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Running Title: VEGETATION AND TOPOGRAPHIC CONTROL ON SOC SPATIAL VARIABILITY

Vegetation and Topographic Control on the Spatial Variability of Soil Organic Carbon^{*1}

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18 ABSTRACT

SOC (Soil Organic Carbon) is one of the most important parameters affecting the hydraulic characteristics of natural soils. Despite being rather easy to measure, SOC is known to be highly variable in space. In this work we used vegetation, climate, and morphology factors to reproduce the spatial distribution of soil organic carbon (SOC) in the mineral horizons of forest and grassland areas (in North-Western Italy) and evaluated the feasibility of the approach. When the overall sample was analysed (114 samples), annual precipitation and elevation were significant descriptors of the SOC variability. However, a large part of the variability remains unexplained. Two stratification criteria were then adopted, based on vegetation and topographic properties. We obtained an improvement of the quality of the estimates, particularly for grasslands and forests in the absence of local curvatures. These results indicate that the spatial variability of soil organic matter is scarcely reproducible at the regional scale, unless an a-priori reduction of the heterogeneity is applied. A discussion on the feasibility of applying stratification criteria to deal with heterogeneous samples closes the paper.

33 Key Words: Natural soils, regression analysis, soil organic carbon, spatial variability

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- INTRODUCTION
- 1 2

Soils are among the most important global carbon cycle reservoirs. They represent 75% of the total terrestrial organic carbon pool, and twice the atmospheric carbon content (Prentice, 2001). Most soil carbon is stored as soil organic matter; inorganic carbonates are largely restricted to dry lands (Lal, 2008). Forest and grassland soils are therefore of utmost importance as their organic matter content is much higher than that of agricultural soils.

8 In addition to its well-known effect on soil fertility, soil organic carbon (SOC) is also one of the 9 most important parameters affecting soil hydraulic properties: by enhancing soil aggregation and 10 increasing pores continuity and stability (Tisdall and Oades, 1982), it ameliorates the water holding 11 capacity and the saturated hydraulic conductivity (Nemes *et al.*, 2005). As a consequence, it is used as 12 an independent variable in several pedotransfer functions to estimate soil hydraulic properties (e.g. 13 Guber *et al.*, 2006).

14 Despite being rather easy to measure, SOC is highly variable in space. Evaluating its concentration 15 in areas greater than an agricultural plot can be therefore rather difficult. A large effort has been made 16 to predict its areal distribution through Digital Soil Mapping (DSM) approaches (e.g., Arrouays et al., 17 1995, 1998; Bell et al., 2000; Chaplot et al., 2001; Abnee et al., 2004a,b; Lagacherie and McBratney, 18 2004; Terra et al., 2004; Thompson and Kolka, 2005). Typically, the approach is implicitly based on 19 Jenny (1941)'s factors of soil formation: it produces empirical quantitative relations between soil 20 characteristics and spatially referenced factors, with the aim of using these relations as soil spatial 21 prediction functions (McBratney et al., 2003).

The most relevant pedogenic factors controlling SOC are climate, vegetation, and topography (Baldock and Nelson, 2000). Climate impacts directly on SOC contents and rate of mineralization primarily through the effects of temperature and moisture. Temperature is a key factor controlling the rate of decomposition of plant residues. For example, reaction rates double for each increase of 8–9 °C in the mean annual air temperature (Bot and Benites, 2005). As a consequence, soils in cooler climates commonly contain more organic matter because of slower mineralization rates. In addition, SOC content increases as mean annual precipitation increases (e.g. Meier and Leutschner, 2010).

Changes in SOC concentration also correlate with changes in vegetation. For instance, herbaceous
 vegetation produces a big root mass compared with the above-ground component whereas, in forests,
 most organic matter is produced above ground and residues are more resistant to decomposition
 (Melillo *et al.*, 1993).

33 The latter pedogenic factor controlling SOC is topography. Topography affects soil properties 34 mainly through its effects on water movements. In terrain depressions, in fact, soils are moister 35 because they receive runoff, sediments (including organic matter), and seepage from the surroundings, 36 leading to a higher SOC concentration than in drier uphill soils (Yoo et al., 2006). On the contrary, 37 soils on steep slopes tend to lose organic matter because the topsoil is constantly eroded. Therefore, 38 the spatial distribution of topographic attributes that characterize the flow paths can help in capturing 39 the soil variability and in predicting soil properties (Moore et al., 1991 and 1993; Florinsky and 40 Kuryakova, 1996).

Landscape characteristics can be expressed by means of geomorphic and hydrological indices
generated with digital terrain analysis (Speight, 1968; MacMillan and Pettapiece, 1997; Wilson and
Gallant, 2000). These indices are widely used in hydrologic modelling, e.g. to characterize the spatial

distribution and the extent of zones of saturation for runoff generation (e.g. Beven and Kirkby, 1979).
 Climatic data are often available through gridded datasets, and vegetation characteristics can be
 derived qualitatively from land cover maps such as CORINE (European Environment Agency, 2005),
 or quantitatively by making use of remote sensing. Quantitative environmental variables can be then

5 associated to SOC, resulting in long sets of potential descriptors of SOC variability.

6 In this work we evaluated the spatial variability of SOC and the feasibility of the prediction of 7 organic carbon concentration by means of quantitative descriptors of vegetation, climate and 8 topography, in forest and grassland soils of alpine and sub-alpine areas of North-western Italy. No 9 specific survey was performed for this study and the data were all derived (and homogenised) from 10 existing databases.

11

12 STUDY AREA

13

14 The Piedmont region is located in North-Western Italy (see Fig. 1). Its area, of about 25 000 km², is 15 characterized by marked heterogeneities determined by the presence of the Western Alps chain.

16 17 Fig. 1

18 Fig. 1 Fig. 1 Shown is a map of the study region with the locations of the sampled sites. The gray tones

19 represent the elevation variations within the region.

20

In few hundreds kilometres the climate changes from a typical Mediterranean regime to an Alpinecontinental regime. The average monthly temperatures range between a minimum of -10 °C in the mountain areas during the cold season and a maximum of +35 °C in the Po Plain during the summer. The mean annual precipitation ranges between 500 mm and more than 2 000 mm.

Forests cover the mountain areas of the region up to an elevation of about 1800 m. Coniferous and broadleaved species, either as monocultures or in admixture, are present in the whole area. Grasslands are found either above the timberline, or scattered at lower elevation and on hilly areas.

The data of soil profiles were taken from a pre-existing database belonging to the DIVAPRA of the University of Torino (67 samples) and to the Regional Soil Survey Service (IPLA, 55 samples). The chemical characteristics which we considered were the soil organic carbon (SOC) and the total nitrogen concentrations in the mineral horizons. The data were available for all genetic horizons (A, B, or C types) and also aggregated on the 0--30 cm depth (SOC₃₀). The chemical characteristics of the dataset are reported in Table I.

35 TABLE I

36

37 Soil organic carbon (SOC), Nitrogen concentration and C/N ratio in soil horizons according to vegetation types.

38 Different (small) letters indicate significant differences in the chemical property among vegetation types ($P < 39 \quad 0.05$)

Horizon			SOC $(g kg^{-1})$		N (g kg	N (g kg ⁻¹)		C/N	
or layer		n	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
А	Broadleaves	72	33.5	23.7	2.2	1.5	15.4 ^b	4.8	
	Mixed Forests	24	34.3	30.2	2.4	1.4	13.4 ^b	4.4	

	Conifers	3	27.3	15.7	1.5	1.0	21.7 ^a	17.1
	Grasslands	21	38.4	24.4	2.9	1.4	12.1 ^b	5.4
В	Broadleaves	38	11.9	11.6	0.9	0.7	12.6	3.6
	Mixed Forests	15	11.6	10.4	1.2	0.7	13.9	7.4
	Conifers	0						
	Grasslands	10	11.5	5.7	1.4	0.2	11.3	
С	Broadleaves	39	9.1	11.6	0.8	0.8	13.3	6.3
	Mixed Forests	8	3.6	1.7	0.6	0.3	6.6	3.0
	Conifers	1	14.4		1.2		12.2	
	Grasslands	7	14.4	8.2	1.6	0.7	8.8	2.1
030 cm	Broadleaves	69	26.4	18.9	2.2	3.3	15.3 ^{ab}	6.2
	Mixed Forests	22	23.8	12.1	1.8	0.6	13.1 ^{ab}	3.6
	Conifers	3	25.2	12.8	1.5	0.6	17.7 ^a	9.8
	Grasslands	20	32.0	15.8	2.7	1.1	10.1 ^b	2.9

¹ 2 3

No significant differences were found in SOC and Nitrogen concentrations between forests and grasslands, while the C to N ratio clearly reflected the differences in organic matter decomposition, (with the lowest values in grasslands and the highest in conifers, both in the A horizon and in the 0--30 cm layer). The concentrations of SOC and N were generally more variable in the genetic soil horizons than in the 0--30 cm layer, reflecting the different thicknesses of the SOC enriched A horizons. The same behaviour was observed for the C to N ratio, with lower standard deviations in the 0--30 cm layer, particularly in grassland samples.

The sample variogram (see e.g., Burgess and Webster, 1980) was fitted by an exponential model with nugget, where the sample and spatial variance were nearly the same (namely 0.196 and 0.195, respectively) with a 10 km range (Fig. 2) The relative weights of the two components indicated that the organic carbon concentration was controlled by two kinds of variables, having very short range and long range variability, respectively.

16 Fig. 2

- 17 Fig. 2 Semivariogram of the natural logarithm of the soil organic carbon concentration for the 0--30 cm layer.
- 18

15

As an attempt to capture the relative roles of the long and short range mechanisms controlling SOC variability at the regional scale we described each sampled point according to its climatic, vegetation and topographic characteristics (also called "morphoclimatic" factors in the following of the paper). The data guaranteed a spatial coverage of the entire region, in view of possible mapping applications. In details:

- To obtain a characterization of the soil water balance in the profiles locations, the average annual rainfall (P, mm) produced by Bartolini *et al.* (2008) for the study region was used. In addition, we calculated the potential evapotranspiration (PET) with the Thornthwaite relation according to the monthly temperature estimates proposed by Claps *et al.* (2008). Precipitation and PET values were also combined by means of the Thornthwaite (1948) Wetness Index (WI) as WI = (P - PET)/PET. The

- also combined by means of the Thornthwaite (1948) Wetness Index (WI) as WI = (P PET)/PET. The
 WI allows a synthetic characterization of the soil water balance in a certain location and provides a
- 30 relative measure of potential biological productivity of the site.
- NDVI maps, derived from SPOT-VEGETATION data (http://free.vgt.vito.be/) for the years 1998 2005, were used to characterize vegetation. For each month the composite NDVI values were

averaged over 1 km² cells. For each cell containing at least one soil sampling we considered the minimum NDVI (identified with the subscript "Min"), the maximum NDVI (identified with the subscript "Max"), the difference between maximum and minimum NDVI (identified with the subscript "Diff") and the mean NDVI (identified with the subscript "Mean"). The CORINE land cover map (European Environment Agency, 2005) and the forests map of the Piedmont Regional Administration were also taken into account for further evaluations of vegetation types in correspondence of the sampling points.

8 - The selection of the terrain descriptors was based on the prior experience by a) Chai *et al.* (2008), 9 who considered elevation, slope and CTI (see Table II) as external drift variables for predicting soil 10 organic matter; b) Mueller and Pierce (2003) and Simbahan et al. (2006), who used terrain attributes as secondary spatial variables to increase the accuracy of predictions at different scales. To determine 11 12 the primary and secondary terrain attributes (Table II), we used a digital elevation model (derived 13 from contour line interpolation) with a spatial resolution of 50 m. The primary attributes in Table II 14 include elevation (EL), slope (SL), profile (kv) and plan curvature (kh). In kv and kh, the sign ensures 15 that positive curvatures refer to convex forms and negative curvatures refer to concave forms. The 16 expected values for a hilly area (moderate relief) can vary from -0.5 to 0.5, while for steep and rugged 17 mountains (extreme relief), they can vary between -4 and 4. A value of zero indicates that the surface 18 is flat. As secondary terrain attributes in Table II, we considered the compound topographic index 19 (CTI), also known as topographic wetness index (Wilson and Gallant, 2000), and the stream power 20 index (SPI). The CTI, expressed as reported in Table II, is related to zones of surface saturation 21 (Moore et al., 1993) and quantifies a point in the landscape in terms of water and sediment 22 accumulation: the higher the value of this index in a cell, the higher the soil moisture that can be 23 found in it. SPI instead, expressed as reported in Table II, is related to erosion processes, being an 24 indicator of the capability of a flow to generate net erosion.

25 26 27

TABLE II

 $\frac{2}{28}$

Definitions, formulas and physical interpretations for the topographic variables considered in the study							
Variable Definitions and formula Interpretation							
Slope gradient (SL), ° Angle between a tangent plane and a horizontal one at a Velocity of substance							
given point of the land surface flows							
Profile curvature (kv), Profile curvature is parallel to the direction of the Relative							
m ⁻¹ maximum slope. A negative value indicates that the acceleration/decelerati	on						
surface is upwardly convex at that cell. A positive profile of flows across the							
curvature indicates that the surface is upwardly concave at surface							
that cell. A value of zero indicates that the surface is linear.							
Plan curvature (kh), Planform curvature (commonly called plan curvature) is Convergence/divergen	ce						
m ⁻¹ perpendicular to the direction of the maximum slope. A of flows across a surfa	e						
positive value indicates the surface is sidewardly convex at							
that cell. A negative value indicates the surface is							
sidewardly concave at that cell. A value of zero indicates							
the surface is linear.							
Compound Extent of potential flow	V						
Topographic Index SL accumulation							
(CTI)							
Stream power Index $SPI = C_A \cdot SL^{a}$ Extent of potential flow	V						
(SPI) erosion							

^{a)} C_A : specific catchment area, *i.e.* upslope area per unit width of contour (Wilson and Gallant, 2000), m² m⁻¹.

30

31 METHODS

Linear multiple regression is the most widely used method to capture soil carbon patterns, as
demonstrated by numerous applications (e.g., Walker *et al.*, 1968; Pennock *et al.*, 1987; Moore *et al.*,
1993; Gessler *et al.*, 1995, 2000; Chaplot *et al.*, 2000). This preference stems from its ease of use,
computational efficiency, and straightforward interpretation (Hastie *et al.*, 2001).

6 In order to select the possible relationships between the soil carbon concentration and the 7 environmental factors, we implemented simple correlation and multiple regression schemes. The 8 simple correlations between SOC and environmental variables were evaluated on all genetic horizons 9 and on the fixed 0--30 depth. The multiple regressions were calculated only on the values related to 10 30 cm depth, to avoid considering horizons of variable thickness.

11 The models were tested against the assumptions of the linear regression analysis (see e.g., 12 Kottegoda and Rosso, 1998), namely lack of multicollinearity, equal error variance 13 (homoscedasticity), and normal and random residuals. In some cases we used the logarithmic 14 transformation of the variable for complying to these assumptions, particularly as regards normality. 15 The goodness of the relationships was verified using the standard error of the estimate (SEE) and the 16 adjusted determination coefficient (Adj R²). The variogram analysis was also applied to the residuals 17 of the regressions in order to assess their residual spatial variability.

18 19

20

1

APPLICATION AND DISCUSSION

Simple correlations between morphoclimatic factors and SOC concentration were tested at first.
 The results are shown in Table III.

Among the topographic variables (Table III, lines 1 to 6), only the elevation was significantly correlated to SOC in all horizons, in agreement with the results obtained in other studies. For example, Powers and Schlesinger (2002) found that elevation explained much of the variability in soil carbon, likely because of the lower decomposition rate of organic matter at lower temperatures. This hypothesis was in agreement with the C to N ratio which, in our case, tended to increase with elevation, particularly in the top horizon (r = 0.24, P < 0.05, not shown).

29 30 TABLE III

Pearson correlation coefficients (r) between SOC and morphoclimatic variables associated to different horizons
 (identified by subscript capital letters)

	$\ln(SOC_A)$	$ln(SOC_B)$	$ln(SOC_C)$	$ln(SOC_{30})$
1. number of samples	120	63	55	114
2. EL (elevation)	0.369 ^{a)}	$0.408^{a)}$	0.399 ^{a)}	0.402 ^{a)}
3. SL (slope)	0.148	0.265 ^{b)}	0.212	0.114
4. kh (profile curvature)	-0.075	-0.157	0.009	-0.001
5. kv (plan curvature)	0.073	0.014	-0.095	0.092
6. CTI (Compound Topographic	-0.111	-0.171	0.009	-0.141
Index)				
7. In SPI (Stream Power Index)	0.012	0.152	0.194	-0.065
8. NDVI _{Max} (maximum NDVI)	0.027	0.216	0.017	-0.061
9. NDVI _{Min} (maximum NDVI)	-0.292 ^{a)}	-0.278 ^{b)}	-0.340 ^{b)}	-0.355 ^{a)}
10. NDVI _{Mean} (maximum NDVI)	-0.220 ^{b)}	-0.088	-0.266 ^{b)}	-0.281 ^{a)}
11. NDVI _{Diff} (maximum NDVI)	0.328 ^{a)}	0.448^{a}	0.322 ^{b)}	0.329 ^{a)}
12. P (average annual rainfall)	$0.477^{a)}$	$0.547^{a)}$	-0.015	$0.464^{a)}$

^{a)}Correlation is significant at the 0.01 level (2-tailed).

^{b)}Correlation is significant at the 0.05 level (2-tailed).

4 All NDVI parameters, except the maximum, were significantly correlated with the soil carbon 5 variables (Table III, lines 7 to 10). The minimum and the mean NDVI decreased with increasing C 6 content. A possible explanation for this behaviour is the high ratio between roots and shoots in 7 grasslands (Jackson et al., 1996), which had a high SOC content compared with forests (Table I). 8 When grasslands were excluded from the analysis, no more correlation was found between C, 9 NDVI_{Mean} and NDVI_{Min}, while a significant correlation appeared between NDVI_{Diff} and SOC 10 concentration in all horizons (r up to 0.54, P < 0.05, not shown).

11 The soil carbon variables were also positively correlated with the precipitation and the wetness 12 index (Table III, lines 11 and 12) in all but the C horizons. This confirms the fact that the amounts of 13 SOC increase when precipitation and soil moisture increase (e.g., McKenzie and Ryan, 1999). The C 14 horizons, instead, presented no correlations with the environmental variables. Probably in these 15 deeper layers, the soil water balance dynamics cannot be fully represented by climatic variables, as 16 they do not provide an estimate of percolation.

17 Several environmental descriptors were therefore related to SOC concentration, even though their 18 correlation coefficients were always low. In the following, the descriptors were combined using 19 multiple regressions only on the carbon concentration of the 0--30 cm layer (SOC₃₀).

20 Four linear regression models were significant, demonstrating to be effective in reproducing SOC 21 within a stepwise procedure (Table IV). The adjusted determination coefficient (Adj R^2), the standard 22 error of the estimate (SEE), and the standardized coefficients (β) for each model are reported, 23 allowing for a thorough evaluation of the model efficiency.

24 25 26 27 TABLE IV

1 23

Significant multiple regre	ssion models for SOC concentra	tion in the 0	-30 cm lay	er based on the v	vhole dataset
Dependent variable	Independent variables	Adj R ²	SSE	$\beta^{a)}$	Р
$\ln(SOC_{30})$	EL, P	0.318	0.530	0.34, 0.41	< 0.001
	NDVI _{Min} , P	0.310	0.533	-0.33, 0.44	< 0.001
	NDVI _{Mean} , P	0.301	0.536	-0.31, 0.49	< 0.001
	NDVI _{Diff} , P	0.250	0.555	0.23, 0.41	< 0.01
	NDVI _{Diff} , P	0.250	0.555	0.23, 0.41	< 0.01

28 29 ^{a)} Standardised coefficients

The best regression model was based on elevation (EL) and precipitation (P), but the percentage of 30 SOC variance explained is low ($R^2 = 0.32$). As visible in Fig. 3a, the model lead to rather poor 31 32 predictions, with remarkable underestimates when the actual SOC concentration was above 50--60 g 33 kg⁻¹ and visible overestimates in correspondence of low values of observed SOC. NDVI parameters 34 contributed to SOC variability in the three other regression models, where the standardized 35 coefficients for NDVI parameters assumed also negative values. This outcome could be related to the 36 large heterogeneity of broadleaved forests which, in the study area, included both relatively highly 37 productive beech stands, with poor understory vegetation, and degraded woodlands, where pioneer 38 tree species, such as birch, shrubs and grasses, were rather abundant and could influence the NDVI 39 parameters. Both the amount of carbon which is added annually to the soil and the recalcitrance to 40 decomposition of organic residues are in fact tree-species dependent (Augusto et al., 2002). 41

Fig. 3

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2 3 4

5

Fig. 3 Comparison between the observed and predicted values of SOC_{30} for: (a) the whole dataset (first model in Table IV); (b) the grasslands subset (best model for grasslands in Table V); (c) the LL subset (best model for the LL class in Table VI); (d) the forest-LL subset (best model for the forest-LL class in Table VII)

6 Fig. 4a shows the sample variogram of the residuals of the best regression model of Table IV (*i.e.*, 7 EL, P). The variance related to the nugget was 0.197, the one for the exponential model was 0.089, 8 the range was 6 km. The regression model therefore reduced the spatial variability but had no effect 9 on the very short range variability represented by the nugget. This was confirmed by analysing 10 separately the variograms of the two environmental factors (data not shown). We found that these 11 variograms had rather large ranges (i.e., 35 and 88 km, respectively, as calculated by fitting an 12 exponential model to the observed variograms). This is due to the fact that these variables are strongly 13 related to large scale phenomena, such as general topography and climate. 14

15 Fig. 4

Fig. 4 Semivariogram of the residuals of the best regression model for (a) the whole dataset (first model in Table
IV); (b) the grasslands subset (best model for grasslands in Table V); (c) the LL subset (best model for the LL
class in Table VI); (d) the forest-LL subset (best model for the forest-LL class in Table VII).

10

20 Although climate and vegetation appeared to be the main drivers of SOC variability, the 21 relationships were still unsuitable to be used for estimation. This could be explained by the 22 heterogeneity of vegetation and topographic characteristics of the samples. In fact, four land cover 23 classes were present, namely broadleaved trees, coniferous, mixed forests, and grasslands, each of 24 them giving rise to different SOC production, accumulation, and decomposition rates, which were 25 only partially accounted for by NDVI parameters. Also the terrain morphology was highly variable: 26 besides the elevation range of the samples, there was a large variety of topographic features, such as 27 hilltops, slopes and plains. Evidences of the heterogeneity effects were found by Arrouays et al. 28 (1995), Homan et al. (1995), Arrouays et al. (1998), Powers and Schlesinger (2002) and Perruchoud 29 et al. (2000). From these studies it emerged that, at the regional and national scales, up to 90% of the 30 SOC variance could be explained when major vegetation types and environmental gradients were taken into account. In addition, site-specific topographic information can also yield correlation to C 31 32 content within regions of similar climate and land cover.

To reduce sample heterogeneity, especially the short range variability, the dataset was stratified.
 Samples were grouped according to vegetation types (see Table V, where conifers are not considered
 because of the low number of cases).

- 36
- 37 TABLE V 38
- Significant multiple regression models for SOC concentration in the 0--30 cm layer after stratification based on
 vegetation type (the number of elements for each class is reported in parenthesis).

91			1	/	
Vegetation type	Independent variables	Adj R ²	SSE	$\beta^{a)}$	р
Broadleaves (69)	a) NDVI _{Max} , EL, P	0.359	0.557	-0.32, 0.32, 0.60	< 0.001
	b) NDVI _{Mean} , P	0.345	0.563	-0.26, 0.57	< 0.001
	c) NDVI _{Max} , WI	0.344	0.563	-0.28, 0.71	< 0.001
Mixed Forests (22)	d) NDVI _{Min} , EL, kv	0.309	0.446	0.72, 0.92, 0.55	< 0.05
Grasslands (20)	e) NDVI _{Mean} , EL, CTI, ln(SPI)	0.695	0.293	1.11, 2.07, 0.86, -0.88	< 0.001
	f) SL, CTI, ln(SPI)	0.594	0.338	1.15, 1.71, -1.33, 0.77	< 0.001
	g) EL, CTI, ln(SPI)	0.564	0.350	0.94, 0.66, -0.65	< 0.001

^{a)} Standardised coefficients

1 2

The proportion of variance explained by the regression models increased up to $R^2 = 0.70$ in the case 3 4 of grasslands. This result was obtained by coupling climate and vegetation with topographic variables, 5 suggesting that in more homogeneous contexts also the topographic variables (CTI and SPI) play a 6 role in controlling SOC amount (e.g., Homan et al., 1995). The standardized coefficients indicated a 7 positive relation with NDVI_{Mean}, elevation and CTI, and a negative effect of SPI. The presence of the 8 two topographic indexes suggested that, when vegetation was more homogeneous, the concentration 9 of carbon in soils was largely determined by erosion and sedimentation. As visible in Fig. 3b, the 10 model lead to an acceptable estimate of the concentrations of SOC in grasslands. The sample 11 variogram of Fig. 4b was constructed on the residuals of the best regression model obtained for 12 grasslands. This variogram had a nugget variance of 0.005 and the exponential model explained a 13 variance of 0.074 in a range of 3 km, evidencing the positive effects of stratification on both the long 14 and short range variability.

Scarce improvements were instead observed in the prediction of SOC in forest soils. In these cases, in fact, the SOC variance accounted for by the models remained rather low (around 30%) and far from the results obtained in the case of grasslands. The NDVI parameters still showed negative coefficients, as happened when the whole dataset was considered. In addition, no evidence of the role of topographic descriptors emerged, suggesting that a further classification based on local morphology could possibly enhance the model performance.

21 A quantitative subdivision of the territory into classes of curvature according to the combination of 22 plan and profile curvature was used, based on a curvature classification model (Olaya, 2004). The 23 original classes were regrouped into four classes according to the profile curvature. We classified as 24 CV the points having a convex profile curvature (33 samples), as CC the points with concave profile 25 curvature (40 samples), as LC the points having linear profile curvature (23 samples), and as LL the 26 elements where both plan and profile curvatures were linear (15 samples). The aim was twofold: on 27 the one hand to avoid classes with few elements, and on the other hand to introduce a hydrological 28 criterion in the classification, by considering dispersion and accumulation characteristics. The 29 approach is akin to the one adopted in Kyungsoo et al. (2006), who found that topographic curvature 30 and soil thickness played a key role on SOC contents. A similar evidence was also pointed out by 31 Johnson et al. (2009) who reported the largest amounts of soil organic matter in well drained soils on 32 gently grading slopes.

The models obtained from the application of the stepwise multiple regression are presented inTable VI.

35

36 37 TABLE VI

38

59 51	gnificant multiple regression models for SOC concentration in the 030 cm layer after stratification based	on
40 _pr	offile curvature (the number of elements for each class is reported in paranthesis).	

				÷	
Profile Curvature	Independent variables	Adj R ²	SSE	$\beta^{a)}$	р
CV (33)	a) EL, SL, CTI, ln(SPI), P	0.514	0.439	0.41, -1.07, -0.95, 1.38, 0.47	< 0.001
	b) SL, CTI, ln(SPI), WI	0.482	0.453	-1.02, -1.02, 1.39, 0.61	< 0.001
	c) NDVI _{Mean} , P	0.461	0.462	-0.43, 0.60	< 0.001
	d) NDVI _{Min} , P	0.457	0.464	-0.42, 0.56	< 0.001
	e) EL, P	0.429	0.475	0.39, 0.52	< 0.001
CC (40)	f) EL, P	0.328	0.555	0.44, 0.35	< 0.001

	g) NDVI _{Min} , P	0.313	0.561	-0.41, 0.38	< 0.001
LC (23)	h) NDVI _{Max} , NDVI _{Diff} , WI	0.418	0.494	0.57, -0.55, 1.16	< 0.01
	i) NDVI _{Min} , WI	0.443	0.483	0.74, 1.14	< 0.001
LL (15)	l) NDVI _{Diff} , kh, kv, ln(SPI)	0.659	0.350	0.82, -0.37, -0.80, -0.82	< 0.01
	m) NDVI _{Diff} , kv, ln(SPI)	0.523	0.414	0.74, -0.83, -0.79	< 0.05
	n) NDVI _{Min} , kv, ln(SPI)	0.425	0.454	-0.59, -0.66, -0.72	< 0.05

^{a)} Standardised coefficients

1 2

3 An improvement of the prediction with respect to the whole dataset was observed, but the accuracy 4 was comparable with the one obtained by grouping according to vegetation types. The models for 5 convex (CV) and concave (CC) classes explained 51% and 33% of the within-class variance, 6 respectively. In the best model for the CV class, the highest standardised coefficients were related to 7 topographic variables, indicating that carbon accumulation decreased with increasing slope, but the 8 effect was partially compensated by the extension of the runoff contributing area (CA, see footnote in 9 Table II). In the CC class, instead, the significant variables were the same as those found in the whole 10 dataset (elevation, NDVI and precipitation). Climatic and vegetation variables were also significant in 11 the models of the LC (linear profile curvature) class, with an explained variance up to 42%. A better regression model was obtained in the purely linear (LL) case ($R^2 = 0.66$). When both the profile and 12 13 plan curvature were linear (*i.e.*, less than 0.1 in module) even small variations in concavity/convexity 14 affected the carbon concentration, with higher amounts of SOC in relative concavities. The quality of 15 the estimate (Fig. 3c) was comparable with that obtained for the grasslands when the dataset was 16 stratified by vegetation type, suggesting that a further improvement of the quality of the estimation 17 might be obtained by combining topography and vegetation classes.

To proceed in this direction and to have enough samples in each class, we merged mixed and 18 19 broadleaved forest samples (Table VII). This further classification significantly improved the estimate 20 and explained up to the 81% of the sample variance in the LL class. In all subsets the models included 21 topographic attributes, NDVI parameters and climatic variables. In general, SOC increased when 22 elevation and wetness (P and WI) increased. The heterogeneity of broadleaved forests, enhanced by 23 the presence of mixed vegetation ones, was probably responsible for the lack of a general trend in the 24 sign of the NDVI variables in the models. The effect of concavity and convexity on carbon 25 accumulation was further enhanced by local slope whose steepness increased carbon concentrations 26 when the curvatures were concave and decreased it in case of convexity. A similar result was found 27 by Grimm et al. (2008), who concluded that the lowest SOC stocks can be found on mid-slopes while 28 the highest were located on toe-slope positions. Also with this stratification the plan and profile 29 curvature contributed to the carbon variance only in the LL class. The lowest determination 30 coefficient was obtained for the LC class, the most heterogeneous one as the plan curvature could 31 induce either flow dispersion or accumulation.

32 33 TABLE VII 34

35 Significant multiple regression analyses for the soil carbon concentration at 30 cm depth according to36 vegetation-curvature classification (the number of elements for each class is reported in parenthesis).

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VegCurv.	Independent variables	Adj R ²	SSE	β^{Ψ}	р
Forest - CV (29)	a) SL, CTI, ln(SPI), WI	0.501	0.452	-1.28, -1.16, 1.70, 0.59	< 0.001
	b) SL, CTI, ln(SPI), P	0.475	0.464	-1.20, -1.11, 1.69, 0.56	< 0.001
	c) NDVI _{Mean} , P	0.481	0.461	-0.37, 0.66	< 0.001
	d) NDVI _{Mean} , WI	0.442	0.478	-0.31, 0.62	< 0.001
	e) NDVI _{Min} , P	0.439	0.480	-0.31, 0.61	< 0.001

Forest - CC (34)	f) NDVI _{Min} , SL, CTI, ln(SPI), P	0.337	0.561	-0.46, 1.09, 1.05, -1.31, 0.41	< 0.01
	g) EL, P	0.275	0.586	0.37, 0.38	< 0.01
	h) NDVI _{Min} , P	0.275	0.586	-0.36, 0.41	< 0.01
Forest - LC (16)	i) NDVI _{Min} , WI	0.317	0.572	0.60, 0.66	< 0.05
Forest - LL (13)	l) NDVI _{Max} , EL, kv, WI	0.807	0.248	-0.70, 0.76, -0.64, 0.60	< 0.001
	m) NDVI _{Max} , EL, kv, P	0.800	0.252	-0.74, 1.02, -0.61, 0.46	< 0.001
	n) NDVI _{Min} , kh, kv, CTI	0.728	0.294	-0.41, -0.56, -0.64, -0.76	< 0.01
	o) kv, P, WI	0.644	0.336	-0.87, -1.26, 1.88	< 0.01
	p) EL, kv	0.606	0.353	0.80, -0.78	< 0.01
	q) kv, WI	0.433	0.424	-0.65, 0.64	< 0.05
	r) kh, CTI	0.387	0.441	-0.68, -0.70	< 0.05
	s) NDVI _{Max} , WI	0.340	0.458	-0.82, 1.02	< 0.05

^{a)} Standardised coefficients

1 2

3 The variogram presented in Fig. 4c was constructed on the residuals of the best regression 4 model in Table VI (model l), where data were classified by morphology. It showed that in the LL 5 class the short-range variability was removed almost completely, while a (spatial) variance of 0.164 6 remained unexplained. In this model both topographic and climatic-vegetation factors were present as 7 independent variables, implying that all the ranges of spatial variability were considered. A better 8 result emerged from the variogram of the residuals of the best regression model in Table VII (model 9 1), associated to a small residual long-range variance (0.075, Fig. 4d). In Fig. 3d the estimates 10 obtained with the best model of the forest-LL class were compared to the observed values. The most 11 evident effect of the combined vegetation-curvature stratification was the improvement in the 12 estimates of the low/high SOC samples, which were largely over/underestimated in the previous 13 cases.

14

15 CONCLUSIONS

16

17 In this work we exploited the information derived from vegetation, climate, and morphology 18 for studying the spatial distribution of the soil organic carbon concentration in forest and grassland 19 areas. The case study was formed by 114 samples belonging to a vast heterogeneous region of the 20 North-West of Italy. The first attempts to statistically reproduce the SOC concentration by means of 21 vegetation and climatic predictors were unsatisfactory. In fact, these explanatory variables allowed us 22 to reduce the long-range spatial variability, but had no effect on the short-range dependence and were 23 therefore unable to take into account all factors influencing organic matter concentration in a highly 24 heterogeneous region. Better results were obtained after stratification of the samples, and by 25 introducing in the regression models topographic variables that, by governing water fluxes, had a 26 large influence on SOC inputs, losses and turnover. When classes of homogeneous vegetation and 27 topography were considered, the quality of the estimates improved, particularly for grasslands and 28 forests in the absence of local curvatures. The results of this work indicate that the spatial variability 29 of soil organic matter can be overcome only when an a-priori reduction of the heterogeneity is 30 applied. The only limitation to the feasibility of the approach is in the availability of the predictors, 31 included the availability of finer scale digital elevation models. Further efforts in this field of 32 investigation will be devoted to introduce more causative factors in the prediction models, provided 33 that additional and more focused data will become available.

34

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Fig. 1 Shown is a map of the study region with the locations of the sampled sites. The gray tones to the elevation variations within the region.











Fig. 3 Comparison between the observed and predicted values of SOC₃₀ for: (a) the whole dataset (first model in Table IV); (b) the grasslands subset (best model for grasslands in Table V); (c) the LL subset (best model for the

LL class in Table VI); (d) the forest-LL subset (best model for the forest-LL class in Table VII)





Fig. 4 Semivariogram of the residuals of the best regression model for (a) the whole dataset (first model in Table IV); (b) the grasslands subset (best model for grasslands in Table V); (c) the LL subset (best model for the LL class in Table VI); (d) the forest-LL subset (best model for the forest-LL class in Table VI).