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# Soil Erosion Quantification using Machine Learning in Sub-Watersheds of Northern Portugal

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**Abstract:** Protected areas (PA) play an important role in minimizing the effects of soil erosion in watersheds. This study evaluated the performance of machine learning models, specifically support vector machine with linear kernel (SVMLinear), support vector machine with polynomial kernel (SVMPoly), and random forest (RF), on identifying indicators of soil erosion in 761 sub-watersheds and PA in northern Portugal, by using soil erosion by water in Europe, according to the revised universal soil loss equation (RUSLE2015), as target variable. The parameters analyzed were: soil erosion by water in Europe according to the revised universal soil loss equation (RUSLE2015), total burned area of the sub-watershed in the period of 1975-2020, fire recurrence, topographic wetness index (TWI), and the morphometric factors, namely area (A), perimeter (P), length (L), width (W), orientation (O), elongation ratio (Re), circularity ratio (Rc), compactness coefficient (Cc), form factor (Ff), shape factor (Sf), DEM, slope, and curvature. The median coefficient of determination ($R^2$) for each model was RF (0.61), SVMpoly (0.68), and SVMLinear (0.54). Regarding the analyzed parameters, those that registered the greatest importance were A, P, L, W, curvature, and burned area, indicating that an analysis which considers morphometric factors, together with soil erosion data affected by water and soil moisture, is an important indicator in the analysis of soil erosion in watersheds.

**Keywords:** soil erosion; sub-watersheds; machine learning; burned areas; protected areas

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## 1. Introduction

The increasing number of large forest fires that affect the Mediterranean area are being influenced by climate changes, human activities, and consequent changes in the soil and land use, with profound effects in the landscape. In different locations around the world, such as California (USA), Canada, Portugal, Spain, and Australia, the intensity of these natural events is enhanced by the effects of climate change and the overexploitation of natural resources by the population [1–6].

Extreme climatic conditions increase the occurrence and propagation of forest fires, accelerating erosion processes. The Northern region of Portugal has a high recurrence of these events, with high intensity and dimension, that are no longer considered a natural process for the renewal of ecosystems [7]. During the 20th century, in addition to evidence of increased temperature and decreased rainfall, changes in land use and cover and variations in socioeconomic characteristics also influenced the increase in the number and intensity of forest fires [8–11].

The consequences of the fires are fundamentally of environmental, social, and economic order, affecting rural properties and their agricultural production, resulting in a significant loss of capital and of environmental order, decreasing the provision of ecosystem services. The forest is responsible for providing different ecosystem services, such as carbon storage in vegetation and soil, food, water filtration, and climate regulation at local and regional levels. With the increase in the occurrence of forest fires, the availability of ecosystem services is altered.

The rivers, lakes, watersheds, and groundwater, on the other hand, provide hydrological ecosystem services, characterized by quantity, quality, and location [12]. According to the Intergovernmental Platform for Biodiversity and Ecosystem Services (IPBES), in the analysis of this category, it should be considered that maintaining the hydrological cycle sustains climatic conditions, soil formation, vegetation growth, erosion, and the biogeochemical cycle, contributing to landscape formation and evolution.

The maintenance of the hydrological cycle, together with the implementation of measures to prevent erosion are important to ensure water availability in the water sources, and the maintenance of ecosystem services. According to Brauman et al. [12], who developed the Common International Classification of Ecosystem Services (CICES), water is classified as a provisioning service and the landscape, considering vegetation, soil, and drainage, must be conserved to provide a source of drinking water for public supply, besides other important ecological functions [13,14].

Studies carried out in different countries have demonstrated the high flow and soil erosion after fires. Generally, in regions of Mediterranean climate, in the first six months after the fires, the potential for erosive processes is greater due to the fires being concentrated in the summer (July–August) and the intense post-fire rains occur between autumn and next winter (November–January) [15–18]. There is a gap of studies regarding geomorphological responses at the level of the small watershed. Even with a high recurrence of fires in the Mediterranean region, small-scale watershed studies focused on the USA, Australia, and South Africa [19–22]. Developing studies in this field is important to predict the risk of floods and erosion in burnt areas and, consequently, to guarantee ecosystem services, minimizing the effects of fires.

There is a lack of studies correlating watersheds as units of analysis in the field of flood and erosion risk prevention in burnt areas. Spatial analysis of the surface-dynamics is important when considering the watershed as a unit [23,24]. In the context of soil erosion, a country like Portugal undergoes substantial changes in its surface dynamics due to increasingly frequent fires [3,7]. It is important to develop studies that provide integrated analyses of landscape components and advance knowledge about surface analysis based on datasets that can be correlated to understand and propose planning measures for these units that minimize the effects of soil erosion [25].

Recent advances in machine learning and the use of algorithms in the analysis of landscape components, when combined with the consolidated knowledge of Geomorphometry, make it possible to develop analyses that provide satisfactory results and can be applied in watershed management.

Geomorphometry is a field that combines the principles of classical morphometry with the mathematical study of the shape and configuration of a watershed's surface to contribute to soil loss analysis [26–28].

Expressed in indices that indicate geometric characteristics, the drainage network and the relief with it is strengthened by the analysis possibilities provided by geographic information systems (GIS) and remote sensing (RS) [29–31].

Analysis of watersheds based on morphometric factors helps to understand the linear, sandy and altitudinal shape aspects, and it is important for the planning of these watersheds. Some indexes are useful in the analysis of the production of sediments resulting from soil erosion in watersheds and may assist in the adoption of measures for the recovery and conservation of these territories [32–34].

Machine learning enables the automation of data analysis. An area of artificial intelligence, machine learning is based on the idea of learning from data, recognizing patterns to make decisions without human intervention [35,36]. Several studies applied the machine learning techniques in soil erosion analysis with a focus on gully erosion and debris flow prediction [37,38].

Our research evaluates machine learning models (support vector machine linear, support vector machine polynomial, and random forest) in sub-watersheds of four hydrographical regions of Portugal with burned areas, analyzing which factors are important in predicting soil loss and evaluating the following hypotheses:

H1: The delimitation of PA alone is not enough for erosion control, an important regulatory ecosystem service provided by Pas that has already been studied by Schirpke et al., Pisani et al., and González-Gárcia et al. [39–41];

H2: The greater recurrence of fires in the watersheds favors soil erosion in the sub-watersheds. The study of Knicker [42] indicates that there is a progressive impoverishment of soil fertility due to the recurrence of fires. Therefore, the lower possibility of vegetation recomposing itself, before a new fire, favors soil erosion in the sub-watersheds.

H3: The sub-watershed is a unit of landscape analysis, resulting from a dynamic that relates geological, geomorphological, pedological, hydrological, climatic, botanical, and human conditions that interact in a non-linear way over time [43,44]. Thus, the relationship between the factors analyzed should not occur in a linear fashion in a soil loss model.

## 2. Study Area

The 761 sub-watersheds (Figure 1) analyzed make up the hydrographic regions of the Douro; Vouga, Mondego and Lis; Cávado, Ave and Leça and Minho and Lima in an area that represents 40.63% (3,741,140.86 ha) of the territory of Portugal. The area of these watersheds accounted for 52.02% (5,357,650 inhabitants) of the population of Portugal and 41.98% (1,570,735.48 ha) of the burned area between 1975 and 2020.

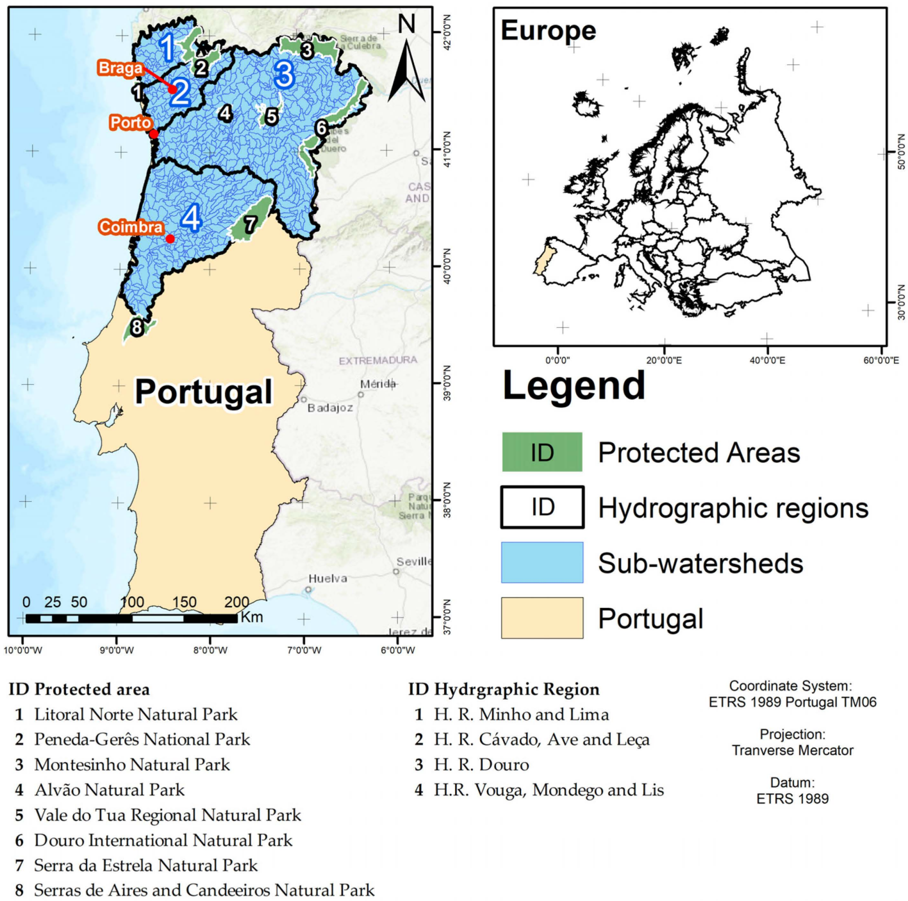


**Figure 1.** The location of the study area, including the delineation of hydrographic regions and protected areas.

These four hydrographic regions have been successively affected by forest fires and some important watersheds are fundamental for the public water supply to important cities in the center-north of the country, e.g., Coimbra, Porto, and Braga.

## 3. Materials and Methods

### *3.1. Controlling Factors*

#### 3.1.1. Morphometric Factors

The morphometric factors area (A), perimeter (P), length (L), width (W), orientation (O), elongation ratio (Re), circularity ratio (Rc), compactness coefficient (Cc), form factor (Ff), and shape factor (Sf) were extracted from the vector of the 761 sub-watersheds using the methodology proposed by Gudowicz and Paluszkiewicz [45].

The analysis of watersheds based on morphometric factors helps to understand the linear, sandy, and altitudinal shape aspects, and it is important for the planning of these territories. Some indexes are critical in the understanding of the production of sediments resulting from erosive processes in watersheds and may thus assist in the adoption of measures for the recovery and conservation of these territories after forest fires [32–34,46]. The concepts of morphometric factors and their application in soil erosion analysis can be found in the work of Horton [32], Rai et al. [47], Dinh et al. [48], and Elhag et al. [49].

#### 3.1.2. Surface Data

The surface data were derived from The European Digital Elevation Model (EU-DEM) with a resolution of 25 m, downloaded from the Land Monitoring Service under the responsibility of the European Environment Agency (EEA). We removed the small imperfections from the DEM data using the Fill tool, available in ArcGIS software (ESRI). After this procedure, slope, curvature (Curv), curvature planform (Curvplan), and curvature profile (Curvprof) data were prepared in ArcGIS. These are important parameters to understand the process of erosion and runoff in watersheds. Sahour et al. [26] used these data in a machine learning analysis applied to soil erosion.

The SLOPE increases the speed of runoff and, consequently, the erosive capacity, favoring the transport of sediments to the watercourse. The concentration of the runoff flow occurs in concave-converging slopes, favoring the occurrence of erosive processes of the ravines or gullies that increase the volume of material transported to watercourses. Together with slope, the altitude range helps to identify variations in the relief indicating more rugged or flatter areas [47,50].

The Curvprof influences the flow acceleration and deceleration. Its value can be used to identify soil erosion patterns and influence on surface runoff velocity [51]. On convex surfaces, soil erosion accelerates the flow of runoff, and on concave surfaces sedimentation is potentiated [52].

#### 3.1.3. TWI

The topographic wetness index (TWI) is an index that measures soil moisture and changes with elevation, the higher the elevation, the lower the moisture. Therefore, the highest TWI values are related to the lowest elevations in the watershed, i.e., close to the rivers [53]. The unit contributed watershed data are required for the calculation of TWI ($\alpha$) and slope ($\beta$). Its calculation formula is:

$$TWI = \ln\left(\frac{\alpha}{\tan\beta}\right) \tag{1}$$

When expressing soil water saturation, the TWI, on the other hand, indicates areas with a greater propensity to erosion in places where there is no or less soil water saturation. Some studies that use the TWI in soil erosion analysis include the work of Sharma [54] and Haile [55].

#### 3.1.4. Burned Area and Fire Recurrence in Watershed

The total burned area by sub-watershed and the recurrence of fires was calculated using the database of burned areas in the period 1975–2020, made available by the Institute for the Conservation of Nature and Forests (ICNF). Recurrence was calculated using the Raster Calculator tool (ArcGIS), applying a sum of all rasters of burned areas in the analyzed period. The total burned area by watershed was calculated by extracting the total burned area by sub-watershed.

### *3.2. Target Variable*

#### Soil Erosion

Soil erosion by water data were downloaded from the Soil Erosion by Water Database (RUSLE2015) of the European Soil Data Center (ESDAC) which provides information on soil loss in t $ha^{-1}$ $yr^{-1}$ [56].

After organizing the initial research database, the Zonal Statistics as Table tool (ArcGIS) was used to extract the minimum, maximum, mean, and standard deviation (std) values from DEM, slope, Curv, Curvplan, Curvprof, and TWI, in addition to the total burned area, fire recurrence, and total soil loss (t $ha^{-1}$ $yr^{-1}$) in sub-watersheds.

### *3.3. Machine Learning*

We evaluated three machine learning models: random forest (RF), support vector machine linear (SVMlinear), and polynomial (SVMpoly) algorithms to analyze soil erosion. The analysis of machine learning models applied to soil erosion has been tested by Sahour et al., Nguyen et al., and Nguyen et al. [26,27,48].

In the present research, we analyze controlling factors to identify linear or non-linear relationships between them and soil erosion (RUSLE), using machine learning models RF, SVMlinear, SVMpoly.

The RF model is a classification and regression analysis model based on decision trees. In this model, the number of trees and predictor variables at each node are essential for the development of the model. Some examples of studies using the RF model include the work of Madarász et al., Paul et al., and Jiang et al. [57–59].

SVM models are based on supervised learning with learning algorithms used in the classification and regression analysis and can be divided into linear and non-linear. In this research, we used the SVMlinear, which divides a dataset into two classes by using a single straight line in classification process and the SVMpoly that models the relationship between a dependent(y) and independent variable(x) in *n* degree polynomial. Some examples of studies using these models are those of Dinh et al., Pourghasemi et al., Onyelowe et al., and Kamran et al. [48,60–62].

To improve the use of machine learning in soil erosion modeling, Nguyen et al. [28] incorporated morphometric factors that measure the efficiency of drainage channels to remove excessive precipitation, resistance to erosion, and permeability of the lithology, which indicates the speed and strength of water flow and help us identify erosion, transport, and sedimentation processes [32,63].

The models were processed in R language, using the caret package and dividing the dataset into training and testing. After running the models, the importance of each variable was computed. The performance evaluation of machine learning models was performed by correlating the observed and predicted values and applying the MAE, RMSE, and $R^2$ metrics.

## **4. Results**

### *4.1. Descriptive Statistic*

The morphometric factors calculated for the 761 sub-watersheds allowed us to trace a profile of these areas (Appendix A). The set of sub-watersheds has a minimum area (A) of 12,999.53 $m^2$ and a maximum area of 287.73 $km^2$ (average of 47.74 $km^2$/median of 31.88 $km^2$/Std.dev 44.46 $km^2$). The median ($M_d$) of the areas (A) of the sub-watersheds

(M d of 31.88 km$^2$) indicates that we are dealing with sub-watersheds that are mostly small. The minimum length (L) is 850,342 meters and the maximum is 54 km (average 11.9 km/median 10.3 km/Std.dev 6.6 km). The width (w) of the sub-basins varies between 3.3 m and 9.5 km (average 3.5 km/median 3.2 km/Std.dev 1.5 km).

The elongation ratio (Re) varies from a minimum value of 0.18 (sub-watersheds with a nested shape) to 0.86 (sub-watersheds with a circular shape) with an average of 0.62, which means that in 0.62 average, the sub-basins under analysis have slightly circular characteristics. Circular and compact basins tend to be more prone to flooding than narrow and elongated sub-watersheds, especially when the phenomenon of intense precipitation occurs throughout its extension. The average values of circularity ratio (Rc) of 0.63 corroborate the existence of sub-watersheds with slightly circular shapes. According to Gudowicz and Paluszkiwwicz [45], in the watersheds where the Rc value is greater than 0.5, the longitudinal processes act with the same intensity as the transversal processes (linear erosion, mass movements, solifluxion, and slope wash), which according to the author are processes that lead to the widening of the valley floor.

Regarding the form factor (Ff) values, the sub-watersheds present a variation between 0.07 (fitted valleys) and 2.35 (perfectly circular shapes). On average, the form factor (Ff) of the sub-watersheds under study is 0.35, which certifies the existence in the study area of a prevalence of rounded basins. The value of shape factor (Sf) is inverse to the form factor (Ff), which means that larger values represent more elongated shapes. Shape factor (Sf) values range from 0.00 to 13.54 (mean of 3.53; Std.dev of 1.44).

The DEM median values are 177.48 m (minimum), 812.06 m (maximum), indicating that the sub-watersheds are located, mostly, between these two values, with an average altitude of 498.56 m and a standard deviation of 101.28 m. As for slope, the median presents a minimum value of 0.01° and a maximum of 39.20°. The minimum Curv value is −50.19 and maximum is 37.66, where the minimum Curvprof is −21.52 and the maximum is 24.75. The minimum Curvplan is −28.45 and the maximum is 21.73. The median values of the maximum values of Curvprof and Curvplan are, respectively, 3.99 and −4.20. The minimum TWI value is −11.83 and the maximum is 28.01, with a median maximum value of 17.01, indicating a higher concentration of wetlands.

### 4.2. Variable Importance

The importance of variables in machine learning models is shown in Figure 2.

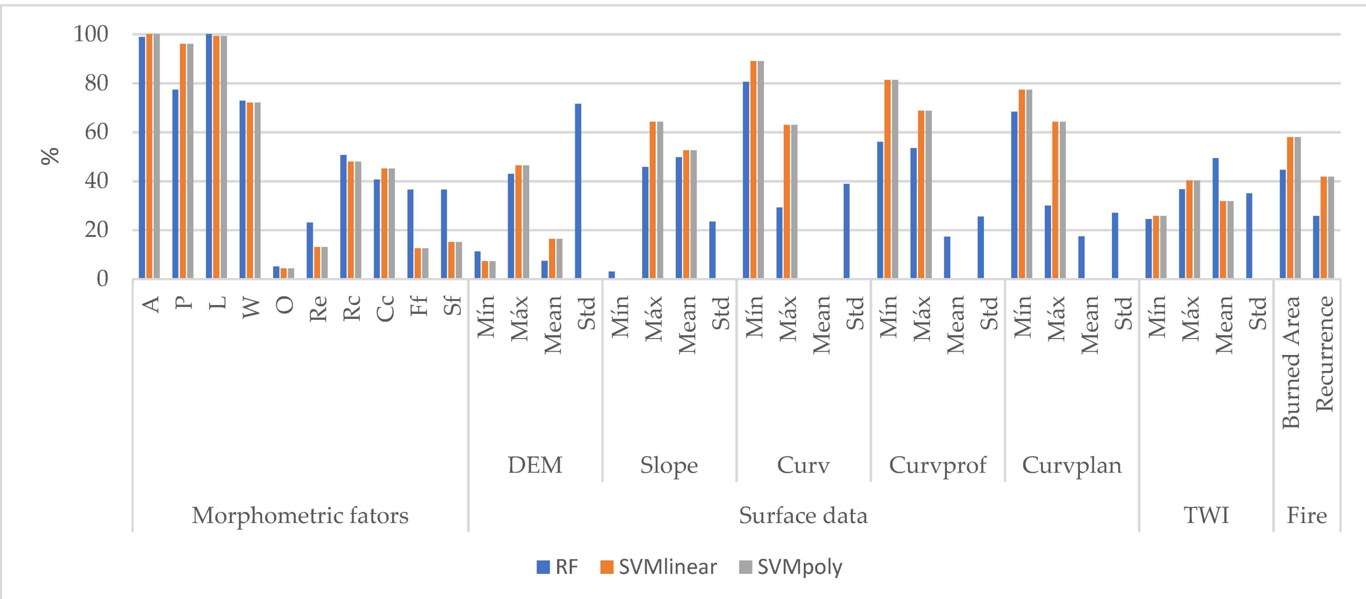


**Figure 2.** Importance of variables in machine learning models.

Among the morphometric factors, A, P, L, and W are more important than 50% in the three models. Only the variable P has a significant difference in the three models. The morphometric factors Rc and Cc have an importance between 40% and 50% in the three models, and in the other morphometric factors the importance is less than 40%. The RF model assigns greater importance to the factors Ff, Sf, and Re, in relation to the SVM models linear and SVMpoly.

Among the surface data, the maximum DEM values are the most important in the machine learning of the three models. Regarding the slope, both the average and maximum values are the most important. However, they were more important in the SVMlinear and SVMpoly models. Regarding the curvature data, the minimum and maximum values for both Curv and Curvprof and Curvplan were more important in the three models, whereas in the RF model their importance was lower. Regarding the values of media and std, they did not show significant importance in the analysis. The maximum and mean values were more important in the models regarding the TWI values. In the RF model, the average of TWI obtained greater importance in relation to the other models.

Data on fire, burned area, and recurrence were more important in the SVMlinear and SVMpoly models than in RF. Furthermore, the total burned area of watersheds is more important for soil loss than the recurrence of fires.

### 4.3. Machine Learning

The results of the RF, SVMlinear, and SVMpoly models are shown in the Figure 3 and Table 1.

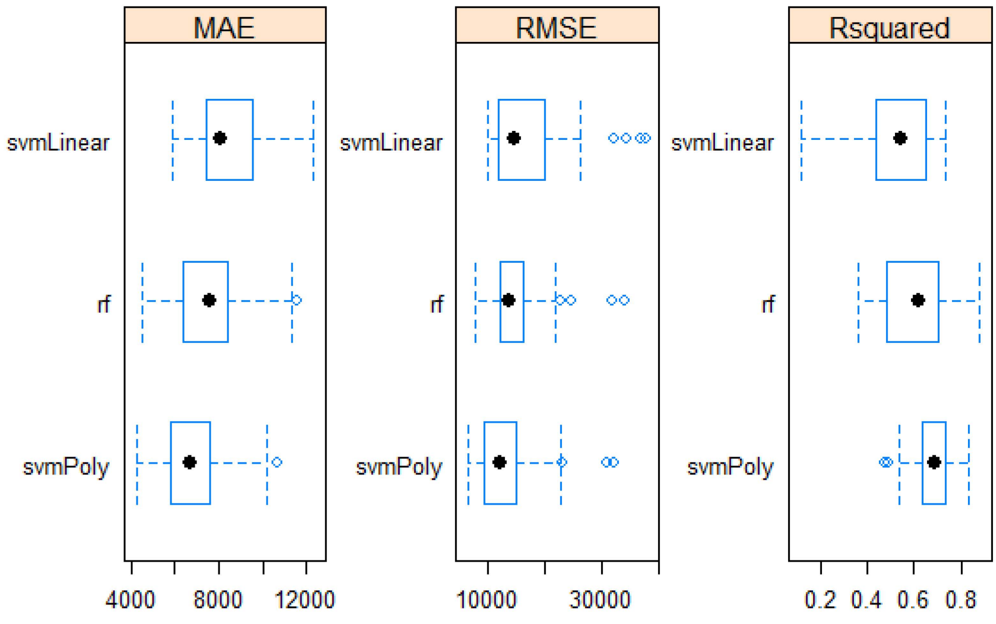


**Figure 3.** Result of the RF, SVMlinear and SVMpoly models.

**Table 1.** Error metrics from the RF, SVMlinear and SVMpoly models.

| | MAE | | | RMSE | | | $R^2$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Min. | Median | Max. | Min. | Median | Max. | Min. | Median | Max. |
| RF | 4469.17 | 7574.94 | 11,544.22 | 7737.58 | 13,546.85 | 34,292.61 | 0.359 | 0.619 | 0.875 |
| SVMlinear | 5891.86 | 8098.76 | 12,305.01 | 9748.46 | 14,680.58 | 37,892.09 | 0.116 | 0.542 | 0.732 |
| SVMpoly | 4232.06 | 6723.43 | 10,659.13 | 6483.56 | 12,180.34 | 32,388.67 | 0.475 | 0.689 | 0.836 |

The MAE and RMSE values express the mean error of the predictive model. Comparing the three models, the best (lowest) MAE and RMSE median was from SVMpoly, followed by RF and SVMlinear. In the SVMlinear model, the MAE and RMSE concentrate data above the average, in addition to more outliers. The RF model presented a high amplitude between the minimum and maximum of MAE and the second-largest amplitude of RMSE. The SVMpoly model presented the best MAE and RMSE error metrics.

In relation to $R^2$, the SVMlinear model obtained the worst values with high amplitude between the minimum and maximum values, in addition to the lowest median values. The RF reached the best maximum result, but the median was smaller than in the SVMpoly model, which also presented the smallest amplitude between the minimum and maximum values.

Applying Pearson's correlation between the observed and predicted data of the three models, a correlation of 0.556 (SVMlinear), 0.706 (RF), and 0.795 (SVMpoly) was recorded.

### 4.4. Soil Erosion and Protected Areas

The relationship between RUSLE and fire recurrence is shown in the Figure 4.

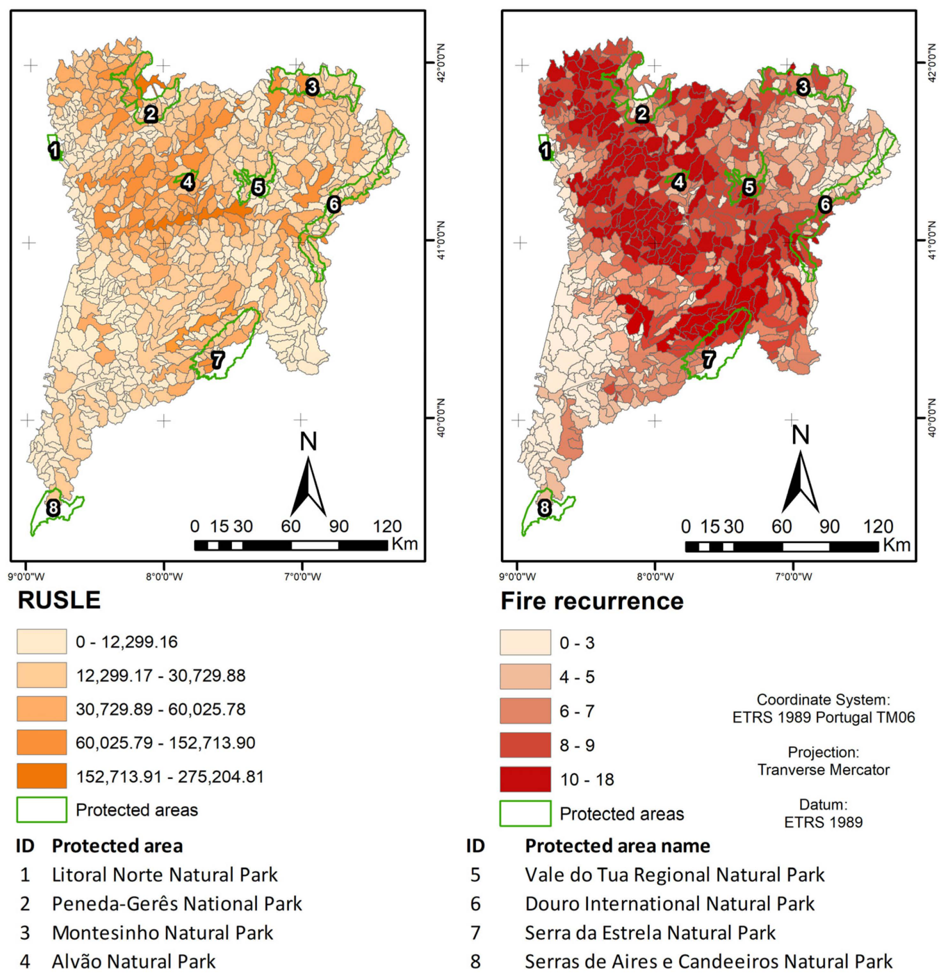


**Figure 4.** Relationship between RUSLE and Fire Recurrence values.

The sub-watersheds (n = 671) recorded a mean of 15,737.07t ha$^{-1}$ yr$^{-1}$ soil loss. The sub-watersheds of the Douro River are located in an embedded valley with a high slope and sectors of Cenozoic sedimentary cover [64]. This characteristic favors erosive processes in this area, recording values above 152,713.91 t ha$^{-1}$ yr$^{-1}$. North of the Douro River, the sub-basins of the protected areas (PAs) of Alvão (ID 4) and Peneda-Gerês (ID 2) record values higher than 60,025.79 t ha$^{-1}$ yr$^{-1}$. Similar values occur in the sub-watersheds near the Serra da Estrela PA (ID 7).

An analysis was carried out on soil erosion in sub-watersheds with PA, in order to understand whether these PAs are contributing to the preservation of places, minimizing the effects of soil erosion (Figure 5).

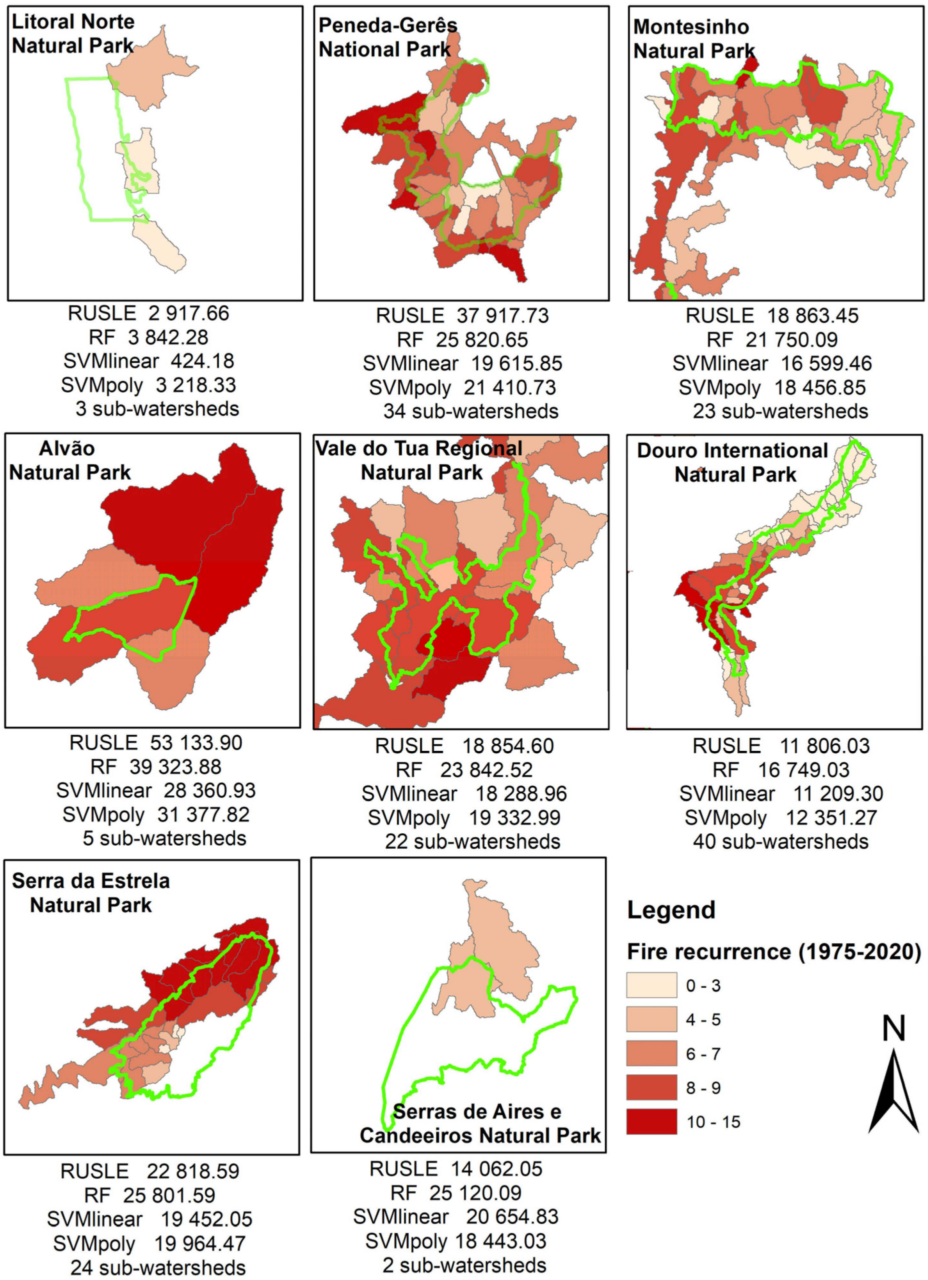


**Figure 5.** Results in sub-watersheds included in PA in four hydrographic regions. * They are at the limit of the hydrographic regions and therefore only the sub-watersheds located in the selected hydrographic regions are not analyzed.

Among all sub-watersheds (n = 761), 20.11% (n = 153) are located in the PA shown in Figure 5. Peneda-Gerês National Park, Alvão Natural Park, and Serra da Estrela Natural Park are the PAs that recorded most significant soil loss (RUSLE). They are also the PAs that recorded the highest recurrence of fires, respectively, 7.11, 9.20, and 7.75, i.e., for at least seven years between 1975 and 2020, the sub-watersheds located in these PAs burned. In addition to these three PAs, Vale do Tua Regional Natural Park registered an average volume of soil loss above the average of the sub-watersheds, which was 15,737.07 t ha$^{-1}$ yr$^{-1}$.

The machine learning models recorded some volume differences compared to the RUSLE values. In the RF model, the PAs Litoral Norte Natural Park, Montesinho Natural Park, Vale do Tua Regional Natural Park, Douro International Natural Park, Serra da Estrela Natural Park, and Serras de Aires e Candeeiros Natural Park registered a greater volume of soil loss in relation to the RUSLE data, and Peneda-Gerês National Park and Alvão Natural Park registered a smaller volume of soil loss in relation to the RUSLE data.

In the SVMlinear model, only Serras de Aires and Candeeiros Natural Park recorded a higher volume of soil loss, while all other PAs recorded a lower volume of soil loss. In the SVMpoly model, the PAs Peneda-Gerês National Park, Montesinho Natural Park, Alvão Natural Park, and Serra da Estrela Natural Park registered a lower volume of soil loss compared to RUSLE and in the PAs Litoral Norte Natural Park, Vale do Tua Re-gional Natural Park, Douro International Natural Park, and Serras de Aires and Candeeiros Natural Park recorded a higher volume of soil loss.

## 5. Discussion and Conclusions

Soil erosion is a significant factor of soil degradation, particularly important in Mediterranean regions where desertification is an ongoing process and where forest fires are a major disturbance factor [65].

The evaluation of soil erosion rates in these areas is fundamental for land management and determination of mitigation and conservation strategies, useful for soil protection strategies implementation.

The implementation of machine learning methodologies increases the prediction capabilities of soil erosion and the possibility of its control and mitigation. Therefore, the analysis presented in this study can support regional watershed planning, providing analysis parameters in a machine learning approach that has already been shown to be effective in past studies, e.g., the work of Nguyen et al. [27], who analyzed machine learning algorithms in the Shihmen reservoir in Taiwan, using 14 environmental attributes. Nguyen et al. [28] modeled soil erosion in a watershed in Taiwan using 26 morphometric factors and 10 environmental factors. Sahour et al. [26] tested machine learning algorithms to identify the relationship between soil erosion and control factors. In all these studies, the algorithms were evaluated taking into consideration predicted and observed values, using MAE, RMSE, and $R^2$.

Our investigation showed that the dimensions of watersheds are crucial for measuring the amount of soil loss, with the morphometric parameters A, P, L, and W being the most associated to soil erosion. The Rc and Cc factors had an importance between 45.12% and 47.96% in the SVMlinear and SVMpoly models and from 40.62% to 50.62% in the RF model, factors that are directly related to the P of the sub-watersheds. The morphometric factors Re, Ff, and Sf had importance between 12.52% and 15.08% in the SVMlinear and SVMpoly models and between 23.08% and 36.59% in the RF. They are morphometric factors related to A, P, and L of the sub-watersheds. The findings of Nguyen et al. [28] also demonstrate the importance of these factors for the calculation of soil loss. Finally, the morphometric factor O registered little importance in the models, 4.32% in SVMlinear and SVMpoly and 5.14% in the RF. It is a factor that relates to solar radiation and wind direction. Therefore, it may be important for the dynamics of fire evolution, but not directly affecting soil erosion, i.e., a consequence, among other factors, of fires.

The parameters Curv, Curvprof, and Curvplan are of great importance in the models because they indicate the concave or convex pattern of the surface of the sub-watersheds, which directly influences the surface runoff and consequently the erosion of soils. These are variables that, together with the slope, influence the flow rate. As for DEM, the maximum values were more important in the modeling. The importance of curvature and slope in modeling soil erosion in burned and non-burned areas has already been discussed by Sahour et al., Perreault et al., and Gray [26,51,66].

The TWI has an importance of less than 50% in the three models, because in the study area predominates sub-watersheds with high slopes, mountainous and abrupt reliefs such as Serra da Estrela, a result of the Alpine tectonics [67]. With these characteristics, the tops of hills and slopes are less humid and, consequently, this variable does not register great importance in the models.

The burned area revealed importance of 57.92% in the SVMlinear and SVMpoly models and 44.62% in the RF model. The recurrence showed an importance of 41.83% in the SVMlinear and SVMpoly models and 25.70% in the RF model.

We implemented these two fire-related variables because this extreme event is the main driver of soil erosion in the Mediterranean region of Europe [68]. According to Germanoski and Miller [69], geomorphic instability after the fire in Crow Canyon (Nevada, USA) lasted more than a decade.

Sánchez et al. [70] state that there is a direct relationship between fires and soil erosion, which can be up to 6.5 times higher in areas with high incidence (recurrence) of fires. The authors used the RUSLE and the normalized burn ratio (NBR) to determine the burned areas. The recurrence of fires, together with the severity, is responsible for hydrological and geomorphological impacts [71].

Fire data are directly related to soil erosion dynamics in Portugal. The fire magnitude and frequency have increased in recent years, directly influencing the erosive dynamics in the country [7,8,72,73].

Territories outside of PAs are not the only places where fires can occur. We have assisted an increasing presence of fires within the limits of PA, with severe consequences for wildlife. Consequently, regarding the topic under discussion, the regulation of ecosystem service, and retaining sediments in PA is not being effectively implemented [39–41]. In fact, it was observed that the sub-watersheds located in PA have high soil loss with the impoverishment of their fertility [42]. Controlled fire management actions are required, as addressed by Pereira et al. [74], to guarantee the maintenance of ecosystems in these areas, but the recurrence observed in our analysis does not indicate control in this type of action, only the recurrence in areas that are historically affected by fires and cause an imbalance in ecosystem services. In this way, we prove our H1 and H2 hypotheses.

The machine learning models presented very different behavior. The SVMlinear model seeks to separate the dataset using an ideal line of separability. This method does not address the complexity of the relationship of variables. Therefore, its results do not demonstrate its applicability in modeling as proposed in this research. Thus, we validate our H3 hypotheses, where the relationship of the elements that constitute the landscape does not have a linear behavior [43,44]. On the contrary, it was not observed in the SVMpoly model, which finds the decision limit in a non-linear way, adapting the model to the data set. Therefore, the results were satisfactory, as observed in the model validation metrics.

We recognize that regional-scale studies on the application of soil erosion prediction have limitations due to the difficulty in collecting data to validate the results. To address this issue, future research conducted in collaboration with a consortium of institutions or multidisciplinary research teams can use the current methodology to improve their results. However, the RUSLE2015 database developed by Panagos et al. [56] is suitable for regional studies on the European continent, and its use at the watershed level has yielded promising results.

Studies that use machine learning to forecast soil erosion, on the other hand, are critical at this stage of the field's development and should be investigated further in order to improve prediction accuracy and test additional machine learning techniques.

As a direction for future research, the methodology presented in this research can be applied in the context of planning large hydrographic regions but considering the sub-watersheds that compose them. This process supports decision-making related to soil conservation and erosion mitigation initiatives, thus ensuring the provision of essential ecosystem services such as soil retention in PA. These are important issues in the context of the discussion of climate change and biodiversity conservation that can contribute to the conservation and maintenance of ecosystems and are in line, for example, with the proposals of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), Intergovernmental Panel on Climate Change (IPCC), Sustainable Development Goals (SDGs), and United Nations Environment Programme (UNEP).

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

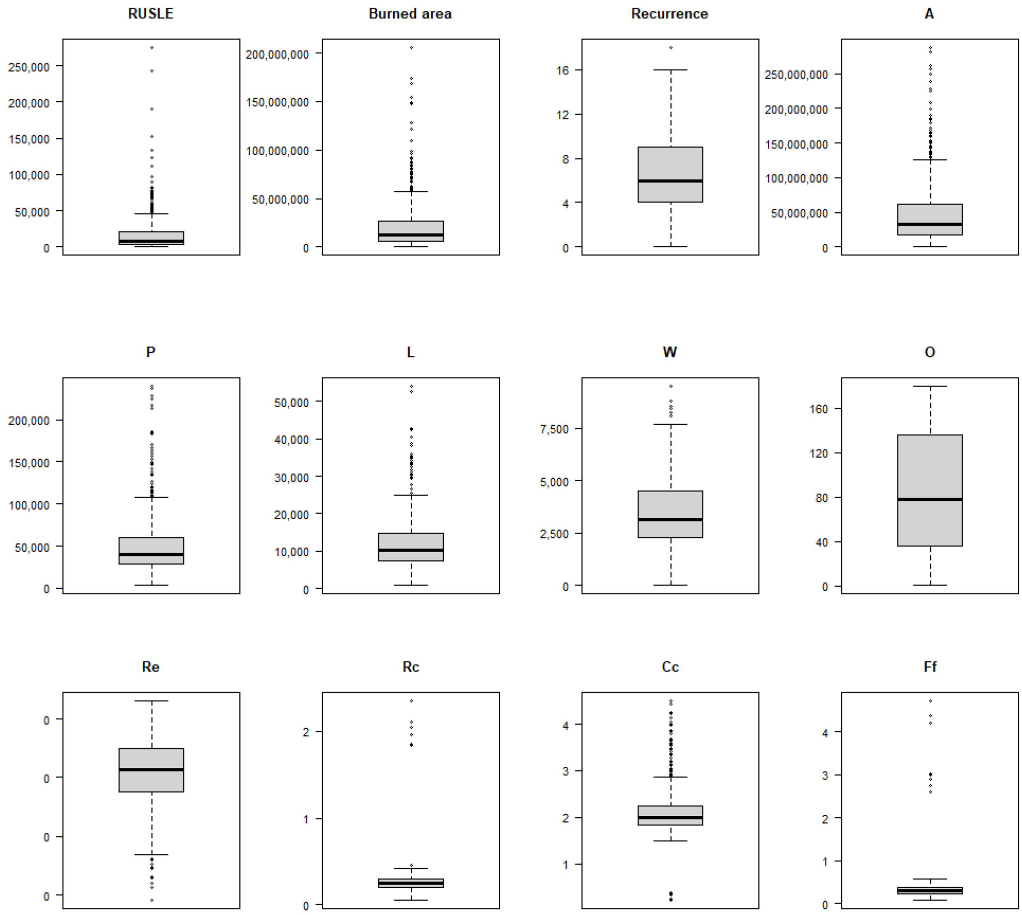


**Figure A1.** *Cont.*

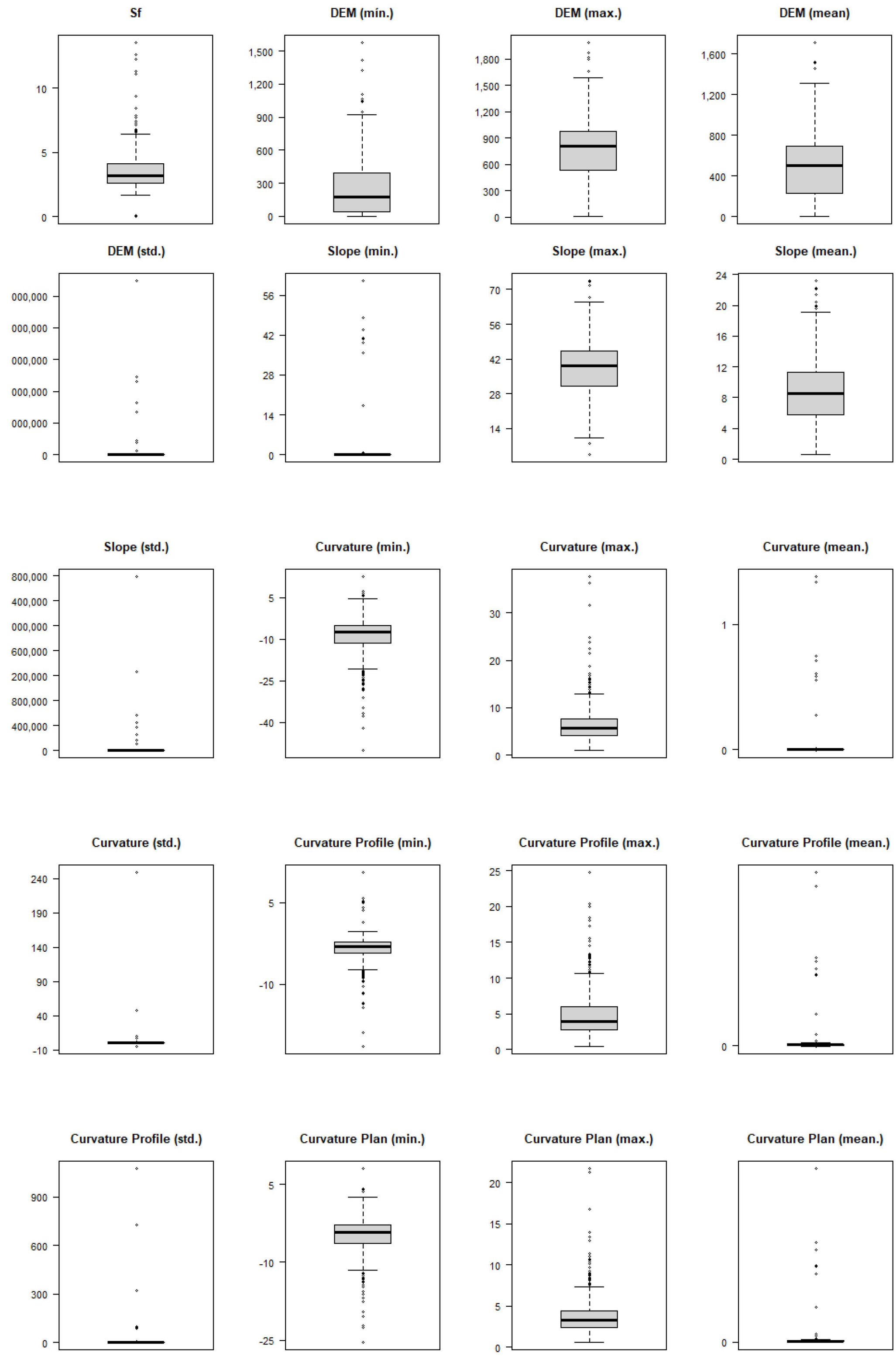


**Figure A1.** *Cont.*

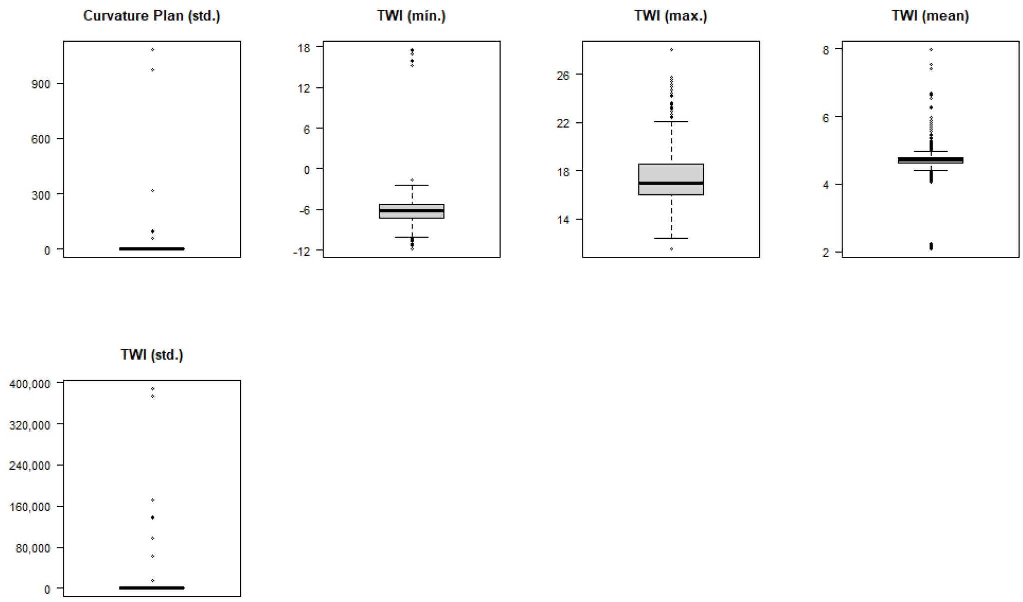


**Figure A1.** Boxplots of the variables analyzed in the study.

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