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# Carbon Storage Patterns and Landscape Sustainability in Northeast Portugal: A Digital Mapping Approach

**Matheus B. Patrício [1,*], Marcos Lado [1], Tomás de Figueiredo [2,3], João C. Azevedo [2,3], Paulo A. A. Bueno [4] and Felícia Fonseca [2,3]**

1 Advanced Science Research Centre, University of A Coruña, Elviña Campus, 15071 A Coruña, Spain; marcos.lado@udc.es
2 Centro de Investigação de Montanha (CIMO), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal; tomasfig@ipb.pt (T.d.F.); jazevedo@ipb.pt (J.C.A.); ffonseca@ipb.pt (F.F.)
3 Laboratório Associado Para a Sustentabilidade e Tecnologia em Regiões de Montanha (SusTEC), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal
4 Federal Technological University of Paraná, Campo Mourão Campus, Campo Mourão 87301-899, Brazil; pabueno@utfpr.edu.br
* Correspondence: eng.matheusbueno@gmail.com

**Abstract:** This study investigated the impact of regional land abandonment in northeast Portugal. It specifically focused on carbon sequestration opportunities in the Upper Sabor River Watershed, situated in the northeast of Portugal, amidst agricultural land abandonment. The study involved mapping the distribution of soil organic carbon (SOC) across four soil layers (0–5 cm, 5–10 cm, 10–20 cm, and 20–30 cm) at 120 sampling points. The quantification of SOC storage (measured in Mg C ha$^{-1}$) allowed for an analysis of its relationship with various landscape characteristics, including elevation, land use and land cover (LULC), normalized difference vegetation index (NDVI), modified soil-adjusted vegetation index (MSAVI), topographic wetness index (TWI), and erosion risk (ER). Six statistical tests were employed, including multivariate approaches like Cubist and Random Forest, within different scenarios to assess carbon distribution within the watershed's soils. These modeling results were then utilized to propose strategies aimed at enhancing soil carbon storage. Notably, a significant discrepancy was observed in the carbon content between areas at higher elevations (>1000 m) and those at lower elevations (<800 m). Additionally, the study found that the amount of carbon stored in agricultural soils was often significantly lower than in other land use categories, including forests, mountain herbaceous vegetation, pasture, and shrub communities. Analyzing bi- and multivariate scenarios, it was determined that the scenario with the greatest number of independent variables (set 6) yielded the lowest RMSE (root mean squared error), serving as a key indicator for evaluating predicted values against observed values. However, it is important to note that the independent variables used in set 4 (elevation, LULC, and NDVI) had reasonably similar values. Ultimately, the spatialization of the model from scenario 6 provided actionable insights for soil carbon conservation and enhancement across three distinct elevation levels.

**Keywords:** terrain features; regression analysis; land use planning; land use and land cover; elevation

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## 1. Introduction

Climate change has become a central topic of global concern due to its severe implications, and there is thus an urgent need for concrete mitigation actions [1]. This phenomenon, driven by the increased concentration of $CO_2$ in the atmosphere since the Industrial Revolution, has led to a significant rise in global average temperatures. Projections suggest that by 2080, the global temperature could increase by 2 °C compared to pre-Industrial Revolution levels, potentially leading to irreversible consequences. Our current juncture demands immediate action to curtail this trend and mitigate the adverse impacts of human activities [2].

However, studies indicate a reluctance on the part of society to participate in complex actions that require more effort. It is therefore up to political decision-makers to develop climate-related public policies that take cultural and behavioral aspects into account. This process must begin with raising awareness of climate change, promoting spaces for discussion that make shared responsibility explicit and integrating climate considerations into the community's daily agendas [1,3,4].

From climate awareness, plans can be created for community action in the context of the landscape in which it is inserted, considering environmental, social, and economic factors [4]. This study was carried out in the Alto Sabor Hydrographic Basin, located in the north-eastern region of Portugal, as the primary landscape unit for analysis.

By focusing on watersheds, we can better implement climate mitigation and adaptation policies, as they encapsulate pre-existing environmental, social, and economic relationships. A watershed perspective helps us understand the challenges from an integrated standpoint, transcending jurisdictional boundaries, and allows for effective solutions tailored to specific regions [4,5].

Consequently, we have an opportunity to implement policies, actions, and initiatives that leverage the community's current transitional phase, aiming to create a more sustainable territory [4,5].

This construction process aligns with a portion of the system of relationships supporting science-based policies, specifically concerning data management, sensorial elements, combined with the assessment and modeling of a specific region or sector. These findings can be utilized in training and education initiatives and in governance institutions [5].

Consequently, this study explores possibilities for these areas, including reversion to agricultural use, reforestation, and urban transformation (Figure 1), aiming to reduce greenhouse gas emissions and enhance carbon sequestration in terrestrial components within the watershed, such as vegetation and soil [4,6–8]. Experiences in sensitive areas, such as wetlands and mountain regions, emphasize the importance of integrated, low-carbon, partnership-focused planning, with projects designed to harness the territories' potential for carbon capture and storage [4].

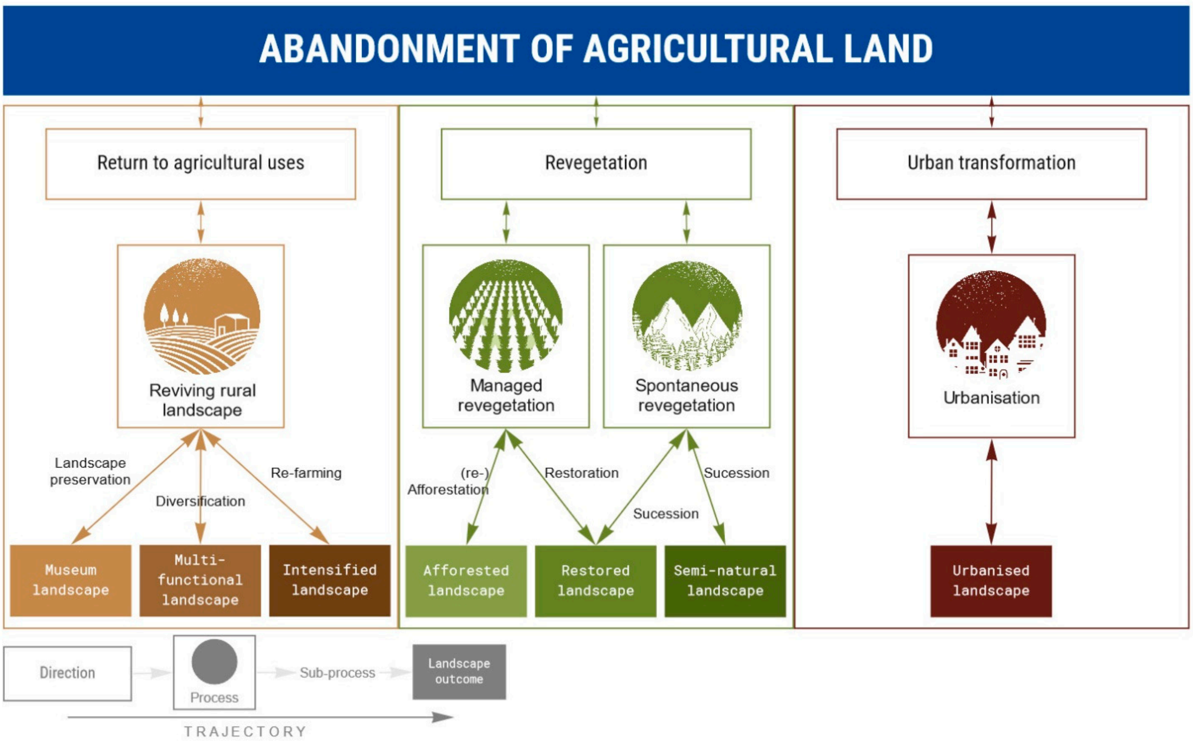



**Figure 1.** Conceptual framework of post-abandonment trajectories in Europe [6].

In this way, terrestrial compartments can play a crucial role in developing a more resilient and sustainable region, seeking to mitigate the impacts of human activities and preserve essential conditions for future generations [9]. This development hinges on regional plans linked to the landscape, encompassing short-, medium-, and long-term actions grounded in robust scientific data, translated into local actions and policies [5,9–11]

When it comes to soils, landscape development plans can consider six central aspects that are interconnected. Among these, the present study is directly related to the "increase provision of ecosystem service and biodiversity" as it deals with enhancing natural carbon sinks [5].

Furthermore, landscape-based planning plays a crucial role in enhancing soil carbon storage, which is a significant strategy to combat the climate crisis [12,13]. These plans emphasize the relationship between the local community and the soil, closely tied to land use and cover, with guidance to accelerate the transition to land uses that aid in carbon sequestration [13]. Actions highlighted in regional planning include fertilizer and organic residue management, liming, mulching, and cover cropping [14].

Research studies stress the importance of spatial analysis to identify priority areas for guiding forest restoration initiatives, reducing fragmentation, and enhancing soil carbon density [15]. Thus, localized studies to identify potential carbon sinks with favorable storage arrangements are significant [8].

Mapping SOC distribution can provide valuable data for discussions with the local community within the context of sustainable regional planning [5]. Scientific findings can help identify issues and shape action plans based on landscape characteristics, contributing to the construction of a more sustainable territory [5,9].

In the case of this study, activities should be designed to connect the management of abandoned areas with the most appropriate soil carbon conservation strategy for the region and its respective characteristics [16–20]. Therefore, it is important to model soil carbon distribution and recognize key landscape elements related to the process to guide society's relationship with the territory, ensuring the maintenance or increase in soil carbon reserves [4,21,22].

In this study, our aim is to map the distribution of organic carbon in the soil within the Upper Sabor Watershed in Northeast Portugal by statistically correlating it with landscape elements. The resulting mapping will aid in proposing actions for conserving carbon pools and increasing soil carbon.

## 2. Materials and Methods

### *2.1. Study Area*

The Upper Sabor River Watershed is in NE Portugal and occupies most of the eastern part of Montesinho Natural Park (MNP), its outlet being defined at Gimonde, about 6 km east of the city of Bragança (Figure 2). A small part of the Watershed falls on Spanish territory, the Portuguese tract covering 30,646 ha. The region is set in the Galaico-Durienses mountain system [22], and the climate, though Mediterranean, has a pronounced continental influence, with wide annual thermal amplitude and sharp thermo-pluviometric gradients [23,24].

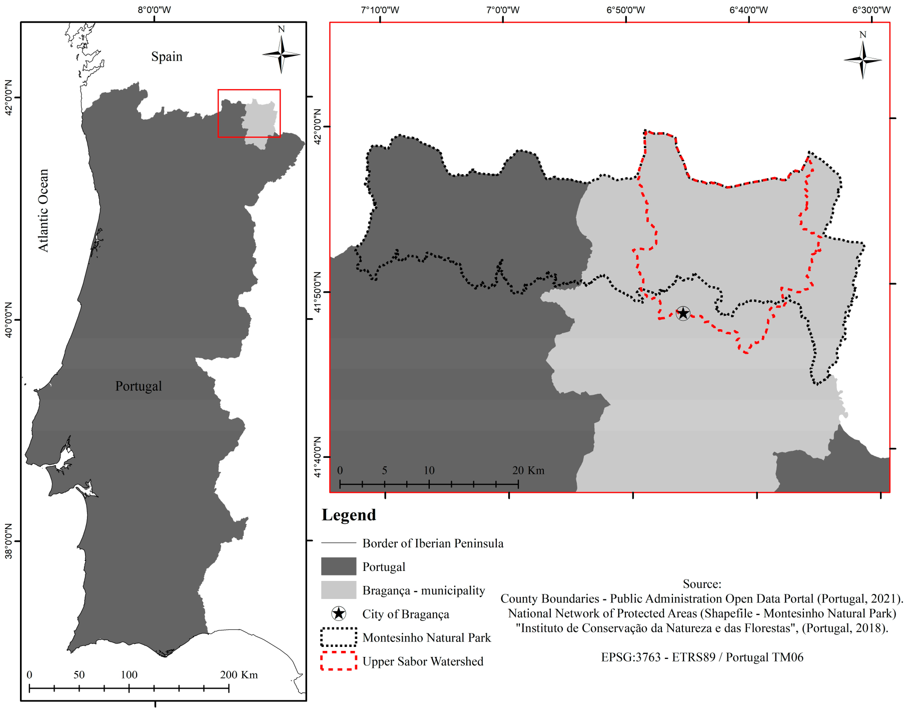



**Figure 2.** Spatial location of the Upper Sabor River Watershed (Portuguese tract) in relation to Mainland Portugal, the Bragança municipality, and Montesinho Natural Park, NE Portugal [25,26].

The NE Portugal region is in the transition from western Atlantic to eastern continental influences, which are mostly reflected in annual precipitation and thermal amplitudes throughout the area. Precipitation in MNP varies from more than 1200 mm year$^{-1}$ (north and west) to less than 800 mm year$^{-1}$ (southeast) [27], while the average annual temperature ranges from 8 °C to 12 °C [23]. These trends are due to the increase in continental and the decrease in oceanic influences on the regional climate [24,28].

To understand the climatic aspects in the territory, it is important to analyze the elevation, which varies from 1482 m to 488 m, with the areas of highest and lowest altitude in the northwest and southeast, respectively (Figure 3).

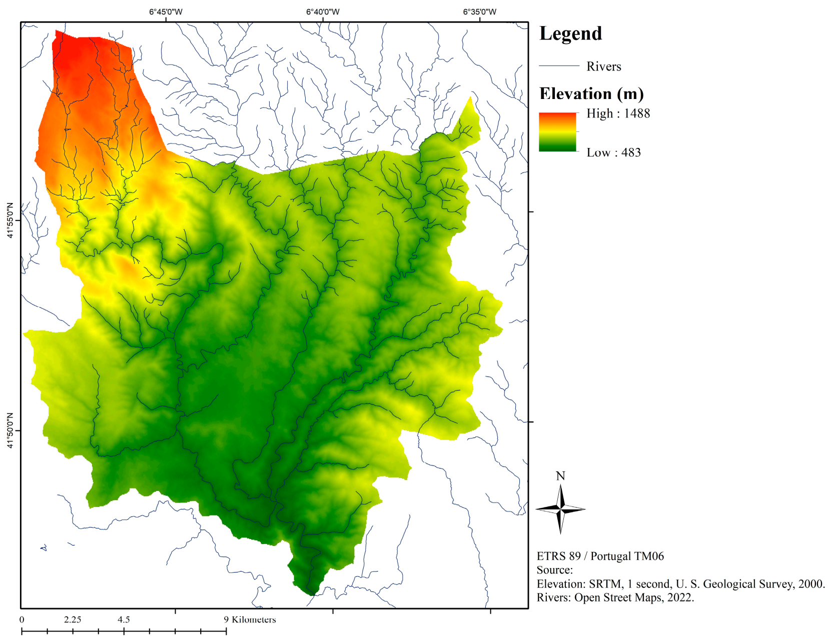



**Figure 3.** Hypsometry of Upper Sabor River Watershed, NE Portugal [29,30].

The highest elevation areas concentrate the highest precipitation amounts and the lowest temperatures due to the strong influence of altitude, the other main regional climate driver [24]. Following these influences, the aridity index derived climate domains found in MNP change from dry sub-humid in the southernmost areas to humid in the northernmost areas [31,32].

Associated with precipitation and temperature regimes, in addition to elevation, other landscape features important for carbon distribution include soil and LULC. Schists are the widest represented soil parent material, but granites, basic rocks and ultramafic rocks are lithological groups that are relatively important in the region. Soil groups are strongly dominated by Leptosols (over 70% of the area), followed by Cambisols, Fluvisols, Luvissols, and Alisols [33,34].

The LULC is conditioned by the existence of the MNP, as a nature conservation area. The native vegetation expresses characteristics of two phytogeographic formations: the Eurosiberian and the Mediterranean [27]. Remnants of these types of vegetation can be found in the Upper Sabor River Watershed, as the main land use found is classified as shrub communities interspersed with clearings of mountain herbaceous vegetation (mainly grasses) (48% of the area), representing the secondary ecological succession in former agricultural lands. Forest areas are also significant (33%), natural or planted for commercial purposes (Figure 4). Farmland includes predominantly annual crops (12%), concentrated preferentially in the south of the watershed, near urban areas [35].

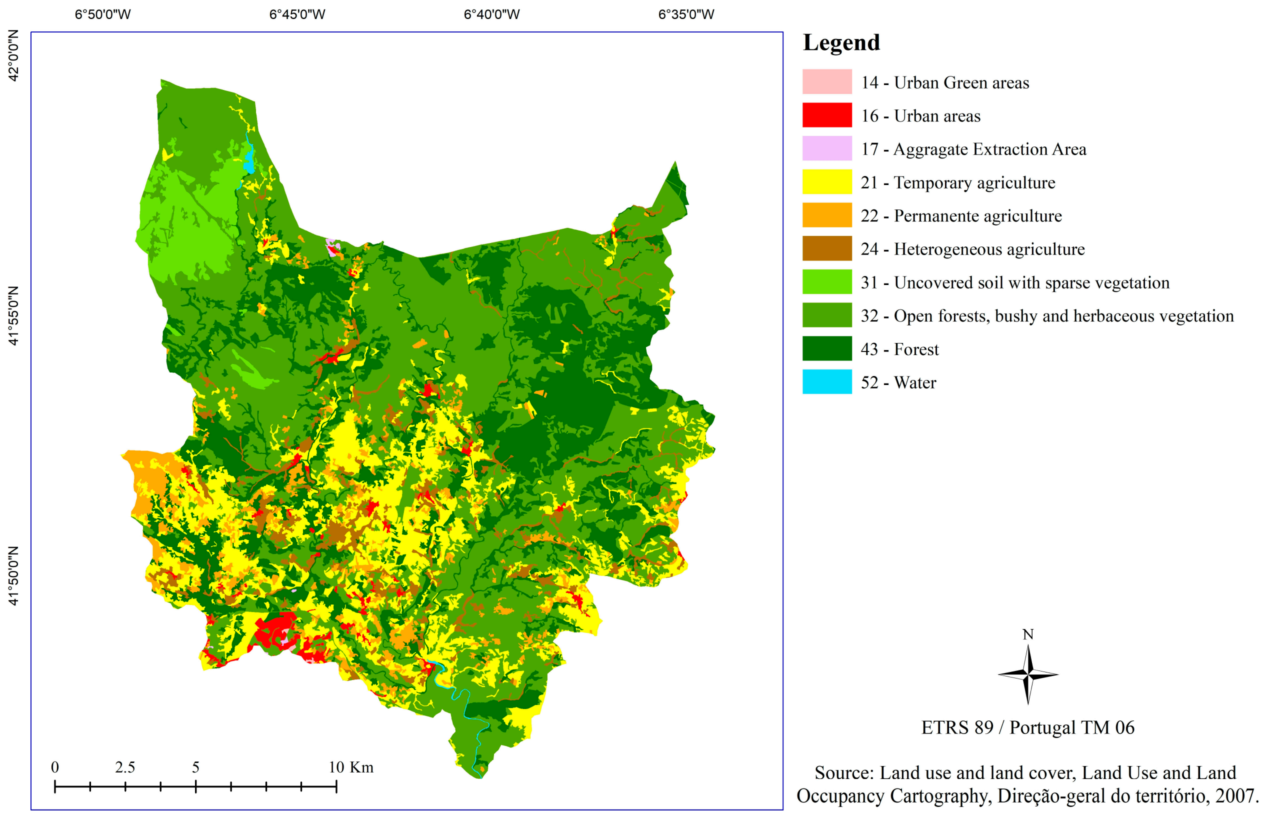



**Figure 4.** Land use and land cover (LULC) of the Upper Sabor River Basin [35], NE Portugal, classified according to Anderson et al. (1976) [36].

## 2.2. Soil Sampling

The soil sampling areas were established in 25 primary units (PU), randomly selected on a regular grid of 1 km $\times$ 1 km in the geographical coordinate system WGS 1984 UTM 29 N. In each PU, five 200 m $\times$ 200 m secondary units (SU) were defined, located on the edges and in the center of each PU (Figure 5). Soil samples were taken in the center of each one of the 125 SU at depths 0–5, 5–10, 10–20 and 20–30 cm, totaling 500 soil samples.

The maximum sampling depth was defined at 30 cm because most soils in the region are shallow (Leptosols). The division into several soil layers has the purpose to obtain greater detail in the distribution of carbon along the soil profile [17,37]. At the same depths, undisturbed soil samples of 100 $cm^3$ were taken for bulk density determination.

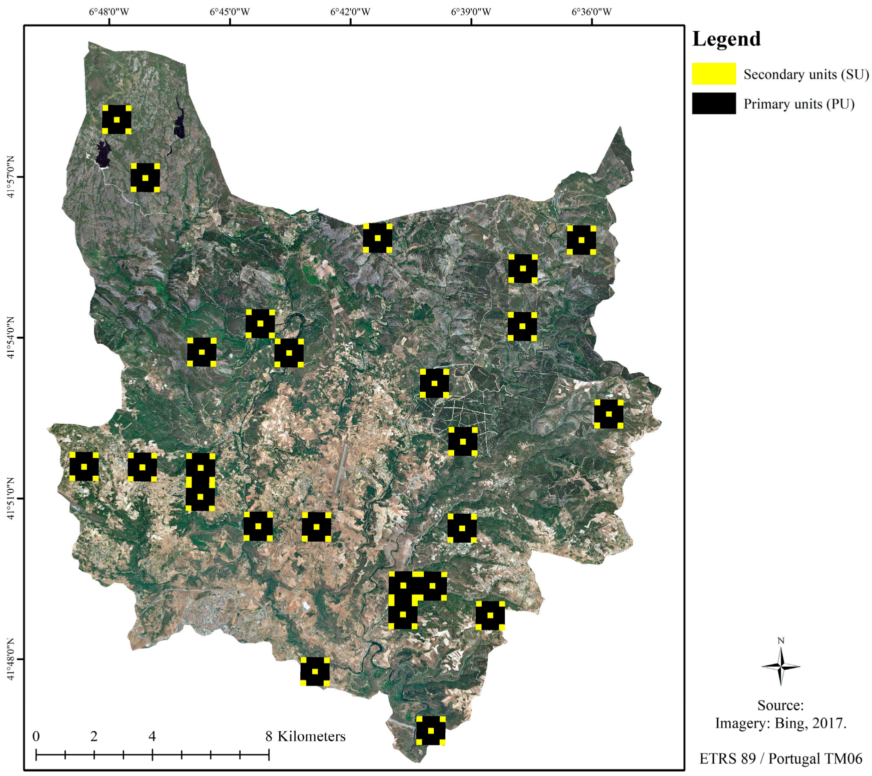



**Figure 5.** Soil sampling sites, represented in the primary (PU) and secondary (SU) sampling units in the Upper Sabor River Watershed, NE Portugal [38].

Furthermore, during the sampling, the land use and land cover types at the sampling points were observed and classified into five types: agriculture (A), forest (F), mountain herbaceous vegetation (H), pasture (P) and shrub communities (S).

## *2.3. Soil Carbon Quantification*

Soil samples were air dried, sieved to determine the coarse fraction (>2 mm), and analyzed for carbon concentration using dry combustion [39]. Equation (1) was used to quantify soil organic carbon storage (SOC) per unit area (Mg C $ha^{-1}$) [18,39–41].

$$SOC = 10 * zCC\left(DA - \frac{2.65 * EG}{100}\right) \quad (1)$$

where CC is the carbon concentration of the mineral soil layer (g $kg^{-1}$ or kg $Mg^{-1}$), DA is the bulk density of the mineral soil layer (g $cm^{-3}$ or Mg $m^{-3}$), z is the thickness of the mineral soil layer (m), and EG is the correction factor for coarse element content (v $v^{-1}$).

## *2.4. Statistical Analysis*

### 2.4.1. Basic Statistics

Excel 2016 software was used to obtain the descriptive statistics of carbon stocks in each soil layer, at depths of 0–5, 5–10, 10–20, 20–30, and 0–30 cm (the latter is the sum of the quantities observed in all layers).

The software Biostat 5.0 [42] was used to perform Tukey's test for multiple comparison of means in evaluating significant differences ($p < 0.05$) between the amount of carbon stored when comparing different elevation intervals and LULC classes observed in the sampling (agriculture (A), forest (F), mountain herbaceous vegetation (H), pasture (P), and shrub communities (S)).

#### 2.4.2. Regression Analysis

Independent Variables

There are several variables that interfere with soil carbon storage, such as topographical characteristics [43], vegetation diversity indexes, climatic factors, the quantity and quality of litter [44], and the reflectance and spectral class [45].

The combination of independent variables that can be used in carbon prediction is diverse. In the present study, six variables were selected based on their occurrence in other studies (Reference—Table 1) and their availability (Data source—Table 1).

**Table 1.** Independent variables used in the regressions to relate with the SOC in the Upper Sabor River Watershed, NE.

| Independent Variables | Description | Reference | Data Source |
|---|---|---|---|
| Elevation (m) | Digital terrain elevation, obtained from SRTM. | Moura-Bueno et al., 2021 [45] | SRTM 1 Arc-Second (~30 m), USGS [29] |
| Land use and land cover (LULC) | Vectorization of land use and occupation for the year 2007. | Feng et al., 2020 [46]<br>Soleimani et al., 2017 [47]<br>Fryer and Williams, 2021 [48] | Diretório-Geral do Território, 2007 [35] |
| Topographic wetness index (TWI) | TWI starts from a relationship between the basin area and slope to determine soil moisture conditions at distinct positions in the area, which can affect the erosive power of runoff. | Bell, 1995 [49]<br>Mohseni and Salar, 2021 [50]<br>Dharumarajan et al., 2021 [51] | Saga GIS 2.3.2 [52] |
| Normalized difference vegetation index (NDVI) | The NDVI is used to evaluate the health of vegetation: positive values for vegetation, values close to zero for rocks and bare soil, and negative for water, cloud, and snow. | Bhunia et al., 2019 [53]<br>Khare et al., 2021 [54] | Landsat 8, USGS, 2019 [55] |
| Modified soil-adjusted vegetation index (MSAVI) | MSAVI is a hybrid vegetation index, with values ranging from 1 to −1, applied to areas with a high degree of exposed ground surface. | | |
| Erosion risk (ER) | Erosion risk refers to the probability of soil loss through erosive processes. | Pena et al., 2020 [56]<br>Martínez-Mena et al., 2008 [57]<br>Guimarães et al., 2021 [58]<br>Abbas et al., 2020 [59]<br>Li et al., 2019 [60] | Agroconsultores and Coba, 1991 [33] |

SRTM: Shuttle Radar Topography Mission. USGS: United States Geological Survey.

The TWI value ranges from 0 to 25.5; areas of higher value represent greater susceptibility to flooding [61] (Figure 5). The erosion risk (ER) values (Figure 6) range from zero to five (higher value, higher ER), most of the basins have values between two and three, and the maximum value is observed to the south. According to Table 1, NDVI is an index that shows biomass production; the observed values range from −0.0448 to 0.942 (Figure 6). Negative values represent inland waters, such as dams in the northern of the watershed, or urbanized areas in the south; higher values may be related to forested regions (as per LULC presented in Figure 4) [53]. The adoption of MSAVI is due to its importance to decrease the influence of soil detection under vegetation and complement the performance of NDVI in the context of regression (Figure 6) [44,62]. MSAVI values range from −0.398 to 0.707; the values increase as the percentage of green cover increases [54,63]. The values of this index, when combined with others (such as albedo), can assist in understanding other aspects of the landscape (Figure 6) [62].

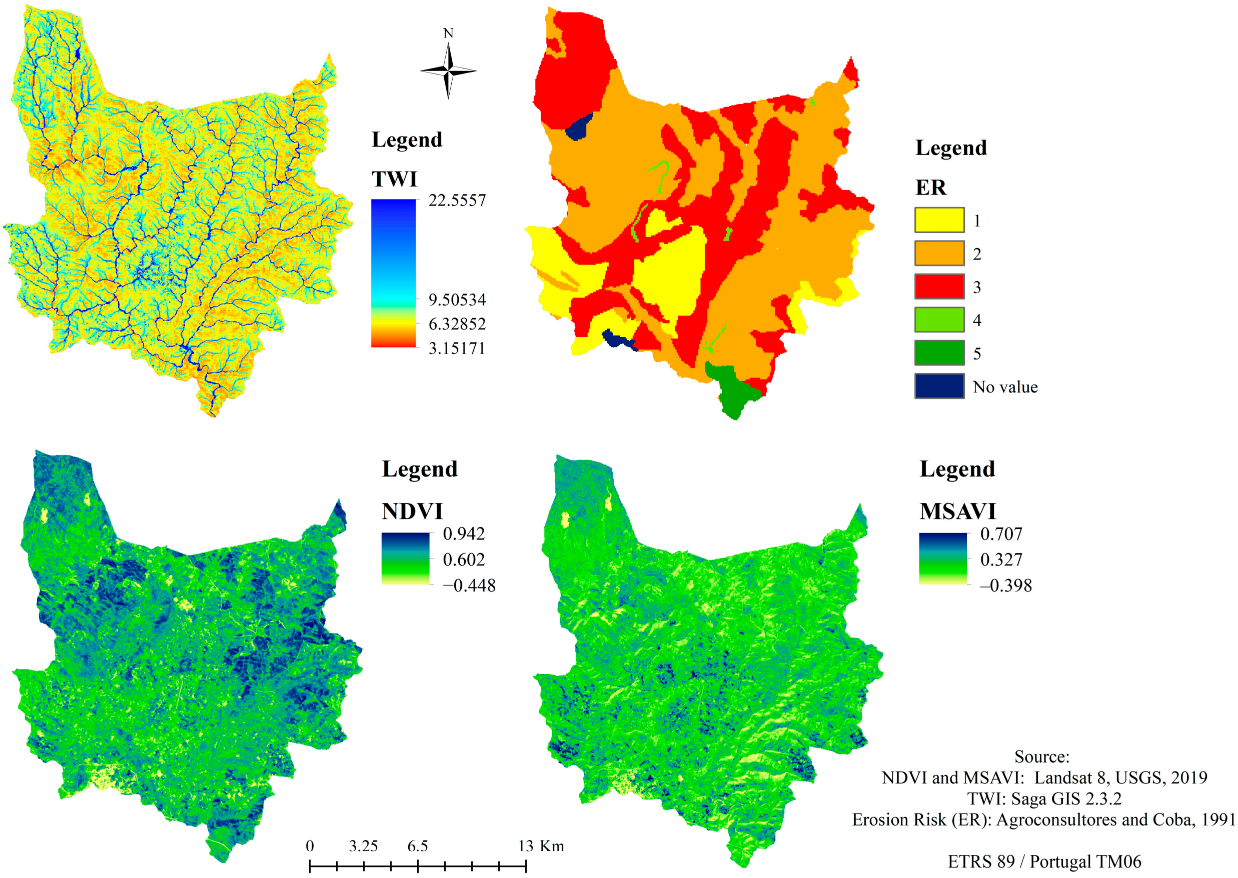



**Figure 6.** Distribution of topographic wetness index (TWI), erosion risk (ER), normalized difference vegetation index (NDVI) and modified soil-adjusted vegetation index (MSAVI) values in Upper Sabor River Watershed, NE Portugal [33,55].

For using the LULC data (Figure 4) in the proposed regression models, the qualitative information was classified according to the numbering proposed by Anderson et al. (1976) [36] and Direção-Geral de Território (2007) [35] (Table 2). ArcMap 10.1 software was used to transform all vectorial layers into raster, as this was a requirement for mapping soil carbon distribution.

Regression Models and Validation

Utilizing the raster package [64] in RStudio [65], we inserted the independent variable files. We then standardized the geographic projection system for all of them to a common one (WGS 84).

Subsequently, the elevation raster functioned as a mask, thereby standardizing the dimensions of the remaining rasters. Following this, we imported a table containing the sampling data, encompassing carbon quantities for each layer and the geographical coordinates (x and y) for each sampling point. This dataset was effectively integrated and organized within the RStudio 1.3.1 software. To extract the values of the independent variables from the sampling points, we employed the 'stack' function from the 'utils' package [51], resulting in a table containing the essential information for the regression models.

For the regression analysis, we opted for the 'caret' package, utilizing six distinct models selected based on their relevance in similar studies (Table 3) [66].

**Table 2.** Land use and land cover (LULC) classification of the Upper Sabor River Watershed, NE Portugal, according to Anderson et al. (1976) [36] [1] and Direção-Geral de Território (2007) [35] [2].

| LULC Code [1] | LULC Classes [1] | Nomenclature of Land Use and Occupancy Cartography [2] |
|---|---|---|
| 14 | Transportation, Communications and Utilities. | Urban green spaces, sports, cultural and leisure equipment, and historic areas |
| 16 | Mixed Urban or Built-up Land. | Urban land |
| 17 | Other Urban or Built-up Land. | Aggregate extraction areas, waste disposal areas and construction sites |
| 21 | Cropland and Pasture. | Temporary crops |
| 22 | Orchards, groves, vineyards, nurseries, and ornamental horticultural areas. | Permanent crops |
| 24 | Other agricultural land. | Heterogeneous agricultural areas |
| 31 | Herbaceous rangeland. | Uncovered areas with little vegetation |
| 32 | Shrub and brush rangeland. | Open forests, bushy, and herbaceous vegetation |
| 43 | Mixed Forest Land. | Forest |
| 52 | Lakes | Inland waters |

**Table 3.** Regression models for predicting SOC distribution in the Upper Sabor River Watershed, NE Portugal.

| Regression Model | Reference |
|---|---|
| Linear (bi- and multivariate) | Bhunia et al., 2019 [53] |
| Linear multivariate with stepwise | Richardson, Hill, Denesiuk and Fraser, 2017 [67]<br>Bhunia et al., 2019 [53] |
| Partial Least Squares (PLS) | Duarte-Guardia et al., 2018 [68] |
| Random Forest | Richardson, Hill, Denesiuk and Fraser, 2017 [67] |
| Cubist | Somarathna, Minasny and Malone, 2017 [69] |

After data organization, six sets of independent variables (bi- and multivariate) were defined (Table 4) [53]. Initially, the "train.control" function was used to separate 30% of the samples for set validation, then the bivariate models (sets 1, 2, 3; Table 3) and multivariate models (4, 5, 6; Table 3) were run [70].

**Table 4.** Sets of independent variables applied in regression models to determine SOC distribution in the Upper Sabor River Watershed, NE Portugal.

| Set | Independent Variables | | | | | | Regression Models |
|---|---|---|---|---|---|---|---|
| | Elevation | LULC | ER | TWI | NDVI | MSAVI | |
| 1 | x | | | | | | Linear |
| 2 | | x | | | | | |
| 3 | | | | | x | | |
| 4 | x | x | | | x | | Random Forest |
| 5 | | x | x | x | x | x | |
| 6 | x | x | x | x | x | x | Linear multivariate.<br>Linear multivariate with stepwise.<br>PLS.<br>Random Forest.<br>Cubist. |

Legend: Land use and land cover (LULC), topographic wetness index (TWI), normalized difference vegetation index (NDVI), modified soil-adjusted vegetation index (MSAVI) and partial least squares regression (PLS).

The regression models applied varied from set to set according to the number of independent variables analyzed. Five regression methods were used for the set with the highest number of variables (Table 4) [71].

The values of $R^2$ help to understand how much of the carbon distribution can be explained by the set of independent variables, especially when applied in linear regression models [72]; Root Mean Squared Error (RMSE) was adopted for the selection of the best-fit regression models, as it is a widely used metric to measure the performance of models for environmental studies, such as meteorology and climate [73], especially when it is necessary to validate the comparison between predicted and observed values [74].

Soil Carbon Mapping

RStudio 1.3.1 software was used to map the distribution of carbon stored in the different soil layers throughout the Upper Sabor River Watershed area [70], using the raster package [64] and predict function.

The criterion adopted for the selection of the regression set was based on the lowest value of RMSE among those obtained, and it was considered that the index deals with the mean square error: the lower it is, the more adjusted the set of variables is [53]. All the raster files with the results were exported, and ArcMap 10.1 software was used for the elaboration of the maps.

Finally, the function "varImp" from the caret package was used to determine the level of importance of the variables to the results for the best-fitting models obtained within the modelling of set 6; these values were scaled to have a maximum value of 100 [66].

## 3. Results and Discussion

### *3.1. Environmental Factors Related to Soil Carbon Storage*

Figure 7 shows carbon storage, distributed by classes, in all analyzed mineral soil layers (0–5, 5–10, 10–20, 20–30 and 0–30 cm) in the Upper Sabor River Watershed. The average global carbon storage in the 0–30 cm soil depth was 50.6 Mg C ha$^{-1}$, the first two layers together (0–5 and 5–10 cm) recording a total of 21.9 Mg C ha$^{-1}$. The 5–10 cm soil layer presented the lowest carbon stocks, which might be related to organic matter translocation processes to deeper layers, as already mentioned in other works (Figure 7) [75,76].

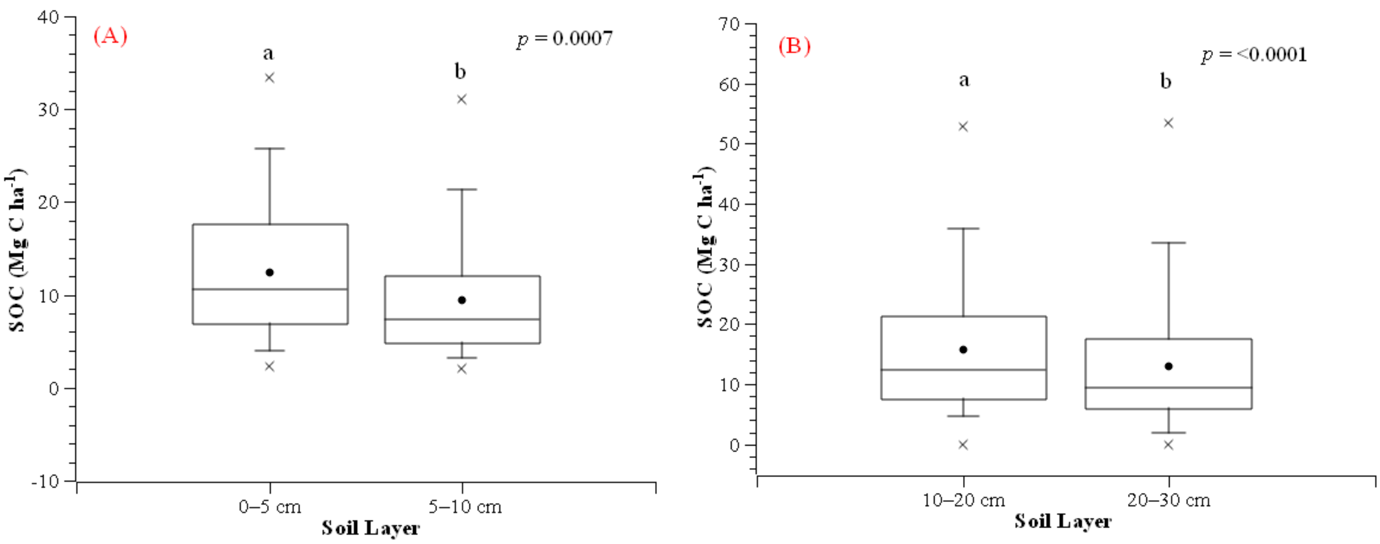



**Figure 7.** Comparison of soil carbon quantification in layers of the same thickness ((**A**) 0–5 cm and 5–10 cm, (**B**) 10–20 cm and 20–30 cm) in the Upper Sabor River Watershed. For each graph, different letters indicate statistically significant differences in the amount of stored carbon.

The carbon values were mostly below 40.6 Mg C ha$^{-1}$, and only 39% of the sampled points showed values above the average (50.6 Mg C ha$^{-1}$) (Figure 8). The largest carbon stocks were found in the north of the watershed (higher altitude and consequently lower temperature and higher precipitation; Figure 3) and the lowest in the south, where farmland is the dominant land use (Figure 4). This is the practical verification of the known effect of rainfall and temperature on soil organic matter accumulation through its influence on biological activity and consequent influence on the decomposition rates of organic residues [77].

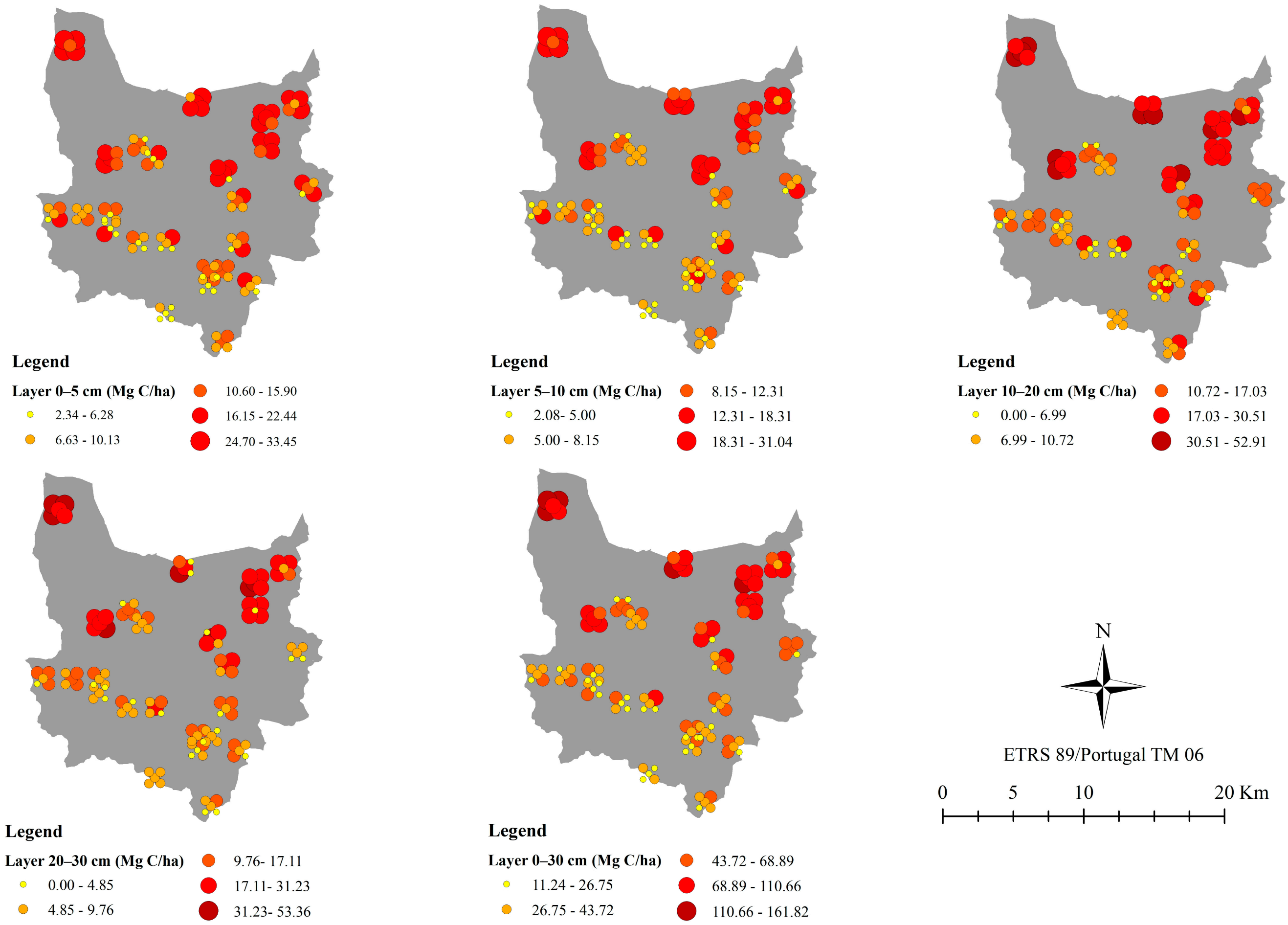



**Figure 8.** Carbon storage (Mg C ha$^{-1}$) in mineral soil layers (0–5, 5–10, 10–20, 20–30 and 0–30 cm) in Upper Sabor River Watershed, NE Portugal.

A study carried out on soil carbon storage in MNP (NE Portugal) showed that the carbon pool is higher in the highest, coldest, and wettest areas (Figure 3), with significant increases in carbon stocks when the average annual temperature drops from 12 to 10 °C and precipitation exceeds 1000 mm [37].

Carbon storage gradually increases with altitude, resulting in significant differences between the areas above 1000 m and below 800 m (Figure 9). This increase has also been observed in other studies when comparing agricultural lands in Switzerland [78] and forest areas in southern China [79]. Although this work has not been verified, it is important to point out that the carbon input into the soil does not always maintain this positive linear behavior with altitude; sometimes the trend reverses. Was observed that in the Kashmir Himalayan Minor foothills, SOC decayed from 1200 m of altitude [80].

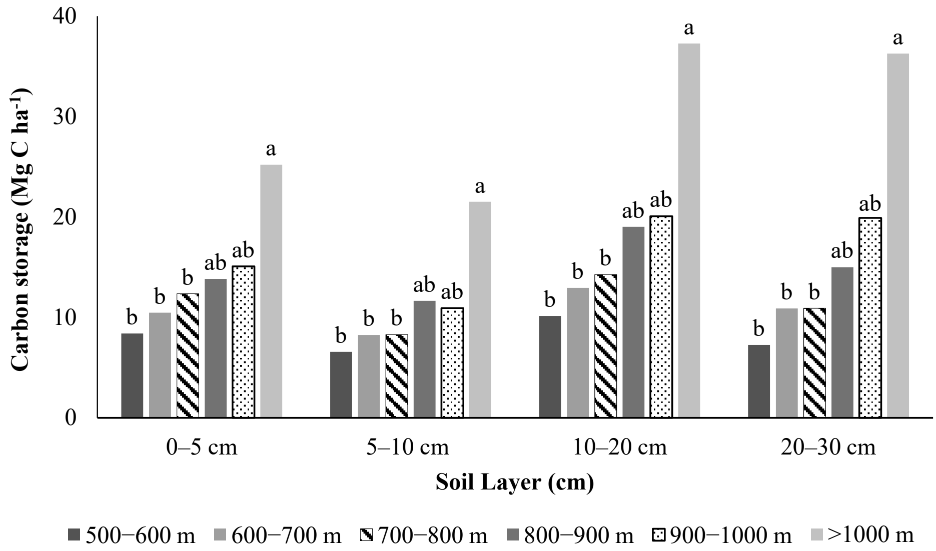



**Figure 9.** Carbon storage (Mg C ha$^{-1}$) in mineral soil layers (0–5, 5–10, 10–20 and 20–30) by altitude intervals in Upper Sabor River Watershed, NE Portugal. For the same layer, different letters indicate statistically significant differences between altitude intervals.

The LULC was another factor that interfered with carbon storage. Overall, forests and shrub communities presented the highest carbon stocks, and agricultural soils were observed to have the lowest. Mountain herbaceous vegetation and pastures registered intermediate values (Figure 10). In the region, forests are composed of natural forest fragments and fast-growing tree species plantations, the latter ones with lower carbon stored in the soil mineral layers when compared to natural forests [41]. Likewise, the soil occupied by the secondary ecological succession (shrub communities) assumes outstanding importance in terms of carbon storage in the region. On the other hand, due to agriculture abandonment and rural exodus, landscapes have been increasing in susceptibility to secondary succession. However, if effectively managed, these areas can be transformed into carbon sinks and consequently add economic value to the territory and protection against external disturbances (e.g., wildfires) and contribute to mitigating climate changes [75,76]. Additionally, it is expected that these areas will become more important as the natural forest settles in, reaching higher values of carbon storage over time [81].

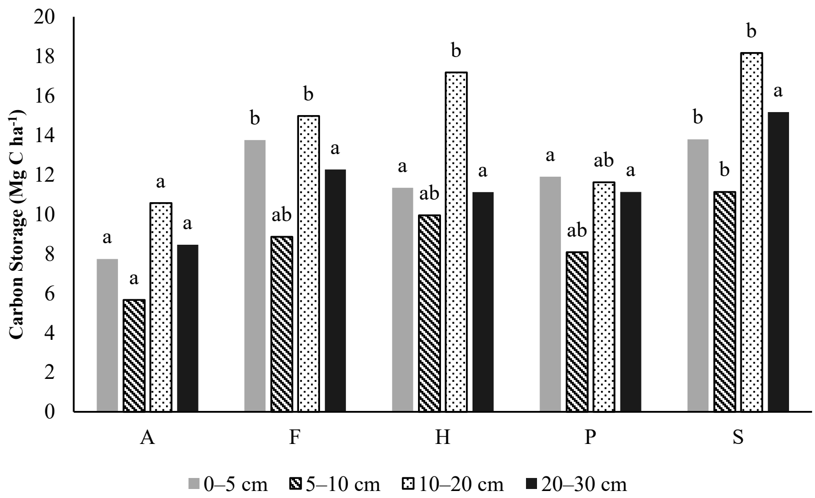
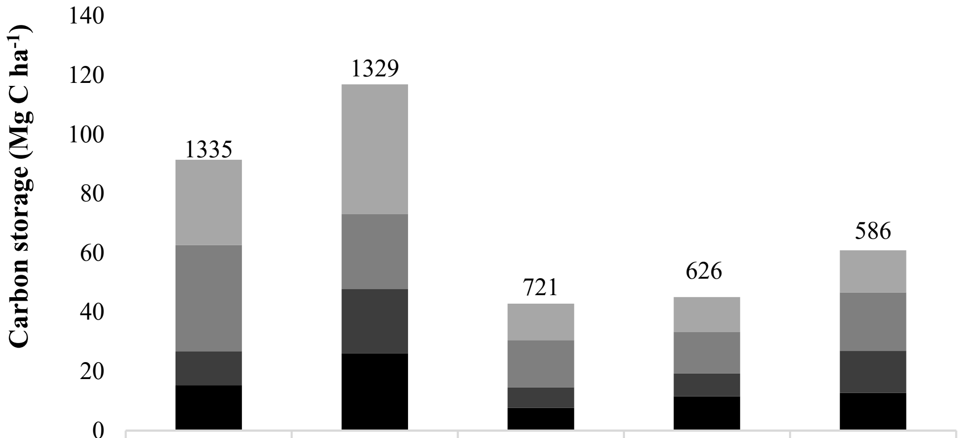



**Figure 10.** Carbon storage (Mg C ha$^{-1}$) in mineral soil layers (0–5, 5–10, 10–20, 20–30 cm) by land use and land cover (LULC) in Upper Sabor River Watershed, NE Portugal. A—agriculture; F—forest; H—mountain herbaceous vegetation; P—pasture; S—shrub communities. For the same layer, different letters indicate statistically significant differences between LULC.

In the surface soil layer (0–5 cm), the carbon storage values were significantly higher for forest and shrub communities, and in the deeper layer (20–30 cm), there were no significant differences among several land uses. This provides evidence that agricultural practices preferentially stimulate organic matter mineralization in the upper soil layers (0–20 cm). Soil tillage, depending on the depth reached, translates into relevant SOC losses [41,82,83].

Studies concluded that pedoclimatic factors had a higher influence on the soil carbon stocks than land use [84]. In the present study, the soil carbon pool distribution was observed for the same land use (shrub communities) when combined with different altitudes and lithologies (Figure 11). Soils derived from migmatites and gneisses (m) show lower soil carbon storage when compared to basic and metabasic rocks (b), despite being located at higher altitudes (721 m versus 586 m) (Figure 11). On the other hand, at identical altitudes, granite soils exhibit significantly higher carbon contents than schist ones.




| | x | g | m | bx | b |
|---|---|---|---|---|---|
| 20–30 cm | 28.8 | 43.8 | 12.3 | 11.7 | 14.2 |
| 10–20 cm | 35.9 | 25.3 | 15.9 | 14.1 | 19.7 |
| 5–10 cm | 11.4 | 21.8 | 6.9 | 7.7 | 14.2 |
| 0–5 cm | 15.4 | 26.0 | 7.7 | 11.5 | 12.7 |

Lithology (x, g, m, bx and b)

**Figure 11.** Carbon storage (Mg C ha$^{-1}$) in mineral soil layers (0–5, 5–10, 10–20, and 20–30 cm) of shrub communities (same land use) and their relationship with altitude (values at the columns top) and lithology (x—schists; g—granite; m—migmatites and gneisses; bx—basic rocks and schists; b—basic and metabasic rocks).

"SOC storage and the diversity-soil carbon relationship are controlled by multiple interrelated processes and complex plant-soil feedback" [85]; when it comes to lithology, this relationship evokes another key factor, the pH. In higher regions, especially where granites occur, hyper acidic reactions inhibit microbial activity and favor an increase in SOC, as this is an environment where biomass production is potentially limited by temperature and vegetation is spontaneous, as characteristic of harsh environments [85,86]. At sites with basic rocks, such as "basic rocks and schists" and "basic and metabasic rocks", SOC values are related to higher biomass production because other environmental factors favor organic matter decomposition, such as high pH and temperature [85,86].

The lithology interferes directly with the contents of coarse elements, which in turn directly affects the soil carbon storage [87]. In layers with the same thickness (5 or 10 cm), an increase in the percentage of coarse fraction and a decrease in the average value of stored carbon were observed (Figure 12).

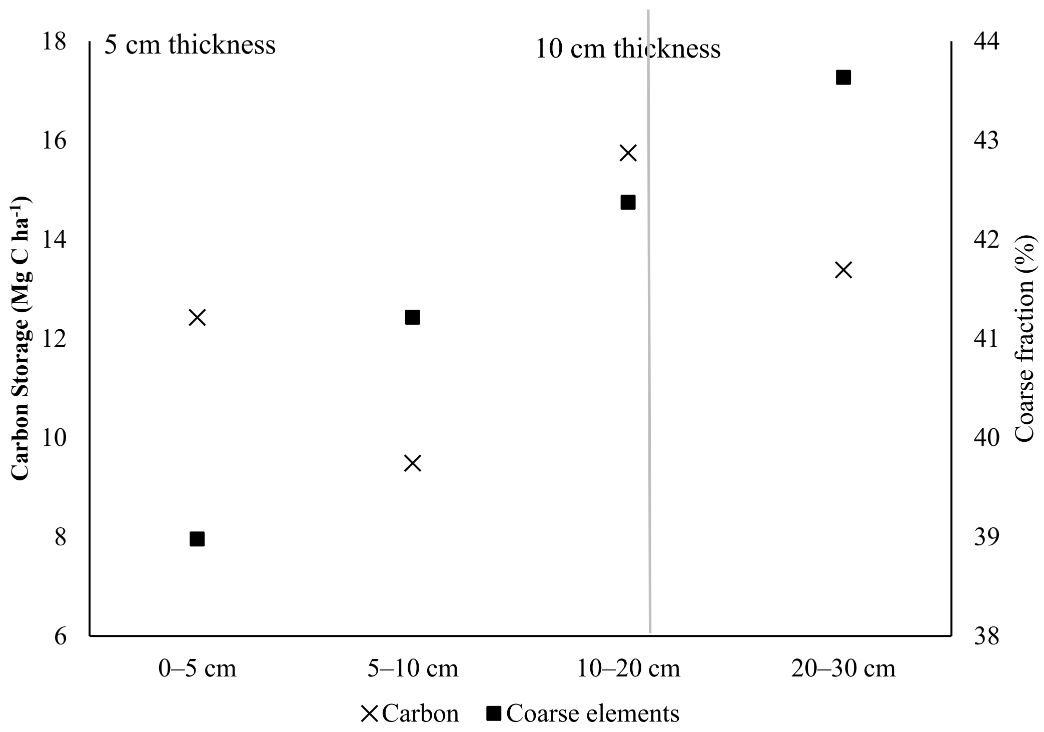



**Figure 12.** Soil organic carbon storage (SOC) and coarse element fraction in four soil depths (0–5, 5–10, 10–20, and 20–30 cm).

### *3.2. Regression Models*

Predict Soil Carbon Storage

In the first three regression models, with only one independent variable, set 1 (elevation), 2 (LULC) and 3 (NDVI) (Table 4), $R^2$ values obtained for set validation were higher than 0.49 and RMSE values vary with layer thickness (Table 4). All bivariate regression models show a significant relationship between the dependent variable (SOC) and the independent variable ($p < 0.05$) (Table 4), and positive trends. The NDVI value is positively related to the amount of SOC [88], and this behavior denotes the relationship between variables because NDVI is directly related to LULC, which, in this case, has strong dependence on altitude because the highest basin areas are protected (MNP), and this brings evidence of the importance of conservation policies for carbon sinks [89]. With the trend presented by the models, it can be inferred that the LULCs with lower values, which correspond to agricultural areas, are those with the lowest SOC storage. Agricultural soils have a lower capacity for permanent carbon accumulation when compared to other land use systems, which is related to increased organic matter mineralization due to anthropic disturbances [90–92].

In a hypothetical situation, where there is a possibility to choose only a single variable to predict SOC, based on the results obtained, the use of elevation would be recommended. The results obtained here reinforce that elevation positively and significantly influences the soil carbon stocks [79,93], which is related to changes in climate and LULC characteristics [37,79,94,95], mainly the temperature and edaphic parameters [96]. Among the models with more than one independent variable, it was observed that the three variables mentioned above (elevation, LULC, and NDVI) present better results when analyzed together (set 4), resulting in a decrease in RMSE values and an increase in $R^2$ values (Table 5) when compared to sets 1, 2, and 3 (Table 4). Furthermore, in some situations, set 4 has better values than set 6, which includes all variables (Table 6). Set 5, which does not consider elevation, presents the worst results among the multivariate models, which signals the importance of this variable for the modeling process (Table 5).

**Table 5.** Performance indicators (RMSE and $R^2$) resulting from the validation of the bivariate regressions (models 1, 2 and 3) used in the SOC prediction in the Upper Sabor River Watershed, NE Portugal.

| Soil Layer (cm) | Set 1 | | Set 2 | | Set 3 | |
|---|---|---|---|---|---|---|
| | RMSE (Mg C $ha^{-1}$) | $R^2$ | RMSE (Mg C $ha^{-1}$) | $R^2$ | RMSE (Mg C $ha^{-1}$) | $R^2$ |
| 0–5 | 5.72 | 0.55 * | 5.95 | 0.51 * | 6.31 | 0.56 * |
| 5–10 | 4.84 | 0.68 * | 5.43 | 0.57 * | 5.57 | 0.60 * |
| 10–20 | 8.53 | 0.61 * | 9.02 | 0.53 * | 9.50 | 0.53 * |
| 20–30 | 8.20 | 0.53 * | 9.23 | 0.39 * | 9.15 | 0.55 * |
| 0–30 | 24.89 | 0.52 * | 27.17 | 0.57 * | 27.84 | 0.49 * |

Independent variables used in each model: set 1 (elevation); set 2 (LULC); set 3 (NDVI). * Significant relationship ($p < 0.05$). Root-mean-square error (RMSE), land use and land cover (LULC) and normalized difference vegetation index (NDVI).

**Table 6.** Performance indicators (RMSE and $R^2$) resulting from the validation of multivariate regressions (Models 4 and 5), used in the prediction of SOC in the Upper Sabor River Watershed, NE Portugal.

| Soil Layer (cm) | Set 4 | | Set 5 | |
|---|---|---|---|---|
| | RMSE (Mg C $ha^{-1}$) | $R^2$ | RMSE (Mg C $ha^{-1}$) | $R^2$ |
| 0–5 | 5.05 | 0.64 | 5.81 | 0.52 |
| 5–10 | 4.47 | 0.63 | 5.17 | 0.50 |
| 10–20 | 7.46 | 0.67 | 8.80 | 0.59 |
| 20–30 | 7.85 | 0.66 | 8.89 | 0.44 |
| 0–30 | 20.62 | 0.77 | 25.37 | 0.63 |

Independent variables used in each model: set 4 (Elevation, LULC and NDVI); set 5 (LULC, ER, TWI, MSAVI and NDVI). Root-mean-square error (RMSE), land use and land cover (LULC), topographic wetness index (TWI), normalized difference vegetation index (NDVI) and modified soil-adjusted vegetation index (MSAVI).

Finally, set 6 uses all independent variables (elevation, LULC, ER, TWI, NDVI, and MSAVI), showing the best results among the various models used (Table 6). The regression models for set 6 with the lowest RMSE values were the Cubist model, which showed the best values for the depths 0–5 and 20–30 cm, and the Random Forest model, which showed the best outcomes for the other layers (5–10, 10–20, and 0–30 cm) (Table 7). The Cubist method has already been shown to be a good option for SOC prediction [45], and Random Forest is a flexible non-parametric method [97] that performs well in SOC prediction [71,98].

**Table 7.** Performance indicators (RMSE and $R^2$) for set 6, resulting from the validation of multivariate regressions used in the prediction of SOC in the Upper Sabor River Watershed, NE Portugal.

| Regression Model | Soil Layer (cm) | RMSE (Mg C $ha^{-1}$) | $R^2$ |
|---|---|---|---|
| Linear multivariate | 0–5 | 5.64 | 0.65 |
| | 5–10 | 4.68 | 0.52 |
| | 10–20 | 8.08 | 0.61 |
| | 20–30 | 8.09 | 0.54 |
| | 0–30 | 24.21 | 0.59 |
| Linear multivariate with Stepwise | 0–5 | 5.22 | 0.64 |
| | 5–10 | 4.68 | 0.64 |
| | 10–20 | 7.87 | 0.61 |
| | 20–30 | 8.02 | 0.64 |
| | 0–30 | 22.96 | 0.62 |

**Table 7.** *Cont.*

| Regression Model | Soil Layer (cm) | RMSE (Mg C ha$^{-1}$) | $R^2$ |
|---|---|---|---|
| Random Forest | 0–5 | 5.08 | 0.67 |
| | 5–10 | 4.4 * | 0.63 |
| | 10–20 | 7.35 * | 0.68 |
| | 20–30 | 7.88 | 0.56 |
| | 0–30 | 19.83 * | 0.70 |
| PLS | 0–5 | 5.43 | 0.54 |
| | 5–10 | 4.69 | 0.62 |
| | 10–20 | 8.19 | 0.65 |
| | 20–30 | 8.15 | 0.55 |
| | 0–30 | 23.56 | 0.69 |
| Cubist | 0–5 | 4.85 * | 0.66 |
| | 5–10 | 4.4 | 0.61 |
| | 10–20 | 7.99 | 0.70 |
| | 20–30 | 7.76 * | 0.62 |
| | 0–30 | 21.9 | 0.72 |

Independent variables used in set 6: elevation, LULC, ER, TWI, MSAVI and NDVI. * Lowest RMSE value obtained for each layer. Root-mean-square error (RMSE), land use and land cover (LULC), topographic wetness index (TWI), normalized difference vegetation index (NDVI) and modified soil-adjusted vegetation index (MSAVI).

With the identification of the most suitable set and regression model, the mapping of the carbon distribution in the soils of the Upper Sabor River Watershed was carried out (Figure 13).

In all soil layers, there is very similar behavior, where the northernmost areas have the highest carbon stocks, which was already expected due to the observations of the sampling values, the elevation (Figure 3), the behavior of the regression bivariate models (Models 1, 2 and 3) and the existence of a protected area (MNP). The mapping shows that creating protected areas in elevated zones is important because these places can store large soil carbon amounts [22].

The modeling also emphasizes the possibility of an increase in carbon stock along the hillslopes (Figure 13). It is not expected that the areas with a greater slope will have the same amount of stored carbon as the higher areas, but instead that there will be actions for the distribution and maintenance of SOC in all layers, especially in the deeper ones, due to favorable processes of translocation of organic matter and possible reduction in susceptibility to erosive processes. Accordingly, a reduction in the variation between soil carbon stored in the top areas, hillsides, and valley bottom can be expected [60,95].

Throughout the soil carbon distribution analysis, the importance of elevation was evident. Furthermore, by determining the most important variable within the best-fitting model, it was observed that elevation remains the most important variable in part of the layers, and LULC was the most important for the second layer (5–10 cm) (Figure 14). Moreover, ER and TWI variables are the ones that least influence the set performance (Figure 14). TWI and ER consider aspects related to slope. Other studies have shown that variables related to slope are less able to predict carbon distribution [99].

The reduced importance of LULC in the deeper layer (20–30 cm) may be related to factors that limit the expansion, growth, and development of the root systems of the species that occur in this region [67]. In this context, it is important to identify key species for the purpose of carbon storage, species that enable a large biomass input above and below ground, considering the limiting factors (such as soil and climate) [22,75,100]. However, the replacement of exotic forest stands, for commercial purposes, with new species should be carried out gradually, especially in protected areas [41,101,102], to reduce the impacts on soil carbon pools and allow an increase in the carbon storage in the mineral soil layers [91,101,103].

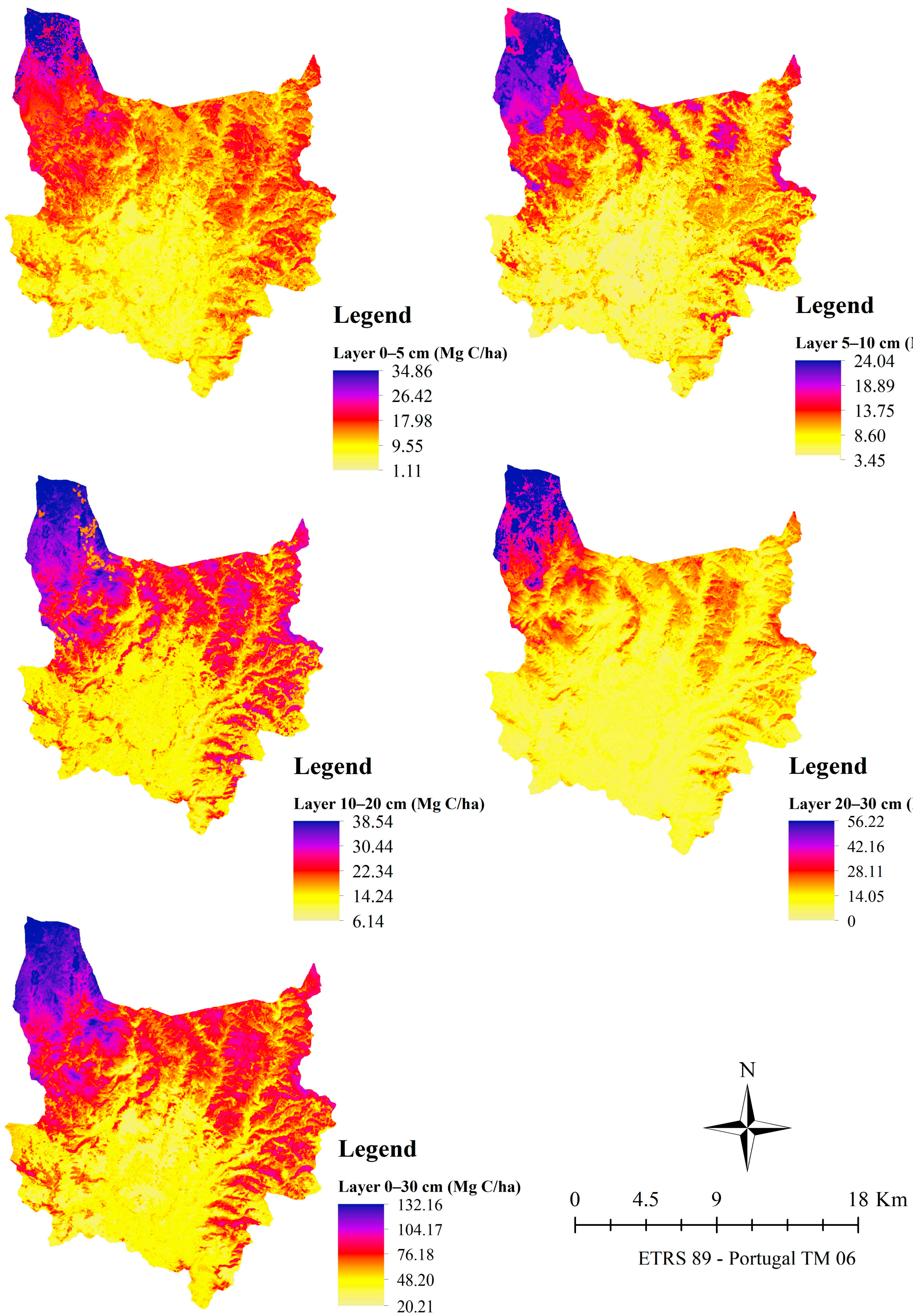



**Figure 13.** Soil carbon distribution mapping by the best-fit regression set (set 6) and regression models (Cubist for 0–5 and 20–30 cm soil layers: Random Forest for 5–10, 10–20, and 0–30 cm soil layers), in the Upper Sabor River Watershed, NE Portugal.

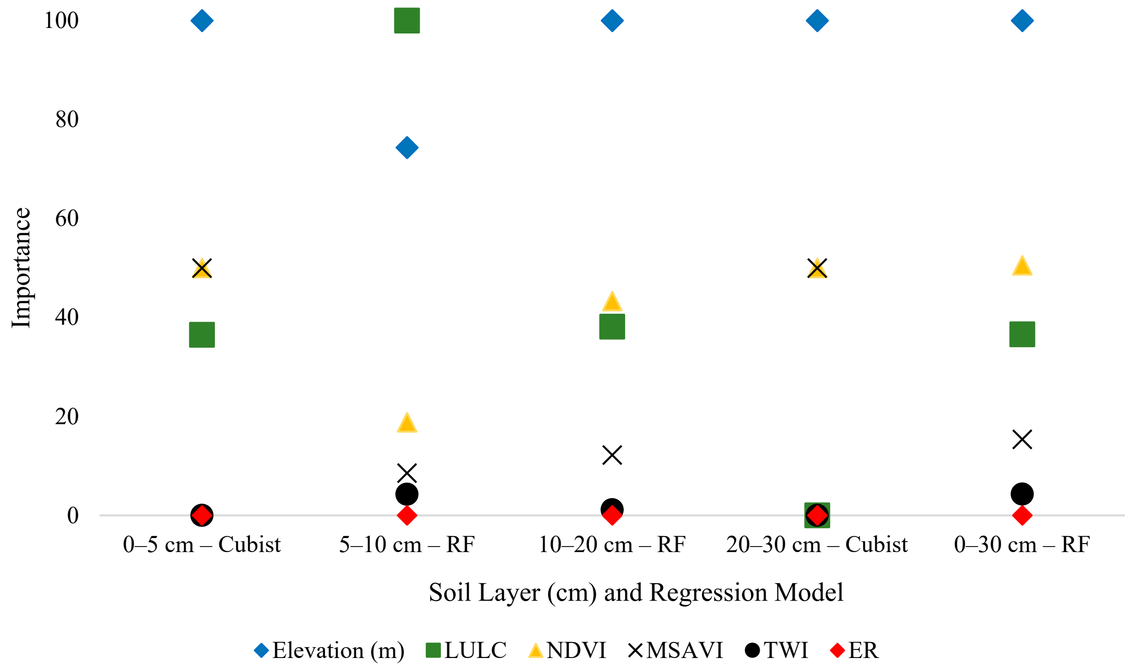



**Figure 14.** Ranking of the importance of variable of set 6, for SOC prediction for each soil layer in the Upper Sabor River Watershed, NE Portugal. Erosion risk (ER), land use and land cover (LULC), topographic wetness index (TWI), normalized difference vegetation index (NDVI) and modified soil-adjusted vegetation index (MSAVI). Regression models: Random Forest (RF) and Cubist.

Finally, the results observed in the analysis of the most important variable showed that the sets of independent variables applied in the analysis of soil carbon distribution can be smaller, because some variables present zero value in the importance scale; this is the case for the ER for almost all layers, except the 5–10 cm one (Figure 14). Furthermore, the proximity between the results obtained in set 4 (elevation, LULC and NDVI) and 6 corroborates the observed result.

### *3.3. Proposals for Upper Sabor River Watershed Planning*

To proceed with territorial planning, it was necessary to define a problem; considering the results obtained and the discussion conducted, it is observed that the challenge lies in "guiding the Enhancing Natural Carbon Sinks" [13]. The presented proposals aim to establish connections between terrestrial carbon cycle compartments to preserve high-altitude areas and increase carbon concentration in areas with elevations below 800 m.

The recommended planning, presented herein, is based on studies that show some impacts caused by LULC change in soil carbon pools along a soil profile 400 cm deep [104]. The results obtained by the authors indicate that the conversion of agricultural lands to uses such as woodland, shrubland, and grassland on China's Loess Plateau significantly increases carbon storage in the layer up to 200 cm, and in most cases, soil carbon stocks increase over time of restoration.

The results obtained and the available literature made it possible to define some strategies, which could be implemented in the watershed or in others, with similar characteristics (Figure 15). The territory was divided into three parts, considering the results of the correlation between SOC and elevation (Figure 9).

For the higher areas, considering their sensitivity and existing LULC, landscape maintenance and protection actions were suggested, combined with activities to cooperate with recovery after events that degrade the landscape, such as the occurrence of wildfires, as they are sensitive environments and slowly recover [95].

On the intermediate slope (800 m to 1000 m), which is the steepest part, it is recommended to adopt techniques to prevent erosion, especially those that favor the accumulation of organic matter, such as terraces [105,106], or spontaneous revegetation actions (Figure 1) [6].

The action planning for the lower regions and river valley bottoms should consider the agricultural use, vegetation rate regeneration, and carbon sinks; therefore, the choice of technique should consider the possibility of enhancing these processes within the environmental limitations of the region (environmental characteristics and time required) [1,11,91,107,108].

Therefore, if a central planning set is adopted, with short-, medium-, and long-term actions, one should aim at maintaining or increasing the organic matter/carbon inputs to the soil, adopting agricultural practices to replenish the carbon sinks, and monitoring the carbon storage to identify the equilibrium point (where the SOC input rates become stable) [4].

In general, planning actions to increase soil carbon stocks is important to comply with international agreements and goals, such as the "4 per mille Initiative", which emerged from COP21 (United Nations Conference on Climate Change 2015—Paris), which seeks a 0.4% annual increase in soil carbon storage (layer 0–30/40 cm); the challenges lie in designing practices that enable this increase in the soil's carbon pool [19].

Therefore, the actions proposed here as well as the results obtained through the statistical analysis of the sampled data can cooperate with the fulfillment of global goals like those of the "4 per mille Initiative"; for this, it is important to connect the technical knowledge provided by academia with the public sector responsible for the execution of the actions in the shortest period. Thus, these practices can become more politically interesting by consolidating a network for the dissemination of good practices (that connect technical and political aspects) that will compose regional planning, which will reinforce the need to join synergies between agents to improve responses to climate and biodiversity crises [19,107,109–111].

Furthermore, bringing soils and their composition into discussion within the context of sustainable regional development contributes to the achievement of the Sustainable Development Goals of the United Nations' 2030 Agenda. This is crucial as some of these goals will not be met due to the insufficient attention given to soils and their management [9].

Regarding the relationship between the Sustainable Development Goals (SDGs) and soil, it is important to consider the following points in the proposed territorial planning: (i) partnership with researchers and universities, (ii) involvement of the private sector and policy makers, (iii) integration of new technologies in collaboration with land managers, (iv) incorporation of the subject matter (soils and natural resources) into the school curriculum at all levels of education, and (v) enhancement of the value of farmers through training and compensation for ecosystem services [9].

The proposals presented, categorized by specific areas, should serve as a starting point for regional planning with the active involvement of the local community, increasing the likelihood of sustainable practices and a harmonious relationship with the landscape [4].

To facilitate the implementation of these actions, it is imperative to consider climate financing for the projects, which can commence using carbon credits and be sustained through various funding sources. Efforts should be directed towards financing models that promote the cultural consolidation of low-carbon approaches, emphasizing long-term financial support to ensure project sustainability [4].

Overall, the present study enabled an understanding of a baseline for future territorial planning for climate change adaptation and mitigation. For future studies, there may be interest in improving the values of performance indicators of the regression models; for this, there may be a need to include variables that consider the micro-climate, microtopography, lithology [112], characteristics obtained from the spectroscopy [45], and clay and silt content [113] because these are variables that are important for understanding carbon variation on a more detailed scale.

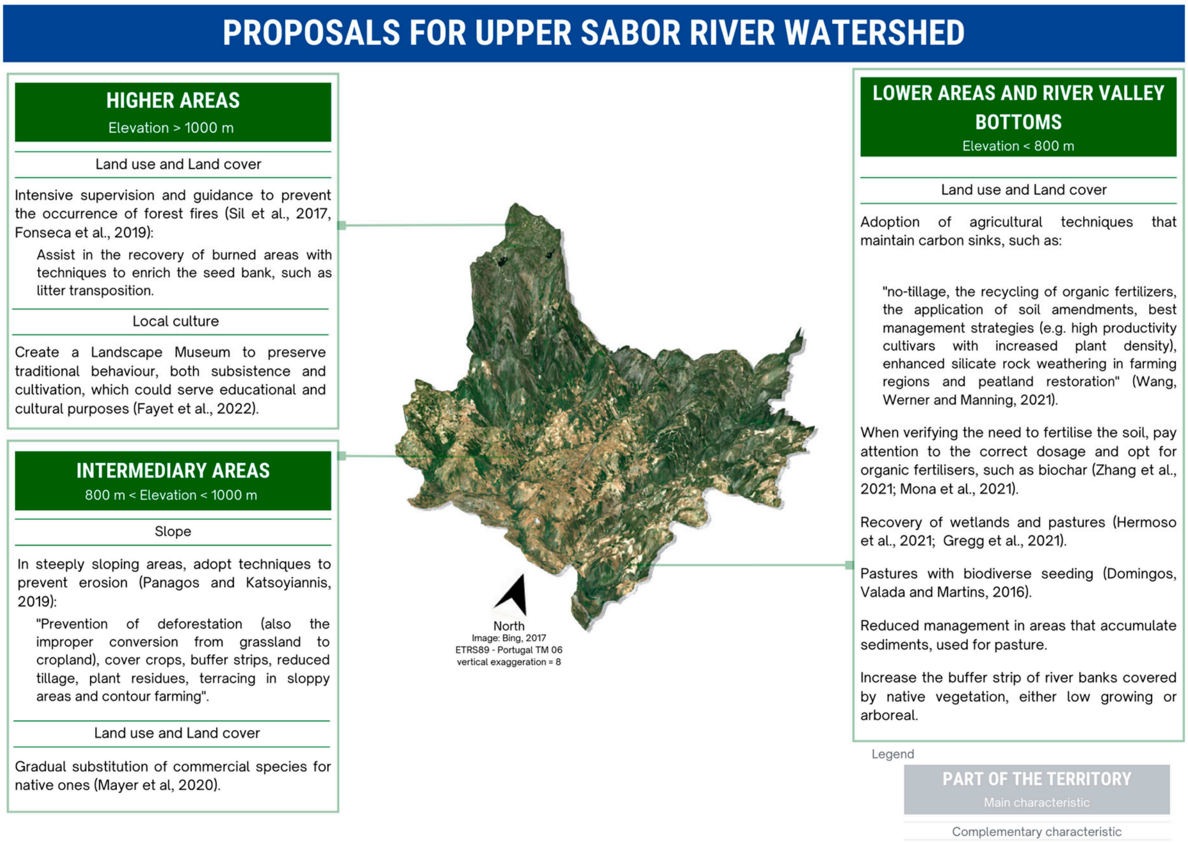



**Figure 15.** Proposals for soil carbon conservation in the Upper Sabor River Watershed divided by location in the landscape and elevation intervals, NE Portugal [6,18,41,94,103,106,108,110,114–116].

## 4. Conclusions

Soil serves as a significant carbon sink, crucial for climate change mitigation efforts, particularly carbon sequestration. Our analysis revealed higher carbon concentrations in elevated areas with restricted land use due to MNP, while anthropogenic activities, primarily agriculture, reduced SOC.

Among the regression analyses, set 6, incorporating more variables, and using Random Forest and Cubist methods, provided the most accurate results, yet set 4, with just three variables (elevation, LULC, and NDVI), delivered similar outcomes. Simpler models are more replicable and, thus, more practical for climate change mitigation planning.

The proposed set of actions demonstrates the possibility of connecting scientific results with action planning, focused on the target of the data sampling: the amount of carbon stored in the soil. Despite this clear focus, it is important to note the possibility of impacting other important aspects of the watershed, such as the availability of other ecosystem services like water availability and quality, as well as the preservation of other socio-environmental aspects of the region.

For future studies, there may be interest in improving the values of the regression performance indicators, for which the addition of independent variables that will serve to analyze the region at a greater level of detail is recommended.

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