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Research Article

Keywords: grazing, land degradation, regional approach, erosion, Curvature Subcarpathians

Posted Date: February 7th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1329577/v1>

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Version of Record: A version of this preprint was published at Scientific Reports on June 21st, 2022. See the published version at <https://doi.org/10.1038/s41598-022-13596-1>.

Designing Grazing Susceptibility to Land Degradation Index (GSLDI) in Hilly Areas

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Abstract. Evaluation of grazing impact on land degradation processes is a difficult task due to heterogeneity and complex interacting factors involved. In this research, we designed a new methodology based on a predictive index of GSLDI (Grazing Susceptibility to Land Degradation Index) built on artificial intelligence to assess land degradation susceptibility in areas affected by small ruminants (SRs) of sheep and goats grazing impacts. The data for model training, validation, and testing consisted of sampling points (erosion and no-erosion) taken from aerial imagery. Seventeen environmental factors (e.g., DEM derivatives, small ruminants' stock), and 55 subsequent attributes (e.g., classes/features) were assigned to each sampling point. The impact of SRs stock density over the land degradation process has been evaluated and estimated with two extreme SRs' density scenarios: missing (0), and double density (overstocking). We applied the GSLDI methodology on the Curvature Subcarpathians, a region that experiences the highest erosion rates in Romania, and found that SRs grazing is not the major contributor to land degradation, accounting for only 4.6%. This methodology could be replicated in other steep slopes grazing areas as a tool to assess and predict areas susceptible to land degradation, and to establish common strategies for good land-use practices.

Keywords: grazing; land degradation; regional approach; erosion; Curvature Subcarpathians

1. INTRODUCTION

Unsustainable grazing is a millennial activity that can trigger land degradation processes if appropriate soil management practice is not put in place (Papanastasis and Peter, 1998; Oertel et al., 2016; Pulido et al., 2018). However, it is a vital activity that ensures food security (Staddon and Faghihinia, 2021) and ecosystems health (Gibbs and Salmon, 2015).

Pastoral land activities are some of the most common farming practices in many parts of the world such as central and southeastern Europe. Some representative areas are located in Poland and Romania (Morales et al., 2019; Wolański et al., 2021) and along the Pyrenees in Spain (Nadal-Romero et al., 2018). Livestock is in many countries the largest agricultural sector and occupies about 37% of the global ice-free land surface (130.4 Mkm²) (IPCC, 2019). Across the world, the domestic stock was estimated as 1,238 billion sheep and 1,094 billion goats in 2019 (FAOSTAT, 2021), which delivered 1/3 of all protein consumed by humanity (FAO, 2021). Small ruminants (SRs) stock (sheep and goats) can be considered as a major contributor to the global economy accounting for about 2% (1995 to 2005) of the global gross domestic product (Steinfeld et al., 2006; Gomez-Zavaglia et al., 2020). In the context of increasing demand for food due to the growing human population, the environmental impact of various sectors of agriculture will also increase (Ritchie and Roser, 2017). The increasing combined pressure of agricultural and livestock productions (e.g., unsustainable grazing) are assumed as one of the main factors expected to accelerate land degradation in the 20th and 21st centuries (WHO, 2020). Soil erosion in agricultural areas (Borrelli et al., 2017; Rodrigo-Comino, 2018; Niu et al., 2021; Zamfir and Crişu, 2021) and intensive grazing are recognized as global environmental issues (Turnbull et al., 2010; Goodarzi et al., 2021).

Grazing, as a component of land use, is associated with certain patterns in hydrosedimentary conditions from event-scale to the catchment scale (e.g., Bartley et al., 2007; Rodriguez-Lloveras et al., 2015) and several studies have analyzed the relationship between unsustainable grazing, grassland status, and animal types (e.g., Warren et al., 1986; Heathwaite et al., 1989; Mwendera and Saleem, 1997; Meyles et al., 2003; Pande and Yamamoto, 2006; Kidron, 2016; Pulley and Collins, 2019; Lai and Kumar, 2020). Unsustainable and prolonged grazing may trigger hydrological changes such as soil water content, but also the activation of runoff with an impact on the streamflow regime (e.g., maximum and minimum flow) affecting runoff coefficients (Gifford and Hawkins, 1978; Gifford et al., 1983; Markart et al., 2006; Sadeghi et al., 2007; Ruggenthaler et al., 2015), even with modifications of the terrestrial water (Vörösmarty and Sahagian, 2000). For example, Meyles et al. (2006) assessed flood frequency

with a higher occurrence of erosion on large areas under intensive grazing process in a small Dartmoor catchment, southwest England. Poesen (2018) stressed the need for more research attention on the hydrological and erosional response of rangelands. Hancock et al. (2020) quantified erosion in a grazing environment typical of the east coast of Australia and discovery that under current management practices soil loss is relatively low (< 5 tonnes/ha/yr). Most hydrological studies have underlined the role that vegetation plays in grazing lands in controlling erosion (Blanco-Canqui and Lal, 2008) and the biocrust (Kidron et al., 2021; Lázaro et al., 2021). Some authors pointed out that about 20% of the world's pasture areas are considered degraded as a consequence of overgrazing and associated erosion and compaction among other main factors (Steinfeld et al., 2006). Nowadays, scholars have highlighted that this relation is complicated and not well understood. One of the most complex mechanisms is related to the SRs where they can influence organic matter and facilitate the adherence of aggregated clay and the formed colluvial layer that serves as a substrate to the expanded vegetation growth (Kulik et al., 2013; Mor-Mussery et al., 2021). Moreover, satellite-derived data as Normalized Difference Vegetation Index (NDVI) can be used in land degradation assessments, but without distinguishing specific signs of degradation/conservation from impacts of adverse/beneficial natural processes (Gibbs and Salmon, 2015; Riva et al., 2017). In the last few years, and the temperate climate of Europe, the analysis of SRs grazing influence on soil and runoff processes has received minimal interest. A few field works have been carried out at the hillslope scales under grazing (e.g., Heathwaite et al., 1990; Cerdà et al., 1998; Meyles et al., 2003; Ries et al., 2014; Bond et al., 2020). Some previous methods and tools used for the quantification of grazing as part of land degradation and erosion have shown several drawbacks. For example, field-based monitoring has to be planned for very long-term periods to foresee future changes, which may become expensive and time-consuming (Peppler and Fitzpatrick, 2004). Therefore, the lack of monitoring and observational data is hampering the assessment of land degradations by grazing. Nowadays, remote sensing techniques and modeling approaches based on landscape unit and vegetation indexes are becoming useful tools. Riva et al. (2017) showed that grazing is a significant cause of land degradation even in partially abandoned areas, and the effectiveness of responses to land degradation is substantially affected by land cover and topography. Given the spatial and temporal variability of various grazing practices that complicates the interpretation within mechanistic models, Ma et al. (2019) highlighted that efforts are needed to reduce inconsistencies among grazing land models in simulated grazing management effects

by carefully examining the underlying processes interacting in each model. Also, interesting results were obtained by Kosmas et al. (2015) using Geographical Information Systems (GIS) at the local scale, concluding that rapid growth in the livestock density increased soil erosion rates. Thus, the relationship between land degradation, erosion, and unsustainable grazing is poorly understood and should be further assessed.

Degraded land occupies over 2% of the land in Romania due to corroboration of natural and anthropogenic causes (Costea, 2013). Recent studies confirmed land degradation by soil erosion (Prăvălie et al., 2017), gullying and landslides (Bălteanu et al., 2010), and reservoir sedimentation (Niacsu et al., 2021), and that statistics of stocking rate and grazing deviate from the optimum (Roman et al., 2019). For the Southern Carpathian Mts., the Romanian, transhumance of sheep prevents the development of serious erosion in otherwise erosion-prone areas that can support little beyond livestock raising (Shirasaka, 2007). Surprisingly, Nicu (2018) found that overgrazing is not influencing or accelerating soil erosion on gullies in the Bahluet River catchment in the northeastern part of Romania. In this context, land degradation under grazing activities is a serious problem in hilly areas of Romania and effective soil conservation is urgently needed. Yet, it remains a knowledge gap in the quantification of the role of grazing among numerous factors on erosion and land degradation in past interdisciplinary investigations at the regional scale. Filling the gap of quantifying the complexity of land degradation drivers could help decision-makers in spatial planning and agriculture to set guidelines for land-use policy.

Therefore, this paper starts from the hypothesis that land degradation and grazing can be assessed using multiple environmental factors and even at larger scales.

The main aim of this research is to quantify the relation between grazing impacts of SRs on land degradation processes using the Grazing Susceptibility to Land Degradation Index (GSLDI). The specific objectives are:

- (1) to develop a novel model using a qualitative assessment of the evidence-support of a hypothesis that integrates weight/partitive factors of land degradation at a regional scale; and
- (2) to investigate a hilly region in Romania (the Curvature Subcarpathians) that is characterized by the highest rates of erosion and SRs density with GSLDI.

2. METHODS AND DATA

2.1. Models description

Based on the recent approach by Costache et al. (2021a, 2021b) and Vojtek et al. (2021), we developed new advancing land degradation knowledge and the SRs grazing pressure using machine learning (ML) algorithms.

The proposed modeling framework consists of: i) land erosion inventory (manually identifying erosion and no-erosion sampling points based on aerial imagery); ii) assigning the geographical characteristics (17 parameters, e.g., lithological structure, altitude), iii) standardizing the dataset (55 subsequent attributes e.g., classes/features), and iv) model training (ML process).

2.2. Data processing

The database for land erosion inventory requires compulsory sampling points (vector data) exhibiting erosion or no-erosion processes detected using open sources imagery (e.g., Google Earth, Bing) for the study area. Manual collecting sampling points procedure necessities available more time work and should be harmonized (checks, validation) with the laboratory staff. Moreover, the point's survey density can be varied between low (e.g., forest sites) and high (land-use fragmentation) and should be agreed upon according to the land-use characteristics.

A database with 17 geographical parameters (Figure 1) converted in thematic layers were extracted from the Digital Elevation Model (e.g., curvature, slope terrain); lithology and soil maps; vegetation features (e.g., Corine Land Cover); rainfall erosivity (Panagos et al, 2015), and SRs parameters (stock and densities) was established to train and validate the proposed model. Available vector (e.g., boundary shapefile for the geomorphologic region and the Local Administrative Units - LAU) and raster format data (e.g., at medium-precision, the scale of 1:25,000) and large maps (e.g., lithological and pedological maps 1:200,000) are required in the database. We chose a regional geographical approach combined with the stock density data of small ruminants mainly because SRs rank as land degradation significant variables.

To implement this analysis, several spreadsheet calculations were required, followed by geospatial processing (e.g., vector to raster format; union/merge, reclassify). Here, we work with a grid at 30 meters horizontal spatial resolution, also resamples are necessary (Figure 1).

Figure 1. The proposed hierarchy predictors and their geographical use to develop the Grazing Susceptibility to Land Degradation Index. (GRAVIPA = Grassland Vegetation Probability Index; LULC = Land Use Land Cover)

Model training procedure consisted in selecting the two models for classification Random Forest (RF), and Gradient Boosted Machine (GBM), which were evaluated with a confusion matrix and by accuracy, specificity, sensitivity, ROC (Receiver Operator Characteristic) curve, and Area Under the Curve (AUC) curve efficiency metrics. RF and GBM models performed very well in the training, validation, and testing sessions (accuracy estimated over 90%). In the GIS environment of the model requires an association of 17 geographical features (e.g., lithological structure, altitude) with subsequent attributes (e.g., classes/features) for each sampling point (Figure 1 and Figure 2). Classes of geographical features (e.g., elevation range) have been determined based on a statistical approach (e.g., Natural breaks classification). In order to calculate the GSLDI, the models were trained to predict the erosion exposure by using the 17 attributes and their classes as predictors, resulting in the probability to have erosion processes on each pixel of the study area. The model set-up consists of randomly splitting the data (erosion and no-erosion points) into three categories: training set (80%), splitted again in training, and validation sets (10% of the training set, splitted other 10 folds) during the cross-validation procedure, and the final test set, which included 20% of the data, used to evaluate the model performance on an independent data set, which was not used in the training phase (Figure 2). To evaluate and estimate the impact of SRs stock density over the land degradation process, we propose two SR's density scenarios: one considered 0 (missing), and another one with double density (overstocking). The outcomes are planned to be presented as a probabilistic map of a chance between 0-100 percent to have exposure to the land degradation process concerning SRs, resulting in a map of land degradation (Figure 2). The results of the analysis were plotted in a GIS environment, using the QGIS version 3.20 software, and R programming language with RF, caret, GBM, and other packages.

Figure 2. Workflow for designing Grazing Susceptibility to Land Degradation Index

2.3. Classification algorithms

Numerous studies have used Random Forest (RF) models to evaluate the erosion process, including Gayen et al. (2020), Mosavi et al. (2020), Amare et al. (2021). Random decision forests were first introduced by Ho (1995) who added randomness in the decision trees with increased accuracy for both training and unseen data. This method builds multiple trees in *randomly selected subspaces of the feature space* and generates the final output by averaging results from all created decision trees. By this way, the bias is reduced and the accuracy improves. RF is a method of ensemble learning by combining multiple decision trees over the same classification task. The output of the RF algorithm is the class that is selected by most trees in the forest.

Given t trees created in random subspaces, a discriminant function is used to combine the classification result by assigning x to class c and optimize the function $g_c(x)$ defined as (Ho, 1995):

$$g_c(x) = \frac{1}{t} \sum_{j=1}^t \hat{P}(c|v_j(x)) \quad (1)$$

In eqn (1) $\hat{P}$ is the optimum posterior probability that a point x belongs to class c ($c = 1, 2, \dots, n$) and is computed as the fraction of class c points to the overall number of points that are assigned to $v_j(x)$ given as:

$$P(c|v_j(x)) = \frac{P(c, v_j(x))}{\sum_{l=1}^n p(c_l, v_j(x))} \quad (2)$$

where $v_j(x)$ is the terminal node of point x when it descends down tree T_j ($j=1, 2, \dots, t$).

Gradient Boosted Machine (GBM) has also been used in soil degradation/erosion susceptibility studies in different forms (Arabameri et al, 2020, 2021; Sahin 2020) and was first introduced by Friedman et al. (2000). Gradient boosting is also an ensemble model, comprising of decision trees. The difference between RF algorithms and GBM is that the combining process is done at the beginning of the tree in the case of GBM while for RF it is done at the end. Also, while RF builds each tree independently, GBM works by building one tree at a time, introducing a weak learner to improve the shortcomings of existing weak learners.

Let $\{(x_i, y_i)\}_{i=1}^n$ be the training dataset and $L(y, F(x))$ the loss function, F being the model predicted values $\hat{y} = F(x)$ where y represents the predicted value, and $\hat{y}$ is the optimum predicted value. First, the algorithm initializes with a constant value as:

$$F_0(x) = \arg \min_{\rho} \sum_{i=1}^N L(y_i, \rho). \quad (3)$$

Next, for $m = 1$ to M :

1. Compute the *pseudo-residuals* as:

$$y_i = - \left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)}, i = 1, N \quad (4)$$

2. Fit a weak learner by training it on the training set as:

$$a_m = \arg \min_{a, \beta} \sum_{i=1}^N [\tilde{y}_i - \beta h(x_i; a)]^2 \quad (5)$$

3. Solve optimization problem as:

$$p_m = \arg \min_p \sum_{i=1}^N L(y_i, F_{m-1}(x_i) + p h(x_i; a_m)) \quad (6)$$

4. Update the model as:

$$F_m(x) = F_{m-1}(x) + p_m h(x; a_m) \quad (7)$$

Thus, a gradient boosting machine involves combining multiple weak classifiers in order to obtain a stronger one of the ensemble model.

2.4. Model efficiency and accuracy evaluation

In order to train the ML models, it was necessary to standardize the different measurements and the qualitative attributes of points (e.g., soil texture) to the same scale with the help of the “*scale*” function of the “*dummies package*” (Brown, 2021) of the R programming language. The cross-validation technique was used in the caret package in R (Kuhn, 2008) to randomly select the training and validation datasets in 10 folds for both models.

The training was conducted using cross-validation, which randomly partitions the dataset into complementary subsets of training and testing in order to test the model’s ability to predict new data that was not used for training. Evaluation of model performance is a critical step towards the classification model selection criteria. The model results were evaluated using a confusion matrix and testing the accuracy, specificity, sensitivity, ROC curve, and AUC curve efficiency metrics (Kuhn, 2008).

The criteria used to evaluate the models are presented below:

$$Sensitivity = \frac{TP}{TP+FN} \quad (8)$$

$$Specificity = \frac{TN}{TN+FP} \quad (9)$$

$$AUC = \frac{\sum_n^I TP + \sum_n^I TN}{(P+N)} \quad (10)$$

where TP = true positive, TN = true negative, FP = false positive, FN = false negative, P = all positives, and N = all negatives.

2.5. Geographic Background of Survey Area

We adopted for the survey of GSLDI a geomorphological unit for 3 reasons; relative geomorphological homogeneity (Posea and Badea, 1984), being one of the largest areas with historical land degradation (badlands) in Romania (Ielenicz, 1984; Jurchescu et al., 2020), and having the highest value of sediment yield (Diaconu, 1971; Ionita et al., 2006).

However, this research starts from the premise that land degradation processes are also due to other local and regional factors (e.g., lithology, morphology, land use). The land-use changes should be considered, as well as agricultural practices such as grazing. Therefore, it was necessary to apply an integrated analysis of the possible determinant factors' assembly to understand and manage the land degradation in the Curvature Subcarpathians.

The Curvature Subcarpathians (6,792 km²) is a geomorphologic region in the central part of Romania that lies between latitudes 44°47'01.77" to 46°09'58.43"N and longitudes 24°11'13.00" to 27°59'34.82"E (Stereographic 1970 projection), having a southern border with the Curvature Carpathians Mts (Figure 3). The study area is prone to land degradation, mainly erosion, due to both natural and socio-economic drivers (e.g., historical deforestation). The estimated peak erosion in Romania occurs in the Curvature Subcarpathians with rates between 30 and 45 t ha⁻¹ y⁻¹ (Ionita et al., 2006). Besides denudation, the Curvature Subcarpathians are characterized by various types of slope processes such as landslides, earth flows, and falls (Micu, 2017), and also by an intense vertical erosion mirrored by incised river valleys (Buzău, Ialomița and Teleajen Rivers) (Chendeș, 2011). The lithology and seismicity explain the susceptibility to landslides (Broeckx et al., 2016), the predominance of low cohesive rocks, sandy clay loam and clay soils, and active neotectonic movements (Armaș, 2012; Micu, 2017; Jurchescu et al., 2020). Deforestations, which is still continuing, may also trigger gravitational processes. The natural vegetation (e.g., broad-leaved forests) has been replaced by human activities into secondary grasses, orchards, vineyards, and croplands. The road network has amplified the disequilibrium of slopes.

The Curvature Subcarpathians receive approximately 600-700 mm of precipitation per year, the maximum occurring in summer (up to 100 mm/month), and the lowest in autumn and winter (Zaharia et al., 2011). Summer months are characterized by heavy rains that transform into overland flow causing aggressive erosion, especially on the bare soil (Chendeș, 2011). The study area appears to be among the regions with the national highest maximum rainfall intensity of for 5 min duration and 1:10 years return period (e.g., 1.48-1.86 mm/min reported by Cheval et al. (2012).

Rivers draining the Curvature Subcarpathians transport large amounts of suspended sediment load (Olariu et al., 2014). As a consequence, the largest rivers form a sandy braided pattern, laterally unstable (Ioana-Toroimac, 2016). Also, the study area is characterized by the highest suspended sediment yield in Romania (Diaconu, 1971; Zaharia et al., 2011). The mean specific suspended sediment yield is about 20-25 t ha⁻¹ yr⁻¹, while the sediment concentration exceeds 25,000 g m⁻³ (Zavoianu et al., 1996). The highest suspended sediment load occurs in spring and summer during the high-water phase of the hydrological regime or during floods when the fluvial erosion or erosion processes on slopes are more intense. It is observed that the variability of the suspended sediment load is higher than the variability of the mean annual water discharge (Zaharia and Ioana-Toroimac, 2009).

Figure 3. The location of Curvature Subcarpathians and the border of Local Administrative Units level 2

3. RESULTS AND DISCUSSIONS

3.1. Assessment of parameters

Firstly, we mapped 4187 sampling points for Curvature Subcarpathians with erosion or no-erosion processes from Google, Esri, and Bing imagery, available for August 2021, using the HCMGIS plugin from QGIS 3.20. Even though imagery has been taken at different periods, using three sources allowed the observers to check if the zone is not erroneously classified as erosion or no-erosion point. It resulted in a database with 61% of the points classified as erosion and the rest of them as no-erosion points.

From geo-spatial.org, we extracted these datasets containing vector geospatial information such as LAUs Boundary dataset; localities dataset, hydrography features dataset and DEM at 30 meters spatial resolution as raster format. Some datasets have been resampled to 30 m (e.g., Tree Cover Density). More relevant morphometric parameters/factors (e.g., slope; profile curvature) was derived from DEM. Lithological and soil features were extracted from the Geological Map of Romania (1:200,000), and the Soil Map of Romania (1:200,000) respectively. LAUs (formerly NUTS level 5) were used as the smallest territorial subdivision by the Nomenclature of Territorial Units for Statistics (NUTS) for statistical purposes (see Supplementary 1).

Therefore, each sampling point has 17 geographical attributes as presented in Table 1. In Figure 4, some predictors (such as lithology, soil properties, and land use land cover) are mapped.

Table 1. Parameters used for training the sampling points

GRAVPI = Grassland Vegetation Probability Index; LULC = Land Use Land Cover.

Some particularities of geographical attributes associated with erosion and no-erosion sampling points in the Curvature Subcarpathians are briefly debated.

The lithological structure (IGR, 1968) of the study region is dominated by Clays, Sands, and Conglomerates, indicating that the under-soil layer is unstable.

Altitude, Slope, and Aspect were extracted from the Digital Elevation Model with the resolution of 30 m, created from topographical maps of scale 1:25,000 (ANCPI, 2021). The classes and percentage shares of the total area are presented in Table 1. The altitudes are generally moderate 300-500 m, slopes are moderate (10-15%) to steep (15-25%) in 45% of the total area, while mild slopes (5-10%) dominate the landscape of the region, especially in the Plains and at the foothills. Aspect favors the exposure to the sun in general, the slopes being east, south-east, south, and southwest facing in over 57% of the area. Thus, the Curvature Subcarpathians region has a high isolation value which favors evapotranspiration, which in turn reduces the water availability, favoring the presence of thermophile vegetation such as vineyards, oak, tilia forest, or common lilac.

Curvature is the second derivative of the land surface, indicating the exposure to erosion of the landform area (Dehn, 2001). Profile curvature influences the acceleration/deceleration of flow while plan curvature indicates the concentration of flow on the land surface. Both profile and plan curvatures are indicators of the rate at which erosion and accumulation take place. These two characteristics values ranging between - 0.5 and 0.5 are not considered very active regarding the erosion process, while the values above or below these thresholds represent areas most exposed to the erosion process. The total curvature combines these two indicators, and more than 8% of the territory is very exposed to the erosion process, compared with less than 3% when using profile and plan curvature.

Topographical Positioning Index (TPI) classifies the relief in different topographical units based on a change in altitude compared with the mean altitude of transect with a radius of 1 km (Weiss, 2001). TPI describe the main landforms of the Subcarpathians region, resulting in over 52% of the relief occupied by flood plains combined with the base of the hills (basin)

landforms, while the torrential valleys, most exposed to the erosion process, have a share of 13% of the total area.

Distance to Streams can be related to the erosive action of the river channels as the closer to the river channel the greater the chance to encounter land degradation processes. Therefore, this indicator allows us to create a relation between the observed soil degradation places and the distance to the stream channel. This indicator has been extracted from a drainage network of support threshold of 1 km² catchment area.

Corine LULC layer has been used in the study area as the main nomenclature for land use with a spatial resolution of 1 ha also, has been resampled to 30 m. It has been divided into 9 classes (label 3), of which 18% are covered by agricultural land, 7% are built areas and almost 6% are represented by vineyards and trees. The most important two classes are forests (47%) and pastures and grasslands (20%).

Grassland Vegetation Probability Index (GRAVPI) constitutes an expert product estimation from the Copernicus Land Monitoring service (Langanke, 2018; Zeug et al., 2020) and is used to represent the spatial distribution of grassland areas within the study zone in a raster with the resolution of 30 m. From this layer, we can observe that almost 87% of the area is covered with LULC types other than grassland areas. This is caused by the fact that the herbaceous zones are mixed with trees or bare land and agricultural land, making it difficult to identify this type of LULC, and in general, is underestimated compared with Corine Land Cover (CLC) 2018.

Tree Cover Density from Copernicus Land Monitoring service (EEA, 2018) represents the density of trees (between 0 to 100%) in forested and non-forested areas in 2018, pixels having a resolution of 20 m. The dataset has been resampled to 30 m to conform to the same resolution of the other layers used in the analysis.

The survey area has a forest cover of over 63%, of which 47% is in patches with densities above 80%, thus considered as a compact forest. The overall cover of 63% is an overestimation of the forest cover, compared with the CLC layer, were only 47% of the study zone is represented by forested areas. This difference is explained by the fact that tree cover density is evaluated in all patches of trees, without considering the mixture of pastures or agricultural areas with the trees.

Hydrologic Soil Groups represent the rate at which water infiltrates into the soil, Soil group A is the most porous (with over 7.6 mm/hr infiltration rate) while the Group D corresponds to soils with lower permeability (0 -1.3 mm/hr) (Mockus, 2012). This dataset has been derived from soil texture classes of Romanian Soil dataset 1:200,000 (Vintilă et al., 2004), using that the method developed by Drobot (2007). The areas with low permeability (Group D) are the

most exposed to soil erosion, favoring surface and rill erosion in the Curvature Subcarpatians. These soils cover almost 30% of the study area while Group B soil has a similar share with almost 32% of the study area.

Curve Number (CN) (Mishra and Singh, 2003) is an indicator of the land capacity to absorb the water into the soil, and the higher its value the lower the infiltration. For the Curvature Subcarpathian region, the soils having low infiltration rates ($CN > 70$) covers almost 60% of the area, a situation that favors runoff and surface erosion.

Rainfall Erosivity, known as R-factor (Panagos et al, 2015), is another indicator of soil exposure to erosion caused by rainfall drops. This indicator was taken from the “European Soil Data Center - ESDAC”, and represents the multi-annual erosion capacity of rain. For the study region, over 70% of the land has an average rainfall erosivity of over 800 ($Mj\ mm/ha\ h\ yr$), which can be considered as a medium-high value compared with values across the country.

Soil Texture (Vintilă et al., 2004), in the study region, is dominated by the Clay Loam class ($> 81\%$), which corresponds to soils with low permeability, favoring runoff and erosion.

The SRs density data were derived by considering the number of goats and sheep, in each LAU (GAC 2010, 2011) to the official area of land used as pastures in the cadastral evidence (AGR 101B, 2021). The 2010 share of SRs has been transferred to the 2019 counts at the county level per each LAU, thus, a more recent and accurate density is acquired (Neculau et al., 2021). This data has been prepared into a raster of the densities per each LAU, and it shows high variability in space making is a good explanatory variable, as long as it is spatially non-homogeneous and exhibits a bell curve distribution.

Pasture surfaces data were obtained from the National Institute of Statistics of Romania by considering the land fund corresponding to “pastures” of each Local Administrative Units at level 2 (LAUs) within the Subcarpathians region (INSSE, 2021b). Curvature Subcarpathians region shows a high national average stocking density of SRs (sheep and goats) of about 4.7 units per ha, with uneven territorial distribution ($SD = 9.26$) (see Supplementary 1).

Figure 4. Curvature Subcarpathians geographic factors: a. Lithology; b. Slope angle; c. Aspect; d. Profile Curvature; e. Forest and Trees Patches Cover Density; f. GRAVPI; g. Hydrologic Soil Groups; h. Curve number; i. SRs Density.

3.2. GSLDI application

Model configuration indicates that grazing of SRs plays a low role in the exposure to land degradation process, being the sixth important parameter among the 17 geographical variables, and contributing to 4.55% of the whole exposure in the Curvature Subcarpathians region.

The ranking of the relative influence shows the highest values for forest (43.7%) and terrain variables (e.g., slope 18.7%; profile curvature 7.19%) in the Curvature Subcarpathians region (Figure 5).

Figure 5. Conditional factors and their relative influence (%) / share/rank (%) to land degradation in the Curvature Subcarpathians region under GBM

In order to assess the grazing impact of SRs and build the GSLDI over the study region, we work with two major scenarios: the absence (0%) and overstocking of 100% (Figure 6).

The absence of grazing pressure signals a decrease of erosion likelihood exposure in the GBM model, while for RF model signals and increase in exposure. An increase of 100% of the grazing pressure indicates an increase in erosion likelihood exposure in both models, suggesting that grazing activity is one of the factors that control erosion exposure in the Curvature Subcarpathians region (Figure 6).

Figure 6. GSLDI probabilistic maps (0 -100%) in CS region with Random Forest (top 3 images) and Gradient Boosted Machine (bottom 3 images) under *initial* (a), zero (b), and 100% overstocking (c) scenarios

Model training with RF and GBM algorithms performed very well, having the same accuracy, over 90%, and were selected for the mapping of land degradation in the Curvature Subcarpathian's region (Table 2; Figure 7).

Table 2. Model efficiency (%) according to multiple efficiency criteria
RF = Random Forest; GBM = Gradient Boosted Machine; AUC = Area Under the Curve; ROC = Receiver Operator Characteristic.

Figure 7. ROC curves with associated AUC values computed from Gradient Boosted Machine and Random Forest

5. CONCLUSIONS: REFLECTIONS AND FINAL REMARKS

We proposed a new methodology based on specific parameters chosen to evaluate small ruminants' (SRs) grazing contribution to land degradation. A novel model has been developed using a qualitative assessment of the evidence-support of a hypothesis that integrates weight/partitive factors of land degradation at the regional scale.

The new tool shows land degradation susceptibility under SRs grazing impact which allows us to present a basic knowledge of the impressive factors for land degradation occurrence under SRs grazing pressure.

In our study case, the modeling framework has been consisted of sampling erosion and no-erosion points (4187 sampling points), assigning the physical and geographical characteristics (17 attributes), standardizing the dataset (55 final attributes), and using them in the training ML models of RF and GBM. The GSLDI indicates that SRs grazing plays an important role, but is not the major factor in the exposure to erosion process, contributing to only 4.6% of the whole exposure to land degradation, according to GMB model rank classification. However, this low percent agrees with the findings of Nicu (2018) who reported for a gully assessment in the northeastern part of Romania that overgrazing does not considerably change the erosion rates. Another explication to land degradation and the high value of erosion rates could be the lithology and neo-tectonic movements (uplift rates of 3–4 m/year) (Micu and Balteanu, 2009). Although, the results have some uncertain stemming from (i) the low-quality resolution of the biophysical predictors; (ii) the required supplementation with field monitoring for evidence in agricultural catchments for quantitative evidence of erosion rates.

Now a critical question here is why the results are different and which one is telling the truth? We found for the areas covered by pastures, natural grasslands, or other grasslands (*Sclerophyllous* vegetation, sparsely vegetated areas), the scenario with the absence of grazing pressure signals a small decrease of erosion likelihood exposure with the GBM model, while for RF model signals an increase in exposure (Table 3). This may indicate that the model sensitivity to this factor is low and not enough to observe the impact of the grazing pressure for RF model. An overstocking of 100% of the grazing pressure indicates a small increase in erosion likelihood exposure for the GBM model, which may indicate again the not major role of the grazing activity in the control to erosion exposure in the Curvature Subcarpathians area (Table 3).

Table 3. GSLDI mean values (%) for pastures and grassland areas

The presence of forests plays a crucial role in land degradation through erosion. More precisely, the forest vegetation density has a relative influence share of approximately 33% in explaining the susceptibility to land degradation. Approximately 11% of results are explained by the simple presence of forest, without regard to any other particular features. This is a very important result confirming that not necessarily the presence of the forest is important, but more important is the presence of tall vegetation with high density that could be named or classified otherwise. This might explain why authors such as Broeckx et al. (2016) show a very weak correlation with sediment yield in the agricultural catchment with strongly contrasting land uses in their work about sheet and rill erosion rates in Romania. Therefore, for future studies on erosion susceptibility or land degradation, we also recommend the use of forest vegetation density instead of simply forest. In the long term, a more adapted classification of grazing range/scale would be necessary to avoid the risk of overestimating the availability potential of land degradation areas.

We did not exclude or minimize the role of grazing impact of SRs, especially at the local scale (Figure 8), but over time will result in complex interactions depending on environmental factors. However, a quantitative known grazing impact of SRs, as pointed out by Evans (1997), Poesen (2018), Boardman et al. (2019), needs observation and empirical survey (e.g., sediment traps and chemical fingerprinting) to understand the hillslope process and the extent of rates of erosion.

Figure 8. Sheet and linear grazing impact of SRs photos - near paddock (left) and trails (right) in the Curvature Subcarpathians (Romania); photograph taken by Gabriel MINEA on August 18th, 2021

We conclude that a better knowledge of the relationship between SRs and land use can be beneficial to society and the environment (e.g., soil conservation, hazard management, subsidy, mitigation measures). Overall, we consider that the proposed GSLDI can be used efficiently to assess land degradation concerning small ruminant grazing in other land degraded regions. Finally, we argue that land degradation induced by SRs can be assessed with success using the GSLDI approach. Also, the GSLDI is helpful as basic support to promote agricultural sustainable policies at the regional-level decisions regarding grazing farming practices.

Supplementary Material S1

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Figures

Figure 1

The proposed hierarchy predictors and their geographical use to develop the Grazing Susceptibility to Land Degradation Index. (GRAVIPA = Grassland Vegetation Probability Index; LULC = Land Use Land Cover)

Figure 2

Workflow for designing Grazing Susceptibility to Land Degradation Index

Figure 3

The location of Curvature Subcarpathians and the border of Local Administrative Units level 2

Figure 4

Curvature Subcarpathians geographic factors: a) Lithology; b) Slope angle; c) Aspect; d) Profile Curvature; e) Forest and Trees Patches Cover Density; f) GRAVPI; g) Hydrologic Soil Groups; h) Curve number; i) SRs Density.

Figure 5

Conditional factors and their relative influence (%) / share/rank (%) to land degradation in the Curvature Subcarpathians region under GBM

Figure 6

GSLDI probabilistic maps (0 -100%) in CS region with Random Forest (first/up 3 images) and Gradient Boosted Machine (second/down 3 images) under initial a), zero b), and 100% overstocking c) scenarios

Figure 7

ROC curves with associated AUC values computed
from Gradient Boosted Machine and Random Forest

Figure 8

Field photographs showing the sheet and linear (rill) grazing impact of SRs photos - near paddock (a) and trails (b) in the Curvature Subcarpathians, Romania; photograph taken by Gabriel MINEA on August 18th, 2021

Supplementary Files

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- [SupplementaryMaterialS1.xlsx](#)