.001	Tamhane
	Aspect (N, NE, E, SE, S, SW, W, NW, flat)	<0.001	<0.001	Tamhane
	Soil type (scl, cl, sl, l, ls, sc) [a]	<0.001	<0.001	–
	Ant. press (none, ill.cut., settl., graz., recr., road, multiple)	<0.01	<0.001	–
	Severity of illicit cutting (none, slight, moderate, severe)	<0.05	<0.001	Tamhane
	Diameter class of stumps (I, II, III, IV) [b]	<0.001	>0.05	Tukey

[a] *scl* sandy clay loam, *cl* clay loam, *sl* sandy loam, *l* loam, *ls* loamy sand, *sc* sandy clay

[b] I. class: 8–19.9 cm; II. class: 20–35.9 cm; III. class: 36–51.9 cm; IV. class: ≥ 52 cm

planning. The findings obtained in the present study showed that SPPI could be calculated using NDVI as a predictor (Eq. 13). In essence, C factor is a more reliable predictor than NDVI; however, C factor modeling is cumbersome due to its field measurement difficulties (Vatandaşlar & Yavuz, 2017). Therefore, we evaluate that calculating NDVI values is much easier than calculating the C factor owing to the multispectral remote sensing images. Thus, the simplest model structure (linear) was used in the following equation. The adjusted coefficient of determination for this equation was 0.90. It was also meaningful in terms of model coefficients, as well as the model itself ($p < 0.05$) (Kalaycı, 2009).

$$SPPI = (0.802 + 0.260 \times NDVI) \times 100 \quad (13)$$

where SPPI is the Soil Protection Performance Index (%), and NDVI is the Normalized Difference Vegetation Index (unitless). Using the NDVI, Eq. 13 estimates the SPPI at the pixel level via remotely sensed optical images. It may also be upscaled to larger (e.g., stand, compartment, landscape) levels in any GIS software.

Actual soil loss and erosion risk maps are the primary outputs of most erosion prediction models, including RUSLE (Renard et al., 1997). Such information is also crucial for ES assessments during forest planning (Baskent, 2020; Knoke et al., 2021; Tiemann & Ring, 2022). In this way, forests located in risky areas are set aside for erosion control ES (aka soil protection function in Turkey and Europe) in forest management plans (GDF, 2017). However, forest planners rarely utilize erosion risk maps in their plan renewals, as they are often challenging to produce in a short time (i.e., 6–8 months). Instead, they allocate these lands based only on slope rate and rough field observations. In Turkey, for example, if the slope is more than 60% in forested areas, these sites are designated for soil protection in forest plans (GDF, 2017). In the present study, a model was developed for the rapid assessment of annual soil loss without running RUSLE (Eq. 14). The model only uses NDVI and ground slope parameters to estimate the soil loss (RUSLE-A). The adjusted coefficient of determination was 0.57. It was also statistically meaningful at the 0.05 significance level.

$$ASL = -2.293 + \frac{1.781}{NDVI} + 0.000091 \times S^2 \tag{14}$$

where ASL is the annual soil loss (the RUSLE's *A* factor in t ha^{-1} year^{-1}) for Olur Forest Enterprise, NDVI is the Normalized Difference Vegetation Index (unitless), and *S* is the ground slope rate of each pixel (%). Using these variables, the equation estimates Olur's ASL at the pixel level using the NDVI layer derived from the 35-cm-resolution, color-infrared aerial photos. It can then be upscaled to the stand or landscape levels.

Besides the regression models, some correlative relations detected in this study could also be used in a management planning context. The statistical analyses showed that the change in LULC classes caused differences in almost all indicators of soil and erosion control ES. In particular, sandy soils prevailed in degraded forest and grassland classes in Olur Forest Enterprise. As sandy soils are generally known to be susceptible to erosion (Renard et al., 1997; Şengönül & Şahin, 2017), soil protection activities should be the focus here. These findings are mostly supported by related literature, such as Yilmaz et al. (2007) and Yilmaz et al. (2015).

On the other hand, poor statistical relationships were found between the structural parameters of forest and soil properties. Nevertheless, the *K* factor (soil erodibility) increased with increasing undergrowth vegetation and ground slope. In another study, Oudenhoven et al. (2015) reported similar results. In their case, soil erosion and surface runoff rates increased with increasing ground slope. Aside from the *K* factor, soil OM content increased with increasing canopy cover and altitude in our study area.

Regarding OM, coniferous stands contained more soil OM than broadleaved and mixed forest stands. Since a high OM content is favorable for soil protection (Renard et al., 1997; Torri et al., 1997), practitioners should increase stand density in the forest. Additionally, they may prefer conifer species over broadleaves in their afforestation and rehabilitation efforts for maximizing erosion control ES value.

As for limitations, we note that our assessments and recommendations are site-specific and generally based on "potential soil losses" in the Olur Forest Enterprise. Therefore, caution should be paid for extending the results from this study to other forest sites. In contrast to the previous recommendation, for example, Vatandaşlar et al. (2020) suggest that mixed stands maximize erosion control in moist forests with a dense and uneven-aged structure. Moreover, potential soil loss estimates may show significant uncertainties. It may negatively affect the outputs yielded by the proposed models, so ideally, models should be validated with other experiments by installing erosion and/or runoff plots on the ground. By doing so, the "actual provision" of erosion control ES can be calculated more correctly. Another limitation of this study relates to the number and distribution of sample plots which are sometimes insufficient for certain categorical variables. While we distributed our plots according to vegetation, slope, and bedrock classes, there was still a lack of samples, for example, for each soil type (e.g., silty clay, loam). Therefore, we could not perform a post hoc test for such categorical variables after ANOVA.

Conclusion

Based on ground measurements, useful models and indicators for evaluating erosion control ES in a semi-arid forest enterprise were developed in the present study. Forest planners can use the presented regression models to quantitatively assess the level of soil protection in various LULC classes (or forest stands) using NDVI as a performance indicator. Besides, they are able to estimate the enterprise's annual soil losses (RUSLE-A) without running RUSLE. Thus, the amount of ES provision, as well as erosion hotspots, can quickly be mapped and forest stands, which will be allocated for erosion control ES, can be determined in forest management plans. Digital elevation models (DEM) and color-infrared aerial photos (or satellite images), supplied to forest planners during the renewal of their plans, are the only data sources that will work for this.

Statistical relationships among the indicators were also examined in this study. Prominent findings showed that soil erodibility was higher in sparsely covered forests on slopes with undergrowth vegetation. In contrast, fully covered forests in highlands had more soil OM, resulting in resistance to erosion. Specifically, soil OM content was significantly higher in coniferous forests than in other forest cover types. Moreover, degraded forests and grasslands had more sandy soils than other LULCs, indicating that they were more prone to water-borne erosion. Indeed, the LULC class was one of the prominent factors affecting almost all soil- and ES-related parameters.

Given the findings and assessments summarized throughout the study, several recommendations can be made to environmental managers for increasing the provisional capacity of erosion control ES;

I. Reaching an uneven-aged stand structure with multiple layers should be aimed at silvicultural interventions in the forest. If it is impossible due to site conditions, pure and two-layered forests with conifers may be promoted. The stand density and canopy cover ratio must be as high as possible.
II. Forest openings, degraded lands, and sparsely covered forests should be afforested or rehabilitated using native tree species, preferably conifers. In Olur Forest Enterprise, priority should be given to degraded lands with a sandy texture since they are most prone to soil erosion. Promoting *Astragalus* species as a shrub layer may be a smart choice.
III. Regeneration activities should be performed at small sites without clear cutting. Regenerated sites should be monitored in the first few years until the seedlings fully cover the soil. If any erosion hazard is observed at these sites, conservation measures such as terracing, fencing, and replacement planting must be urgently taken by field foresters.

Acknowledgements This study is a part of the PhD thesis of the first author, which is being supervised by the second author. The authors would like to express their gratitude to the Republic of Turkey's General Directorate of Forestry (GDF) and the Japanese International Cooperation Agency (JICA) and their employees for their support during fieldwork for the Coruh River Watershed Rehabilitation Project (2012-2019).

Author contribution C. V. and M. Y. conceived, designed, and performed the experiments, analyzed the data, contributed to materials/analysis tools, and wrote the paper.

Code availability Not applicable.

Availability of the data and material The data and material can be shared by the corresponding author upon reasonable request.

Declarations

Ethics approval All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Conflict of interest The authors declare no competing interests.

References

Akgöz, R., Deviren Saygin, S., Erpul, G., & Tel, S. (2022). Monitoring seasonal and phenological variability of cover management factor for wheat cropping systems under semi-arid climate conditions. *Environmental Monitoring Assessment, 194*, 395. https://doi.org/10.1007/s10661-022-10064-1

Aytop, H., & Şenol, S. (2022). The effect of different land use planning scenarios on the amount of total soil losses in the Mikail Stream Micro-Basin. *Environmental Monitoring Assessment, 194*, 32. https://doi.org/10.1007/s10661-022-09937-2

Arnoldus, H. M. J. (1977). Methodology used to determine the maximum potential average annual soil loss due to sheet and rill erosion in Morocco. *FAO Soils Bulletin, 34*, 39–44.

Asan, Ü. (2017). *Forest management (planning systems)*. İstanbul University Publishing. (in Turkish).

Barnes, B. V., Zak, D. R., Denton, S. R., & Spurr, S. H. (1998). *Forest ecology* (4th ed.). Wiley Publishing.

Baskent, E. Z. (2020). A framework for characterizing and regulating ecosystem services in a management planning context. *Forests, 11*, 102. https://doi.org/10.3390/f11010102

Berg, B., & Laskowski, R. (2006). Litter decomposition: A guide to carbon and nutrient turnover (Vol. 38). In Y. Luo (Ed.), *Advances in Ecological Research* (p. 448). San Diego: Elsevier.

Bilgili, E., Öztürk, M., Coskuner, K. A., Baysal, İ, Serdar, B., Yavuz, H., Eroğlu, M., & Usta, Y. (2018). Quantifying the effect of pine mistletoe on the growth of Scots pine. *Forest Pathology, 48*(4), 1–9. https://doi.org/10.1111/efp.12435

Bouyoucos, G. J. (1962). Hydrometer method improved for making particle size analysis of soils. *Agronomy Journal, 54*, 464–465.

Boyce, R. C. (1975). Sediment routing with sediment delivery ratios. In: Present and prospective technology for predicting sediment yields and sources. USDA Publishing, No: ARS-S-40, 61–65, USA.

Bulut, S., Günlü, A., & Keleş, S. (2016). Estimation of some stand parameters using Göktürk-2 satellite image. 1st International Symposium of Forest Engineering and Technologies (FETEC 2016), 2–4 June 2016 Bursa, 118−124.

Burkhard, B., de Groot, R., Costanza, R., Seppelt, R., Jorgensen, S. E., & Potschin, M. (2012). Solutions for sustaining natural capital and ecosystem services. *Ecological Indicators, 21*, 1–6. https://doi.org/10.1016/j.ecolind.2012.03.008

Burkhard, B., & Maes, J. (2017). *Mapping ecosystem services*. Pensoft Publishers.

Caglayan, İ, Yeşil, A., Kabak, Ö., & Bettinger, P. (2021). A decision making approach for assignment of ecosystem services to forest management units: A case study in northwest Turkey. *Ecological Indicators, 121*, 107056. https://doi.org/10.1016/j.ecolind.2020.107056

Chi, Z., Yao, Z., Shen, S., Hiroyuki, N., Haruyoshi, I., Peng, C., & Jun, F. (2008). Development of GIS-based FUSLE model in a Chinese fir forest sub-catchment with a focus on the litter in the Dabie Mountains, China. *Forest Ecology and Management, 255*, 2782–2789. https://doi.org/10.1016/j.foreco.2008.01.045

CICES. (2018). The Common International Classification of Ecosystem Services. *Version, 5*, 1.

de Jong, S. M. (1994). Derivation of vegetative variables from a Landsat TM image for modeling soil erosion. *Earth Surface Processes and Landforms, 19*, 165–178. https://doi.org/10.1002/esp.3290190207

Deviren Saygın, S., Basaran, M., Ozcan, A. U., Dolarslan, M., Timur, O. B., Yilman, F. E., & Erpul, G. (2011). Land degradation assessment by geo-spatially modeling different soil erodibility equations in a semi-arid catchment. *Environmental Monitoring and Assessment, 180*, 201–215.

Duman, A. (2017). Determination and modelling of soil properties of degraded forest and grassland areas in some micro catchments of Artvin, Erzurum and Bayburt using satellite images. PhD thesis, Artvin Coruh University, Artvin (in Turkish).

Egoh, B., Drakou, E. G., Dunbar, M. B., Maes, J., & Willemen, L. (2012). Indicators for mapping ecosystem services: A review. Technical report, JRC Scientific and Policy Reports, Publications Office of the EU, Luxemburg.

Erinç, S. (1965). *A research on the impacts of precipitation and a new index*. İstanbul: İstanbul University The Institute of Geography Publishing (PN: 40).

Erinç, S. (1996). *Climatology and its methods (4th edition)*. Alfa Publishing, İstanbul, 538 p, (in Turkish).

Erpul, G., Şahin, S., İnce, K., Küçümen, A., Akdağ, M. A., Demirtaş, İ, & Çetin, E. (2018). *The erosion atlas of Turkey*. The Turkish General Directorate of Combating Desertification and Erosion Publishing. (in Turkish).

FAO. (2000). On definitions of forest and forest change. Forest Resource Assessment Working Paper No. 33, Rome. Retrieved November 12, 2019, from http://www.fao.org/3/ad665e/ad665e00.htm#TopOfPage

GDF. (2014). Orman hayattır [Brochure]. Republic of Turkey General Directorate of Forestry, Ankara (in Turkish).

GDF. (2015). *Ecosystem-based multifunctional forest management plan of Olur Forest Enterprise (2015–2034)*. Republic of Turkey General Directorate of Forestry.

GDF. (2017). Act No 299. General Directorate of Forestry, Forest Management and Planning Dept., Ankara (in Turkish). Retrieved November 9, 2020, from https://www.ogm.gov.tr/ekutuphane/Tebligler

Guerra, C. A., Teresa, P. C., & Marc, J. M. (2014). Mapping soil erosion prevention using an ecosystem service modeling framework for integrated land management and policy. *Ecosystems, 17*, 878–889. https://doi.org/10.1007/s10021-014-9766-4

Kalaycı, Ş. (2009). *Multivariable statistic technics with SPSS applications* (9th ed.). Asil Publishing. (in Turkish).

Kalıpsız, A. (1982). *Forest yield and growth.* İstanbul: İstanbul University Publishing (PN: 3052) (in Turkish).

Kantarcı, M. D. (2000). *Soil science.* İstanbul: İstanbul University Publishing (PN: 462) (in Turkish).

Karahalil, U., Başkent, E. Z., Sivrikaya, F., & Kılıç, B. (2017). Analyzing deadwood volume of Calabrian pine (Pinus brutia Ten.) in relation to stand and site parameters: A case study in Köprülü Canyon National Park. *Environmental Monitoring Assessment, 189*, 112. https://doi.org/10.1007/s10661-017-5828-3

Kayitakire, F., Hamel, C., & Defourny, P. (2006). Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. *Remote Sensing of Environment, 102*(3–4), 390–401. https://doi.org/10.1016/j.rse.2006.02.022

Kinnell, P. I. A. (2001). Slope length factor for applying the USLE-M to erosion in grid cells. *Soil and Tillage Research, 58*(1–2), 11–17.

Knoke, T., Kindu, M., Schneider, T., & Gobakken, T. (2021). Inventory of forest attributes to support the integration of non-provisioning ecosystem services and biodiversity into forest planning—from collecting data to providing information. *Current Forestry Reports, 7*, 38–58. https://doi.org/10.1007/s40725-021-00138-7

Koralay, N., & Kara, Ö. (2022). Creating erosion risk map and determining sediment delivery ratio of the Trabzon Değirmendere-Çatak subwatershed. *Turkish Journal of Forestry Research, 9*, 41–54. https://doi.org/10.17568/ogmoad.1095264. (in Turkish with English abstract).

Koschke, L., Fuerst, C., Frank, S., & Makeschin, F. (2012). A multi-criteria approach for an integrated land-cover-based assessment of ecosystem services provision to support landscape planning. *Ecological Indicators, 21*, 54–66. https://doi.org/10.1016/j.ecolind.2011.12.010

Oudenhoven, A. P. E., Veerkamp, C. J., Alkemade, R., & Leemans, R. (2015). Effects of different management regimes on soil erosion and surface runoff in semi-arid to sub-humid rangelands. *Journal of Arid Environments, 121*, 100–111. https://doi.org/10.1016/j.jaridenv.2015.05.015

Panagos, P., Meusburger, K., Ballabio, C., Borrelli, P., & Alewell, C. (2014). Soil erodibility in Europe: A high-resolution dataset based on LUCAS. *Science of the Total Environment, 479*, 189–200. https://doi.org/10.1016/j.scitotenv.2014.02.010

Renard, K. G., Foster, G. R., Weesies, G. A., McCool, D. K., & Yoder, D. C. (1997). *Predicting soil erosion by water: A guide to conservation planning with the revised universal soil loss equation (RUSLE).* Washington: United States Department of Agriculture (USDA).

Renard, K. G., & Foster, G. R. (1998). R factor-rainfall/runoff erosivity. In: Galetevic. J.R (ed) Guidelines for the use of the revised universal soil loss equation (RUSLE) version 1.06 on mined lands, construction sites and reclaimed lands. The Office of Technology Transfer Western Regional Coordinating Center Office of Surface Mining, Denver, CO, s 2.1–2.8.

Schmidt, S., Ballabio, C., Alewell, C., Panagos, P., & Meusburger, K. (2018a). Filling the European blank spot−Swiss soil erodibility assessment with topsoil samples. *Journal of Plant Nutrition and Soil Science, 000*, 1–12.

Schmidt, S., Alewell, C., & Meusburger, K. (2018b). Mapping spatio-temporal dynamics of the cover and management factor (C-factor) for grasslands in Switzerland. *Remote Sensing of Environment, 211*, 89–104.

Schmidt, S., Tresch, S., & Meusburger, K. (2019). Modification of the RUSLE slope length and steepness factor (LS-factor) based on rainfall experiments at steep alpine grasslands. *MethodsX, 6*, 219–229.

Schumacher, B. A. (2002). Methods for the determination of total organic carbon in soils and sediments. Ecological Risk Assessment Support Center, Office of Research and Development, US Environmental Protection Agency, NCEA-C-1282. Retrieved September 19, 2020, from http://bcodata.whoi.edu/LaurentianGreatLakes_Chemistry/bs116.pdf

Seki, M., Sakici, O. E. (2022). Ecoregional variation of Crimean pine (*Pinus nigra* subspecies *pallasiana* [Lamb.] Holmboe) stand growth. *Forest Science*, fxac030. https://doi.org/10.1093/forsci/fxac030

SPSS. (2012). SPSS 20.0 for Windows. Statistical Package for the Social Sciences Inc., New York.

Suriyaprasit, M., & Shrestha, D. P. (2008). Deriving land use and canopy cover factor from remote sensing and field data in inaccessible mountainous terrain for use in soil erosion modelling. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37*(PartB7), 1747–1750.

Şengönül, K., & Şahin, A. (2017). Determining the criteria for allocating soil protection forests. IV. Nature and Forestry Symposium towards 2023, 3−6 December 2017, Antalya, 429−449 (in Turkish).

TEEB. (2010). *The economics of ecosystems and biodiversity for national and international policy makers*. Earthscan.

Thomsen, L. M., Baartman, J. E. M., Barneveld, R. J., Starkloff, T., & Stolte, J. (2015). Soil surface roughness: Comparing old and new measuring methods and application in a soil erosion model. *The Soil, 1*, 399–410. https://doi.org/10.5194/soil-1-399-2015

Tiemann, A., & Ring, I. (2022). Towards ecosystem service assessment: Developing biophysical indicators for forest ecosystem services. *Ecological Indicators, 137*, 108704. https://doi.org/10.1016/j.ecolind.2022.108704

TMS. (2018). The observed climate data from the Olur weather station (1990–2018). Turkish State Meteorological Service, Ankara.

Tokgöz, G., & Say, N. (2021). Quantification of the impact of land use/land cover changes on ecosystem services: A case study in Adana-Karaisalı. *OKU Journal of the Institute of Science and Technology*, *4*(3), 466–482. https://doi.org/10.47495/okufbed.1003000

Torri, D., Poesen, J., & Borselli, L. (1997). Predictability and uncertainty of the soil erodibility factor using a global dataset. *CATENA, 31*(1), 1–22.

Torri, D., Poesen, J., & Borselli, L. (2002). Corrigendum to "Predictability and uncertainty of the soil erodibility factor using a global dataset" [CATENA 31: 1–22 (1997)]; and to "Erratum to Predictability and uncertainty of the soil erodibility factor using a global dataset" [CATENA 32:307–308 (1998)]. *CATENA, 46*(4), 309–310.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127–150.

Tüfekçioğlu, M., & Yavuz, M. (2016). Estimating surface soil erosion losses and mapping erosion risk for Yusufeli micro-catchment (Artvin). *Journal of Artvin Coruh University Forestry Faculty*, *17*(2), 188−199 (in Turkish). https://doi.org/10.17474/acuofd.47342

USDA. (1983). *Sediment sources, yields and delivery ratios* (Chapter 6). In: United States Department of Agriculture, Soil Conservation Services, National Engineering Handbooks Section 3, Washington.

van der Knijff, J. M., Jones, R. J. A., & Montanarella, L. (1999). Soil erosion risk assessment in Italy. European Soil Bureau, Joint Research Centre, EUR 19022 EN.

Vatandaşlar, C., & Yavuz, M. (2017). Modeling cover management of RUSLE using very high resolution satellite imagery in a semiarid watershed. *Environmental Earth Sciences, 76*, 65. https://doi.org/10.1007/s12665-017-6388-0

Vatandaşlar, C. (2020). Integrating erosion control value of forest ecosystems into forest management planning process. PhD thesis, Artvin Coruh University.

Vatandaşlar, C., Yavuz, M., & Leuchner, M. (2020). Erosion control service of forest ecosystems: A case study from Northeastern Turkey. In S. Nedkov, G. Zhelezov, N. Ilieva, M. Nikolova, B. Koulov, K. Naydenov, S. Dimitrov (Eds.), *Smart Geography* (pp. 443−455). Switzerland: Springer. https://doi.org/10.1007/978-3-030-28191-5_32

Vatandaşlar, C., & Zeybek, M. (2020). Application of handheld laser scanning technology for forest inventory purposes in the NE Turkey. *Turkish Journal of Agriculture and Forestry*. https://doi.org/10.3906/tar-1903-40

Vihervaara, P., Mononen, L., Santos, F., Adamescu, M., Cazacu, C., Luque, S., Geneletti, D., & Maes, J. (2017). Biophysical quantification. In B. Burkhard & J. Maes (Eds.), *Mapping Ecosystem Services* (pp. 93–101). Pensoft Publishers.

Walkley, A., & Black, L. A. (1934). An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. *Soil Science, 37*, 29–38.

Wischmeier, W. H., & Smith, D. D. (1978). Predicting rainfall erosion losses - A guide to conservation planning. In: Agriculture Handbook, USDA, Science and Education Administration, Washington DC.

Yavuz, M., & Alkan, G. (2016). The effects of mechanical removals of mistletoe on radial growth in Scots pine stands: A case study In Kilickaya Forest Enterprise. Project report, Artin Coruh University Scientific Projects Coordinatorship, Grant Number: 2012.F10.02.14, Artvin, Turkey.

Yavuz, M., & Hall, M. H. (2018). A five-step protocol for estimating forest cover and rate of change in the New York City watershed. *Environmental Monitoring and Assessment, 190*(8), 466. https://doi.org/10.1007/s10661-018-6855-4

Yavuz, M., & Tufekcioglu, M. (2019). Estimating surface soil losses in the mountainous semi-arid watershed using RUSLE and geospatial technologies. *Fresenius Environ Bulletin, 28*(4), 2589–2598.

Yener, İ. (2022). Development of high-resolution annual climate surfaces for Turkey using ANUSPLIN and comparison with other methods. *Atmósfera*, https://doi.org/10.20937/ATM.53189

Yilmaz, M., Usta, A., Altun, L., & Tilki, F. (2007). Effects of land-use regime on soil erodibility indices and soil properties in

Unye Turkey. *Fresenius Environmental Bulletin, 16*(12), 1638–1644.
Yilmaz, M., Usta, A., Çakir, G., & İnce Kahveci, S. N. (2015). The effects of land use type on soil erodibility indices in Galyan-Atasu Dam Watershed, Trabzon, N.E. Turkey. *Fresenius Environmental Bulletin*, *24*(3), 1082−1090.
Zengin, M., Ozer, S., & Ozgu, M. (2009). Determining of erosion situation of the Coruh watershed by GIS and solution suggestions. *The Journal of Ataturk University Agriculture Faculty*, *40*(1), 9–19 (in Turkish). https://doi.org/10.17097/zfd.30898

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.