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Research article

Determining the relative importance of climate and soil properties affecting the scores of visual soil quality indicators with dominance analysis

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Abstract: In this study, we have analyzed the relationships of four manageable soil properties, soil texture, and climate variables on the scores of visual indicators of 132 soils across Europe and China. Correlations differed in acid-to-neutral and alkaline soils, both in strength and direction, which gave rise to the different rankings of the importances of the explanatory variables for each visual indicator. In alkaline soils, higher soil pH values significantly affected the score of the visual indicators and dominated other variables for most visual indicators; in acid soils, only the "presence of a tillage pan" was affected by pH, and, for most visual indicators, soil organic matter (SOM) and labile organic carbon (LOC) dominated other manageable variables. In both soil reaction groups, climate variables covaried similarly in terms of direction but with different significances for different indicators; the dominance of the variables was dependent on soil reaction. Eight out of 16 visual indicators (eight per reaction group) had a statistically significant dominant explanatory variable (soil property or climate variable). The soil pH must be accounted for when interpreting visual indicators of soils with more extreme pH (both acid and alkaline).

Keywords: New Zealand Visual Soil Assessment method; VSA; explanatory variables; Spearman correlations; semi-partial correlations

1. Introduction

Most agronomists and farmers agree that a good soil structure is necessary for plant growth and a higher crop yield. However, there is no operational definition of soil structure, i.e., we do not have a physically quantifiable variable (or group of variables) that unequivocally represents the soil structure, or at least one allowing practical day-to-day use. Thus, soil scientists and agronomists have proposed several methods to assess soil structure based on the magnitudes of observable soil morphological characteristics, such as soil friability, observable macroporosity, color, presence of reduced metals and sulfur (anaerobic conditions), presence of earthworms, and so on, that can be individually or aggregately scored [1–3]. These methods have been deemed of use solely for on-farm soil management and seemingly confirm the statement that the soil is "… a dynamic living system that emerges through a unique balance and interaction of its biological, chemical, and physical components" [4]. This latter assertion suggests a high level of complexity and randomness. Nevertheless, true as it may be, for the agronomist or the researcher, knowing that the visual soil quality indicators would covary with different soil and climate features would be valuable.

Understanding which climate characteristics and soil properties affect the visual soil quality indicators is necessary for soil managers, for planning interventions and allocating resources to enhance soil quality. To untangle the effects of soil properties and climate characteristics on the scores of the visual indicators, the first step is to check for correlations between readily available data and the scores. Except for those explanatory variables that are truly independent—the correlations with all other explanatory variables having a coefficient $r \approx 0$—the unique effect of a variable on the score of each visual indicator (friability, macroporosity, color, and so on) can only be calculated by removing the effects shared with other variables contributing to the observed score. However, the visual indicators are ordinal variables; the lack of scales (no physical measurement is performed when these visual indicators are assessed in the field) prevents us from using parametric statistics, as no assumptions can be made about the population (no parametrized probability distribution).

The visual soil assessment scheme studied in this work is the New Zealand Visual Soil Assessment method [2]. This method comprises several indicators scored individually in one of three levels (poor, moderate, and good). To model the visual indicators, i.e., to predict their scores based on the effect (explanatory value) of soil properties, climate variables, and so on, we need to select the variables with higher unique explanatory values. When in the presence of a set with a relatively high number of independent variables, establishing their relative importances may be convenient (by ranking them according to their unique effects on the scores), allowing one to save time and implement a better modelling strategy [5]. One way to achieve this ranking is by dominance analysis [6]; the relative importances of the explanatory variables is determined by pairwise analysis of the correlations between them and the correlations and semi-partial correlations they have with the visual indicators. This step, identifying the parameters and relationships that are relevant to the soil functions, is essential to creating the models needed to develop meaningful visual soil assessment methods.

With the above in mind, the main objectives of this study were i) to calculate the correlations between the variables (Spearman correlations); ii) to calculate the correlations of each visual indicator with the explanatory variables; iii) to calculate the correlation of each visual indicator with each explanatory variable, after the removal of the shared effect of other explanatory variables (one at a time), but not from the response variable (semi-partial Spearman correlation); iv) to assess the relative importances of the independent variables (dominance) to the scores of the visual indicators for use with spatial upscaling (different soils and climates).

2. Materials and methods

2.1. Dataset

2.1.1. Overview

This study was devised to assess the relative importances of different soil properties and climate variables affecting the scores of visual indicators of the New Zealand Visual Soil Assessment method (VSA) [2]. The dataset used was recorded during a survey in the spring and summer of 2016 at 132 locations across eight pedoclimatic zones in Europe and China and is a result of the iSQAPER research project (Interactive Soil Quality Assessment in Europe and China for Agricultural Productivity and Environmental Resilience). Each record features eight visual soil quality indicators (Table 1), seven soil properties, and six climate variables and indices (Table 2). Only soils managed with traditional practices were used.

2.1.2. Visual soil assessment

The visual soil quality indicators recorded in the survey followed the protocols and standards proposed by Shepherd [2]. The method assesses soil structure by performing a drop shatter test of a topsoil volume (0.2 m × 0.2 m × 0.2 m) and observing the size distribution of the particles produced, i.e., clods and finer aggregates, the macroporosity, color, earthworms, and the presence of a tillage pan on the soil profile created by the extraction of the soil cube and by recording signs of erosion and surface ponding. Only soils of arable land were surveyed. Although the soil aggregate stability in water is not a visual soil quality indicator of the VSA method, it was also assessed with a field test adapted from Tongway and Hindley [7]. All visual indicators and soil stabilities were classified into one of three possible categories, "poor", "moderate", and "good". A (brief) description of the protocols is provided in Table 1 and Figure 1 in the Supplemental Materials. The frequencies of each score of each visual indicator are presented in Table 1.

2.1.3. Soil properties and climate variables

The soil properties and climate variables are presented in Table 2. The soil physical and chemical analysis was performed on samples from the topsoil cube used to perform the visual indicators' tests. Labile organic carbon (LOC) was measured with a diluted solution of 0.02 M of $KMnO_4$ following a protocol proposed by Weil et al. [8] and adapted by Alaoui and Schwilch [9]. Soil pH in water was measured with soil-to-water ratios of 1:1 [10]. The soil penetration resistance measurement was performed with an Eijkelkamp penetrologger (0–0.4 m). Soil texture and soil organic carbon (SOM) were measured following the lab methods available at each location (see Table 2 in Supplemental Materials). Differences in method and protocol for measurement of the granulometric fractions (clay, lime, and sand) and SOM increase the uncertainty, as no inter-lab calibration was performed. All sites were georeferenced; the data is not shown. Climate variables were estimated using the "Local Climate Estimator" New Loc_Clim software [11]. The records were divided into two groups according to soil reaction: an acid-to-neutral group (pH ≤ 7: for the remainder of the text, it will be identified as "acid group") and an alkaline group (pH > 7). The threshold (pH = 7) to divide the two soil reaction groups is because of the bimodal distribution of world soils, with a minimum of about pH 7 [12], a minimum that is in agreement with the usually low buffering capacity of the soils for this pH (about 7). Tables 3 and 4 in Supplemental Materials present the arithmetic mean, standard error and kurtosis for each pH group and the pH statistics per case study sites and pedoclimatic zones. From a plant nutrition point of view, other thresholds could be considered; however, they are not needed or desired: the correlations study the relationship between the variables (how they covary) irrespective of whether the pH threshold is 6, 6.5, or 7. Using other thresholds could originate slightly different correlation coefficients, but a valid argument has to be presented to justify their use.

Table 1. Visual soil quality indicators. Frequency.

Visual indicator	Total	Frequency			Standard
		Poor	Moderate	Good	
Soil structure and consistency (STR)	132	21	80	31	Photographs
Soil porosity (POR)	132	28	66	38	Photographs
Soil stability (STA)	132	24	75	33	Photographs
Soil color (COL)	132	23	67	42	Photographs
Presence of cultivation pan (PAN)	132	24	69	39	Photographs
Earthworm count (EAR)	132	69	48	15	Count: number in 5 min.
Surface ponding (under cropping) (PON)	120	2	29	89	Count: number of days
Susceptibility to wind and water erosion (ERO)	128	9	32	87	n.a.

2.2. Statistical analysis

The visual indicators are ordinal variables. Thus, the analysis performed was nonparametric.

We used the Spearman correlation coefficient to calculate the relationships between the scores of the dependent variables (visual indicators) and potential covariates (potential explanatory variables). All potential covariates were ranked in ascending order (dense ranking), i.e., the smallest measurement value of the variable corresponds to the highest ordinal position. For example, if quantity 15 is the smallest quantity of a given variable, it occupies the first position, 1. Thus, if one has 60 different measurements of a continuous variable, the measurements were ranked from 1 to 60, independently of the scale. The correlation coefficients were defined as no correlations for $r \leq |0.10|$, weak correlations for $|0.10| < r \leq |0.3|$, moderate correlations for $|0.3| < r \leq |0.7|$, and strong correlations for $r > |0.7|$.

To assess the relative importances of the covariates to explain the scores of the visual indicators, we have used the Spearman correlation coefficients between the dependent variable (the visual indicator) and the covariates, controlled for the effect of other covariates, one at a time, i.e., we have calculated the semi-partial Spearman correlation (Equation 1).

$$Corr(yx_1|x_2) = \frac{Corr(yx_1) - \left(Corr(yx_2) \times Corr(x_1x_2)\right)}{\sqrt{1 - \left(Corr(x_1x_2)\right)^2}} \quad (1)$$

Although we cannot partition the variation of the response variables (the visual indicators) with semi-partial correlations (with the square of the semi-partial correlations), they allow us to assess the relative importances of the explanatory variables (two at a time) on the response variable, by using dominance analysis [6,13], a qualitative relationship. The principle of dominance analysis is as follows: Let y be the dependent variables and x_i (e.g., i = 1 to 4) be four independent variables. If $(Corr(yx_1))^2 > (Corr(yx_2))^2$, and $(Corr(yx_1|x_3))^2 > (Corr(yx_2|x_3))^2$, and $(Corr(yx_1|x_4))^2 > (Corr(yx_2|x_4))^2$, then x_1 D x_2 (x_1 dominates x_2). The same is repeated for all other variables. One must be aware that the square of the Spearman correlation does not have a straightforward interpretation as the square of the Pearson correlation (coefficient of determination), allowing only a qualitative one (ordinal). To assess the covariations between the explanatory variables, we calculated the Spearman correlation coefficients between the variables. The number of pairs of all independent variables is presented in Tables 5, 7, and 9 in Supplemental Materials.

Table 2. Soil properties and climate variables (minimum, maximum, and median).

		Acid soils				Alkaline soils			
	unit	n§	Min.	Max.	Med.	n§	Min.	Max.	Med.
SOM	%	39	0.3	9.2	2.2	47	0.4	14.4	2.0
LOC	$mg.g^{-1}$	62	0.06	8.88	0.81	63	0.10	6.80	0.74
pH		65	4.2	7.0	6.2	63	7.1	8.7	7.7
PR	MPa	48	0.6	4.6	2.2	39	0.5	5.9	2.6
Sand	%	59	10	93	50	53	4	80	44
Silt	%	59	7	73	36	53	9	71	33
Clay	%	59	0	44	11	53	0	52	17
T	°C	65	4.7	18.7	9.5	63	4.7	18.7	15.7
P	mm	65	437	1393	667	63	250	1393	533
PET	mm	65	504	1507	642	63	510	1507	896
AI		65	0.33	2.24	1.06	63	0.20	2.24	0.53
NPP	$g(DM)\ m^{-2}\ yr^{-1}$	65	756	1794	1071	63	459	1794	894
GCI		65	2	80	29	63	2	76	27

Note: n§: the size of the sample (four fields were not included for lack of physically measured data); Min.: minimum value; Max.: maximum value; Med.: median value. SOM: soil organic matter; LOC: labile organic carbon; PR: soil penetration resistance; T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean (dimensionless); NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}). GCI: Gorczynski continentality index (dimensionless).

The calculations were executed with Microsoft Excel spreadsheets. The Excel functions used were RANK, to rank the variables; CORREL, to calculate the correlation coefficients (the Pearson correlation coefficient performed on ranked variables has the same outcome as the Spearman formula); and T.DIST.2T, the Student's t-test to test the significance of the correlations. The semi-partial correlations were calculated using Equation 1.

3. Results

3.1. Correlations between the explanatory variables

Climate variables and climate indices had strong correlations between them (Table 3). Concerning continentality, the correlations with climate variables and indices were weak. The correlations between climate variables, according to soil reaction, are in Tables 8 and 10 in Supplemental Materials.

Table 3. Spearman correlation coefficients between climate variables and indices.

	T		P		PET		AI		NPP	
	r_s	p-val.	r_s	p-val.	r_s	p-val.	r_s	p-val.	r_s	p-val.
T										
P	0.09	0.33								
PET	**0.80**	0.00	**−0.26**	0.00						
AI	**−0.18**	0.04	**0.80**	0.00	**−0.63**	0.00				
NPP	**0.20**	0.02	**0.96**	0.00	−0.10	0.24	**0.70**	0.00		
GCI	**−0.23**	0.01	0.02	0.85	**−0.18**	0.04	0.13	0.13	0.00	0.97

Note: T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

Regarding the soil properties, the correlations between the explanatory variables within each pH group were very distinct (Table 4). The correlation coefficient between SOM and LOC for acid soils ($r_s = 0.75$) was twice the observed for alkaline soils ($r_s = 0.38$). In acid soils, there was a positive correlation between SOM and pH values ($r_s = 0.29$), a trend for a higher SOM content for soils with a reaction nearer neutral, not observed in alkaline soils ($r_s = −0.03$); LOC and SOM showed negative correlation coefficients with silt and soil penetration resistance and positive coefficients with clay. In alkaline soils, SOM showed a positive correlation coefficient with mean annual evapotranspiration ($r_s = 0.41$), not observed in acid soils ($r_s = 0.02$); the correlation coefficient of SOM with soil penetration resistance changed direction ($r_s = 0.41$ vs. −0.34 in acid soils), and the correlation with clay was stronger ($r_s = 0.66$ vs. 0.39 in acid soils).

Table 4. Spearman correlation coefficients between all explanatory variables for soil pH ≤ 7, left side, and pH > 7, right side. Coefficients written in bold are statistically significant for α < 0.05 (p-values are available in Tables 11 and 12 in Supplemental Materials).

	pH ≤ 7							pH > 7						
	LOC	SOM	pH ≤7	Sand	Silt	Clay	PR	LOC	SOM	pH >7	Sand	Silt	Clay	PR
LOC														
SOM	**0.75**							**0.38**						
pH ≤7	0.00	0.29						−0.01	−0.03					
Sand	0.12	0.07	0.05					−0.08	−0.26	**−0.49**				
Silt	**−0.42**	−0.30	0.09	**−0.83**				−0.07	−0.14	**0.44**	**−0.77**			
Clay	**0.58**	**0.39**	-0.07	**−0.36**	-0.15			**0.27**	**0.66**	0.20	**−0.45**	−0.16		
PR	**−0.48**	−0.34	0.19	0.07	0.13	**−0.34**		−0.17	**0.41**	0.00	−0.06	−0.24	**0.49**	
T	−0.21	0.17	−0.07	**−0.46**	0.23	**0.28**	0.09	0.12	**0.30**	**0.38**	**−0.49**	**0.36**	**0.35**	−0.11
P	−0.01	0.31	0.06	**−0.42**	**0.34**	0.11	0.24	−0.02	0.02	**−0.45**	−0.02	0.07	−0.19	−0.08
PET	0.03	0.04	**−0.25**	**−0.31**	-0.06	**0.59**	**−0.28**	0.13	**0.41**	**0.37**	**−0.33**	0.08	**0.55**	0.09
AI	0.06	**0.36**	0.16	−0.24	**0.29**	−0.14	**0.34**	0.08	−0.27	**−0.45**	0.08	0.13	**−0.47**	−0.29
NPP	0.02	0.26	−0.02	**−0.40**	**0.25**	0.21	0.15	0.05	−0.04	**−0.32**	−0.05	0.09	−0.16	−0.15
GCI	0.12	−0.06	**−0.30**	**−0.41**	0.17	**0.52**	−0.17	−0.02	−0.08	−0.03	0.01	−0.12	0.01	0.22

Note: LOC: labile organic carbon (mg/g); SOM: soil organic matter (%); pH; PR: penetration resistance (MPa); sand, silt, and clay (%); T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

3.2. Correlations between the scores of the visual soil quality indicators and explanatory variables

The correlation coefficients between the scores of the visual soil quality indicators and the explanatory variables are in Table 5.

LOC and SOM showed statistically significant correlations with three visual indicators in the acid soils; in the alkaline soils, only the correlation between SOM and the "presence of tillage pan" was statistically significant (and positive). Contrastingly, soil pH had a much higher effect on the score of the visual indicators in the alkaline group (six)—a trend for higher scores for all indicators as the pH values neared neutral. Meanwhile, for the acid soils, the relationship between pH values and visual indicators was only statistically significant for the "presence of tillage pan"—positive, a trend for higher scores for soils nearer neutral. Soil penetration resistance had a positive and statistically significant correlation with the scores of "soil color" in the acid soils; in alkaline soils, it had negative correlations with the scores of "soil structure and consistency" and with "surface ponding".

Soil texture also correlated differently with the scores of the visual indicators according to soil reaction. For example, the negative correlation of clay with "soil color" in acid soils and that of clay with "surface ponding" in alkaline soils is inexistent in both cases in the other soil pH group.

Table 5. Spearman correlation coefficients between visual soil quality indicators and soil properties and climate variables, in soils with pH ≤ 7, left side, and pH > 7, right side. The sample size can be consulted in the Supplemental Materials in Tables 5 and 7. Coefficients written in bold are statistically significant for α<0.05 (p-values are available in Tables 13 and 14 in Supplemental Materials).

	pH ≤ 7								pH > 7							
	STR	POR	STA	PAN	COL	EAR	ERO	PON	STR	POR	STA	PAN	COL	EAR	ERO	PON
LOC	0.15	**0.26**	0.11	-0.05	**-0.43**	0.16	**0.31**	0.17	0.21	0.22	-0.02	0.13	0.19	0.23	-0.04	0.06
SOM	0.23	**0.62**	0.15	0.16	**-0.36**	-0.20	0.13	-0.09	-0.19	0.16	-0.05	**0.36**	0.15	-0.03	-0.12	-0.01
pH	-0.03	0.20	0.04	**0.31**	-0.09	0.08	0.10	0.13	**-0.28**	**-0.28**	**-0.25**	**-0.37**	**-0.33**	-0.14	-0.10	**-0.37**
Sand	0.02	0.06	**-0.27**	0.07	-0.01	-0.12	-0.16	0.00	**0.30**	0.02	-0.08	0.12	0.05	0.03	0.02	0.17
Silt	0.06	-0.03	0.25	-0.06	**0.29**	0.18	0.10	0.16	-0.14	-0.04	0.24	-0.04	-0.04	0.05	0.01	0.05
Clay	-0.10	-0.02	0.00	-0.05	**-0.61**	0.03	0.20	0.03	-0.26	0.12	**-0.27**	-0.05	-0.10	-0.25	-0.13	**-0.43**
PR	0.04	0.01	0.06	0.14	**0.38**	0.22	-0.08	0.14	**-0.32**	0.07	-0.13	-0.21	-0.10	-0.21	-0.10	**-0.48**
T	-0.11	0.00	0.12	-0.02	-0.08	**-0.39**	0.04	-0.21	-0.23	-0.08	0.13	-0.01	-0.09	-0.12	**-0.36**	0.08
P	0.00	0.22	**0.35**	0.04	0.07	-0.03	**0.32**	-0.04	-0.09	0.13	**0.50**	0.15	**0.39**	**0.29**	**0.39**	0.23
PET	0.08	-0.12	-0.16	-0.07	**-0.36**	**-0.37**	0.03	-0.17	-0.18	-0.13	-0.08	-0.07	-0.23	**-0.27**	**-0.37**	-0.15
AI	-0.08	0.23	**0.43**	0.04	0.24	0.21	0.23	0.02	0.04	0.11	**0.42**	0.14	**0.29**	**0.37**	**0.34**	**0.28**
NPP	-0.03	0.17	**0.29**	0.04	0.01	-0.07	**0.34**	-0.07	-0.09	0.00	**0.43**	0.07	**0.27**	0.19	**0.40**	0.09
GCI	0.05	0.05	0.05	-0.11	-0.21	0.12	0.22	**0.30**	0.10	0.24	-0.22	0.01	0.13	0.15	**0.26**	0.05

Note: Str: soil structure; Por: soil porosity; Sta: soil stability (slake test); Pan: presence of a tillage pan; Col: soil color; Ear: earthworm count; Ero: susceptibility to wind and water erosion; Pon: surface ponding. LOC: labile organic carbon (mg/g); SOM: soil organic matter (%); pH; PR: penetration resistance (MPa); sand, silt, and clay (%); T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

Regarding climate variables, indicators with statistically significant correlations had better scores with increasing P, AI, and NPP and lower scores with increasing T and PET, irrespective of soil reaction. However, the strengths of the correlations with the indicators were distinct and dependent on the soil reaction. The correlation coefficients between continentality (GCI) and visual indicators were only statistically significant for soil erosion in alkaline soils and water ponding in acid ones.

3.3. Semi-partial correlations between visual soil quality indicators and the explanatory variables

Individual semi-partial Spearman correlation coefficients between each visual soil quality indicator and each variable, controlled for the effects of all other variables, and the p-values of the coefficients are presented in Supplemental Materials (Tables 15 to 30). Table 6 summarizes the semi-partial correlation coefficient range.

Table 6. Range of the semi-partial Spearman correlation coefficients of each visual soil quality indicator with all variables, controlled for all other variables, one at a time. Individual semi-partial correlation coefficients with all other variables and the p-values of the coefficients can be consulted in Supplemental Materials, Tables 15 to 30. Ranges are written in bold and red when all semi-partial correlations were statistically significant for α < 0.05.

		STR	POR	STA	PAN	COL	EAR	ERO	PON
LOC	pH≤7	[−0.04,0.25]	[−0.31, 0.33]	[0.00, 0.24]	[−0.26,0.02]	[−0.46,−0.08]	[0.08,0.47]	[0.24,0.39]	[0.14,0.36]
	pH >7	[0.16,0.31]	[0.18, 0.24]	[−0.06, 0.05]	[−0.01,0.15]	[0.15, 0.23]	[0.20, 0.31]	[−0.07,0.01]	[−0.02,0.18]
SOM	pH ≤7	[−0.31,0.29]	[0.57, 0.67]	[−0.01, 0.23]	[0.07, 0.30]	[−0.47,−0.06]	[−0.49,−0.13]	[−0.16,0.17]	[−0.33, −0.04]
	pH >7	[−0.30,−0.03]	[0.08, 0.23]	[−0.09, 0.18]	[0.34, 0.52]	[0.08, 0.29]	[−0.12,0.18]	[−0.12,0.04]	[−0.04, 0.36]
pH	pH ≤7	[−0.13,0.25]	[0.02, 0.33]	[−0.02, 0.24]	[0.28, 0.32]	[−0.19, 0.02]	[−0.01,0.15]	[0.07,0.18]	[0.11, 0.21]
	pH >7	[−0.31,−0.16]	[−0.31, −0.25]	[−0.40, −0.03]	[−0.39, −0.33]	[−0.35,−0.17]	[−0.18,0.03]	[−0.11,0.09]	[−0.4, −0.28]
Sand	pH ≤7	[−0.03, 0.11]	[0.02, 0.17]	[−0.33, −0.11]	[−0.09, 0.09]	[−0.25,0.41]	[−0,36,0,05]	[−0.20,−0.01]	[−0.10, 0.22]
	pH >7	[0.19, 0.32]	[−0.14, 0.08]	[−0.24, 0.16]	[−0.07, 0.22]	[−0.13,0.09]	[−0.10,0.10]	[−0.18, 0.04]	[−0.02, 0.33]
Silt	pH ≤7	[0.04, 0.13]	[−0.11, 0.16]	[0.04, 0.32]	[−0.12, −0.01]	[0.13, 0.50]	[0.13,0.29]	[−0.05, 0.25]	[0.12, 0.27]
	pH >7	[−0.22, 0.15]	[−0.05, 0.09]	[0.19, 0.39]	[−0.10, 0.13]	[−0.08,0.11]	[0.00,0.12]	[−0.04,0.14]	[−0.07, 0.29]

Continued on next page

		STR	POR	STA	PAN	COL	EAR	ERO	PON
Clay	pH≤7	[−0.23,−0.08]	[−0.06, 0.08]	[−0.09, 0.10]	[−0.05, 0.21]	[−0.66,−0.45]	[−0.09, 0.29]	[0.03, 0.25]	[−0.10, 0.16]
	pH>7	[−0.33,−0.12]	[0.09, 0.25]	[−0.38,−0.20]	[−0.12, 0.08]	[−0.26, 0.04]	[−0.33,−0.08]	[−0.14,0.08]	[−0.56, −0.22]
PR	pH≤7	[0.01, 0.07]	[−0.07,0.08]	[0.01, 0.08]	[0.08, 0.21]	[0.19, 0.41]	[0.11, 0.34]	[−0.17,0.07]	[0.09, 0.25]
	pH>7	[−0.41,−0.21]	[0.05, 0.24]	[−0.15, 0.01]	[−0.23, 0.04]	[−0.18,−0.02]	[−0.25,−0.10]	[−0.16,0.00]	[−0.52, −0.31]
T	pH≤7	[−0.19,−0.05]	[−0.18, 0.14]	[−0.13, 0.20]	[−0.01, 0.10]	[−0.18, 0.23]	[−0.54,−0.19]	[−0.24,0.11]	[−0.26, −0.12]
	pH>7	[−0.34, 0.08]	[−0.27, 0.03]	[0.10, 0.44]	[-0.04, 0.32]	[−0.14, 0.20]	[−0.15, 0.19]	[−0.40,−0.09]	[0.03, 0.39]
P	pH≤7	[−0.08, 0.11]	[0.03, 0.27]	[0.01, 0.37]	[−0.01, 0.07]	[−0.21, 0.21]	[−0.34, 0.23]	[−0.03, 0.36]	[−0.10, 0.09]
	pH>7	[−0.25,−0.03]	[0.00, 0.36]	[0.28, 0.52]	[−0.01, 0.24]	[0.26, 0.39]	[−0.01, 0.29]	[0.05, 0.39]	[0.03, 0.40]
PET	pH≤7	[0.05, 0.22]	[−0.16, −0.03]	[−0.33,0.01]	[−0.12, 0.01]	[−0.42, 0.00]	[−0.48,−0.14]	[−0.12, 0.12]	[−0.27, −0.04]
	pH>7	[−0.22, 0.03]	[−0.23, 0.00]	[−0.36,0.27]	[−0.24, 0.07]	[−0.32,−0.05]	[−0.30,−0.02]	[−0.38, −0.12]	[−0.41, 0.10]
AI	pH≤7	[−0.18,−0.06]	[0.00, 0.25]	[0.24, 0.43]	[−0.01, 0.06]	[0.11, 0.40]	[0.08, 0.40]	[−0.04, 0.27]	[−0.05, 0.09]
	pH>7	[−0.12, 0.17]	[−0.02, 0.19]	[0.04, 0.51]	[−0.03, 0.25]	[−0.02, 0.34]	[0.24, 0.38]	[0.06, 0.35]	[0.09, 0.34]
NPP	pH≤7	[−0.09, 0.06]	[−0.15, 0.21]	[−0.16, 0.34]	[−0.01, 0.07]	[−0.20, 0.14]	[−0.29, 0.23]	[0.13, 0.41]	[−0.11, 0.09]
	pH>7	[−0.19,−0.01]	[−0.34, 0.01]	[−0.10, 0.45]	[−0.20, 0.08]	[−0.26, 0.27]	[−0.20, 0.19]	[0.10, 0.40]	[−0.34, 0.10]
GCI	pH≤7	[0.03, 0.12]	[0.02, 0.12]	[−0.06, 0.10]	[−0.12,−0.02]	[−0.27, 0.12]	[0.08, 0.24]	[0.14, 0.26]	[0.28, 0.37]
	pH>7	[0.00, 0.17]	[0.20, 0.25]	[−0.31, 0.18]	[−0.03, 0.06]	[0.01, 0.16]	[0.01, 0.20]	[0.07, 0.29]	[−0.04, 0.16]

Note: Str: soil structure; Por: soil porosity; Sta: soil stability (slake test); Pan: presence of a tillage pan; Col: soil color; Ear: earthworm count; Ero: susceptibility to wind and water erosion; Pon: surface ponding. LOC: labile organic carbon (mg/g); SOM: soil organic matter (%); pH; PR: penetration resistance (MPa); sand, silt, and clay (%); T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

When the correlation coefficients of the scores of the visual indicators with the explanatory variables (Table 5) are compared with the range of semi-partial correlations (Table 6), we observe that different variables can potentially explain the same or part of the variation of the scores of the visual indicators. Except for the "soil structure and consistency", "earthworm count", and the "susceptibility to wind and water erosion", all other visual indicators had one or two variables that statistically significantly covaried with them, irrespective of the removal of the shared effects (coefficients in red in Table 6).

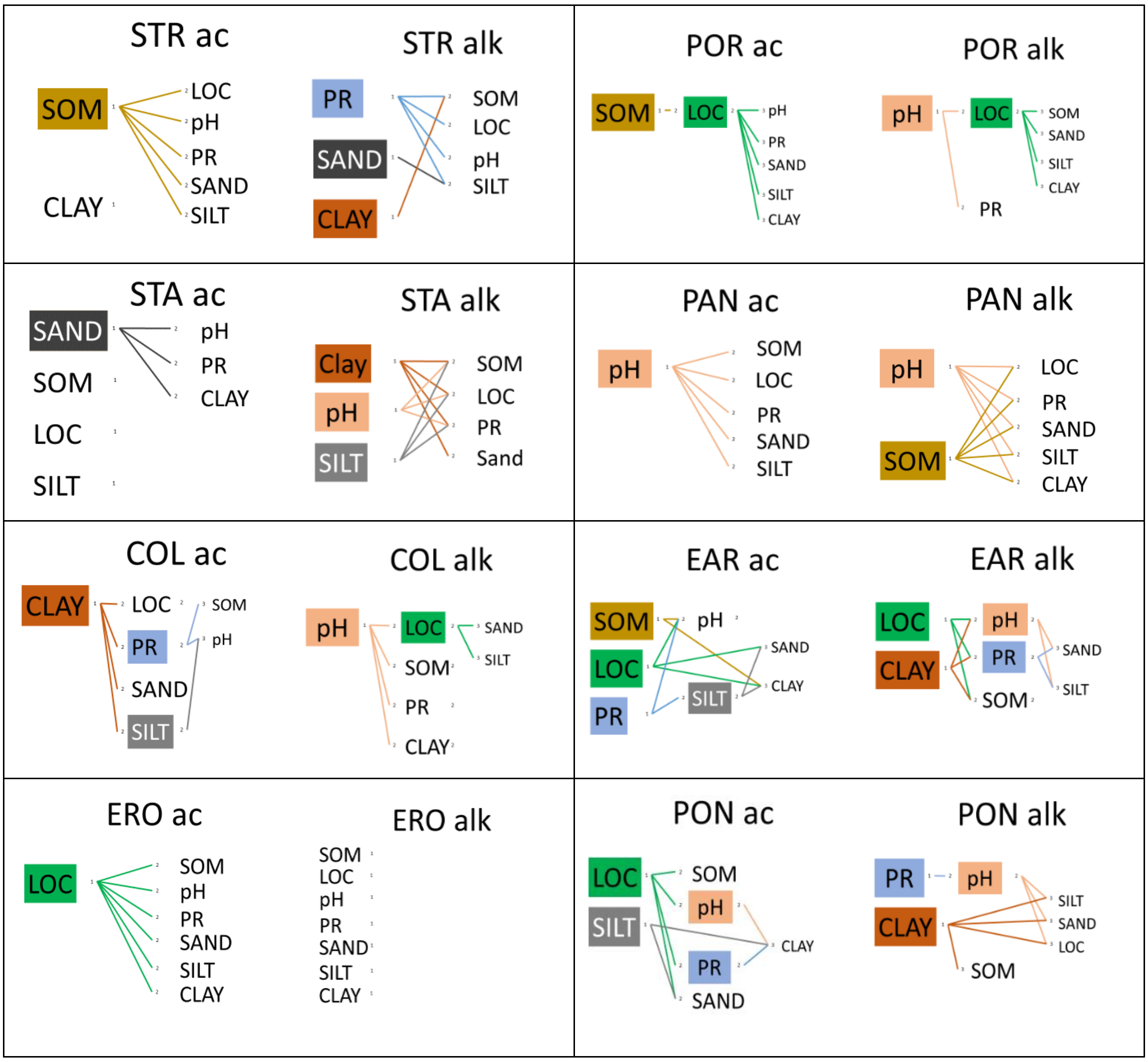

Figure 1. Dominance relationships between soil properties. Variables in a colored box dominate the variables standing on their right side (if there is a connecting line).

Note: Str: soil structure; Por: soil porosity; Sta: soil stability (slake test); Pan: presence of a tillage pan; Col: soil color; Ear: earthworm count; Ero: susceptibility to wind and water erosion; Pon: surface ponding. LOC: labile organic carbon (mg/g); SOM: soil organic matter (%); pH: ranked; PR: penetration resistance (MPa); sand, silt, and clay (%); T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

The dominances of the explanatory variables for each visual indicator are in Figures 1 (soil variables) and 2 (climate variables). To select the most important explanatory variables, along with dominance relationships, the arithmetic mean of the squares of Spearman's semi-partial correlation coefficients is of interest (Table 31 in Supplemental Materials). This is because when one variable dominates another, the arithmetic mean of the squares of the semi-partial correlations is always higher; however, the same cannot be said if no dominance is demonstrated. The squared coefficients were used to eliminate the directions of the correlations. The interpretation of the squared number of a Spearman correlation is not as straightforward as it would be in the presence of a Pearson correlation (i.e., the coefficient of determination); it is used only as a support for the assessment of the relative importances of the variables (not for the measurement of the variance of the scores).

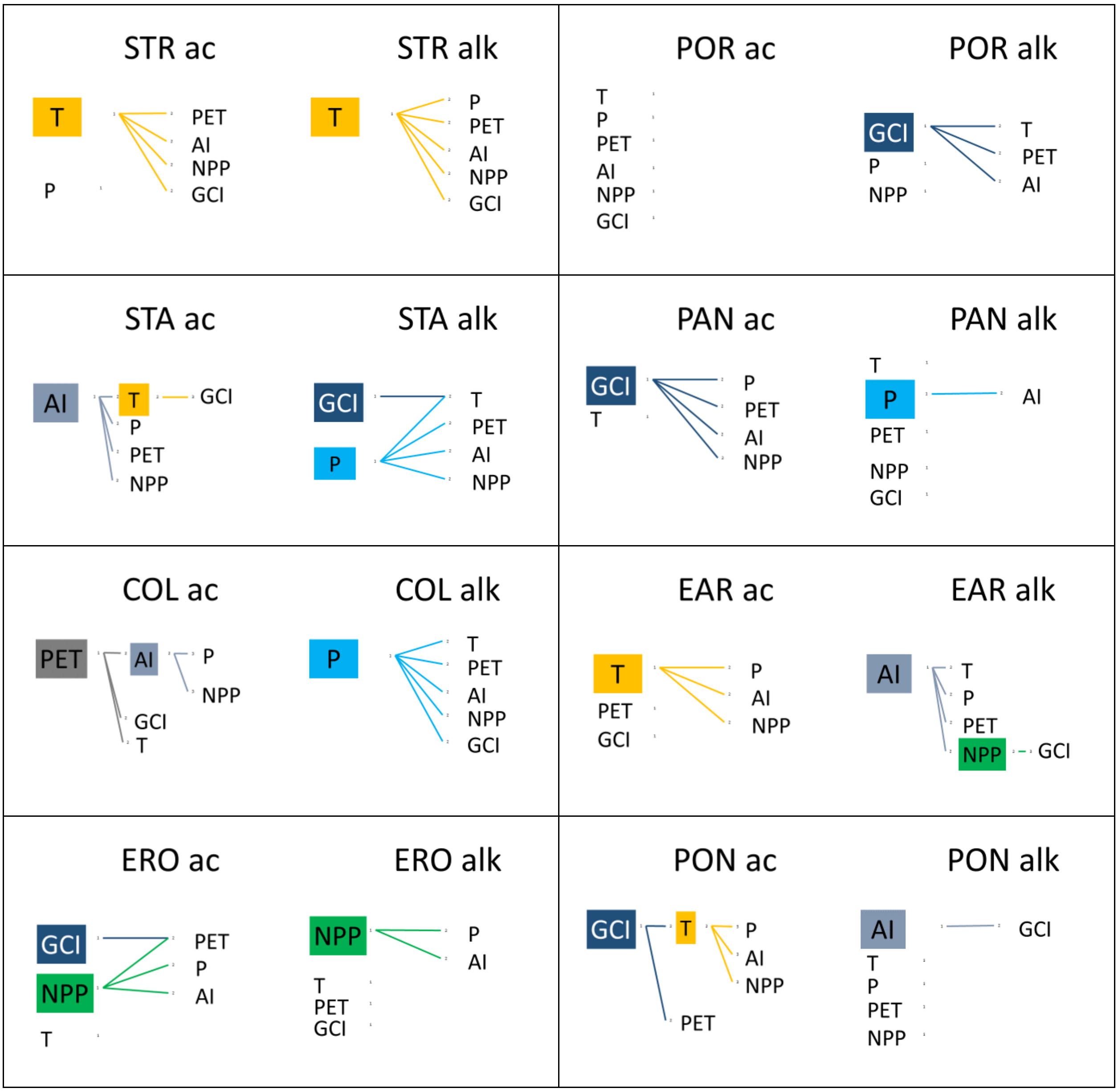

Figure 2. Dominance relationships between climate features. Variables in a colored box dominate the variables standing on their right side (if there is a connecting line).

Note: Str: soil structure; Por: soil porosity; Sta: soil stability (slake test); Pan: presence of a tillage pan; Col: soil color; Ear: earthworm count; Ero: susceptibility to wind and water erosion; Pon: surface ponding. LOC: labile organic carbon (mg/g); SOM: soil organic matter (%); pH: ranked; PR: penetration resistance (MPa); sand, silt, and clay (%); T: mean annual temperature (°C); P: mean annual precipitation (mm); PET: mean annual potential evapotranspiration (mm); AI: aridity index = P annual mean / PET annual mean, dimensionless; NPP: net primary production potential, limited by temperature or precipitation (g (DM) m^{-2} yr^{-1}); GCI: Gorczynski continentality index.

The existence of a dominant relationship between two climate variables does not necessarily mean that the dominant variable has a high explanatory value; it only means that between the two, it is better (i.e., other variables than the ones being analyzed may have a higher explanatory value).

In acid soils, SOM and LOC were the manageable variables with higher explanatory potential for all visual indicators except for the "presence of a tillage pan", for which pH had the highest explanatory potential. Conversely, in alkaline soils, pH was the manageable variable with higher explanatory potential for most visual soil quality indicators; but, contrastingly with the observation in the acid soils, SOM is equally important regarding the "presence of a tillage pan". In alkaline soils, other manageable variables that had higher explanatory potential than pH were penetration resistance (soil structure and surface ponding) and LOC (earthworm count). The dominance of particle-size fractions over soil-manageable properties was only observed for two indicators in acid soils (soil stability and color) and four in alkaline (soil structure, stability, earthworm count, and surface ponding).

The relative importances of the climate variables on the scores of the visual indicators are very distinct according to soil reaction. For most, the indices (AI, NPP, and GCI) dominate the other variables (T, P, and PET); however, in alkaline soils, P dominates other variables for soil stability, color, and the "presence of a tillage pan".

4. Discussion

These results must be interpreted with caution because of the large geographic extent represented and the relatively small size of the sample. Another cause for attention is arguably the uncertainty associated with the values of SOM, lime, and sand, resulting from the different methods used for their determination at each location. However, Spearman correlations assess the monotonicity of two variables; and, if the errors are relatively small, they will not cause significant changes in the ranking order.

Correlations. Soil reaction affects the relationships between the variables and, therefore, their potential explanatory values concerning the scores of the visual indicators. The lower correlation coefficient between LOC and SOM in alkaline soils, compared to acid soils, might be explained by a different balance of the biologically mediated processes behind the relationship or by other unknown variables or interactions [14]. In alkaline soils, the arithmetic mean of LOC content was almost half the amount observed in acidic soils, while the arithmetic means of SOM were virtually the same. The ratios of LOC to SOM were 0.12 (SD = 0.12) and 0.07 (SD = 0.10) in acid and alkaline soils, respectively. These differences might be explained by a higher constraint to microbial growth under acid conditions, leading to soil LOC accumulation [15,16]. In the acid soils, there were no correlations between pH and the particle-size soil fractions (the correlations measuring the relationship between the gradient of pH (up to 7) and that of the magnitude of the particle-size fractions). On the other hand, in alkaline soils, moderate correlations were observed with sand and silt, negative and positive, respectively; i.e., there were trends for lower alkalinity with increasing sand content and for higher alkalinity with increasing silt content (one may speculate that this is probably the result of soils developing on carbonate rocks). These relationships between soil pH and particle-size soil fractions might affect the LOC and SOM dynamics [16]. When comparing acid and alkaline soils, the correlation between LOC and clay in acid soils was much higher than between SOM and clay, while the inverse was observed in alkaline soils. These results allow speculation that different organic matter materials, more or less labile, are occluded by clay [17], depending on the soil reaction and microbial activity. The negative correlation observed between LOC and silt in acid soils, inexistent in alkaline soils ($r_s = -0.07$), suggests that higher silt contents favor microbial activity and, thus, LOC decomposition in acid soils. Chenu et al. [18] observed that, after adding glucose, the aggregates of one sandy acid soil had a higher microbial development than one clayey neutral soil because of a higher porosity volume of convenient size (6–30 μm), allowing a higher surface area for microbial growth on the surface of the aggregates and inside them. Other relationships were found dependent on the soil reaction and are, hypothetically, connected to biologically mediated processes: for example, the opposite direction of the correlations between penetration resistance with SOM and clay in acid and alkaline soils.

Climate explains, to a great extent, the soil reaction [12]. Thus, different correlations between climate variables were expected and observed for the acid and alkaline soil groups. Climate and the parent material also affect soil genesis, along with other factors. The differences between the correlations of particle-size soil fractions and climate variables in the two soil reaction groups were also expected. However, one can also expect the existence of soils with a pH value that does not conform to modern climate (acid soils under arid climates and vice versa). Under these circumstances, other variables might help understand the processes and model the scores of the visual indicators; one such variable might be the presence of carbonate rocks [19].

The strong correlation between two highly correlated climate variables could suggest that either one would have the same explanatory potential on the score of the visual soil quality indicators. However, taking the mean annual temperature (T) and evapotranspiration (PET) as an example, although these variables have a strong correlation with one another ($r_s = 0.80$, p-value = 0.00), their correlations with other variables are very different. For example, the aridity index (AI) has a weak correlation with T ($r_s = -0.18$, p-value = 0.04) and a much stronger correlation with PET ($r_s = -0.63$, p-value = 0.00). Thus, depending on the set of climate variables and indices chosen to model the soil response to climate, the relative importances of each variable will change.

Climate governs the soil's moisture and temperature regimes, affecting the soil processes. The soil properties covary differently with climate features and indices. A trend exists for higher SOM content with a higher aridity index in acid soils; in alkaline soils, this positive relationship was observed with mean annual potential evapotranspiration and temperature. Although similar relationships between SOM, AI, and PET are known, e.g., [20], the pattern observed suggests the importance of pH to the microbial community composition [16] and how these different communities relate to climate. On the same note, pH statistically significantly correlates with continentality (GCI) and potential evapotranspiration in acid soils and with all but GCI in alkaline soils. Hence, the magnitude of the soil processes is purportedly affected by climate, and the climate variables that better account for these effects will depend on soil reaction. These relationships merit, per se, further analysis but are out of the scope of the present study. All these relationships result in a high degree of complexity when selecting the variables with potential explanatory value for the scores of the visual indicators.

The relative importances of the explanatory variables. The semi-partial Spearman correlations allowed us to establish the relative importances of the variables but not the measurable effects of each variable on the scores of the visual indicators. The latter can only be accomplished in a definite set of variables by regression analysis, accounting for possible interactions and suppression [6]. In all, soil organic matter (both SOM and LOC) showed dominance over the other soil properties in acid soils, and pH showed dominance in alkaline soils on the scores of the visual indicators. Taken individually, the dominances of other variables on the scores of the visual indicators were observed—e.g., pH dominates other variables in acid soils regarding the "presence of a tillage pan"—in conformity with the soil processes they are assessing. Regarding the example, one may speculate that the changes in the microbial communities as a result of soil compaction and soils' ability to recover are inextricably connected to pH [21]. Soil stability in water seems to be an exception, as the correlation with organic matter is weak (both LOC and SOM), and climate (P and AI), soil texture, and pH in alkaline soils seem to be the variables with higher explanatory value. The correlation between aggregate stability in water and soil organic matter content is frequently reported in the literature, e.g., [5]. The main mechanisms involved are aggregate cohesion, promoted by the binding between organic molecules and clay particles, and aggregate wettability [22]. The data in the present study come from different locations, with contrasting soils and climates, and not from a controlled experiment. The weak correlations observed are, hypothetically, attributable to unknown variables, interactions, or suppression effects. Another lack of conformity seems to be "soil color", an indicator associated with the soil organic matter status. In acid soils, better scores were correlated with depleted SOM and LOC contents, especially the latter, suggesting that soil color might be an indicator of the magnitude of microbial activity rather than SOM content. One might speculate that soil color changes are due to microbial biofilms [23]; furthermore, clay is negatively and moderately correlated with the scores ($r_s = -0.61$), which may further impact microbial activity (see discussion above). In alkaline soils, contrastingly, soil color is positively correlated with LOC and SOM but weakly and positively moderately correlated with precipitation, negatively correlated with pH, and with no correlation with clay, suggesting a different microbial dynamic or other unknown causes.

Regarding the dominance of the climate indices (AI, NPP, and GCI) over the other variables (T, P, and PET), this could be expected because indices integrate more information than a single climate feature, i.e., an index combines climate variables or climate variables and geographic (e.g., latitude), topographical (e.g., altitude), and even biological (e.g., photosynthesis) variables. Regardless of the relation of dominance between the variables, the correlations with the indicators were moderate, weak in some cases, or non-existent. Indicators with weak or non-existent correlations with climate variables—soil structure, porosity, and presence of tillage pan—would suggest a lack of climate effect on the scores or, if there is an effect, that the scores are dependent on interactions between the climate variables. In concomitant work [24], using logistic regression, the interactions between the variables herein were studied, and, with three exceptions (soil structure and soil erosion in alkaline soils and soil stability in acid soils), interactions between climate variables accounted for much of the variation in the scores of the indicators (the interaction model with the highest logistic R-squared (RL2), earthworm count in acid soils, featuring T and P as independent variables and an interaction term (T × P), had an RL2 of 0.72, an increase of 0.53 compared to the RL2 of the model featuring only the main effects).

In a previous study, it was found that soil structure and soil porosity are visual indicators sensitive to soil management practices [25]. In the present work, SOM was found to be a dominant variable regarding porosity in acid soils; similar relationships can be found in the literature, where SOM's relative importance is higher than any other candidate explanatory variable [5,26]. However, the size of the effect of different soil management practices and their interactions with climate and soil properties on the scores of the visual indicators still has to be established. Plausibly, with a dataset of convenient size, these effects can be estimated, and other indicators can be proven responsive. The present work can only **hint** at the soil management practices that enhance the scores of the visual indicators. One such practice is increasing the mass of crop residues left on the fields (or by incorporating it into the soil) [27,28]. In alkaline soils, pH values had negative statistically significant correlations with six indicators, out of eight. Thus, for pH threshold values that are still to be determined, the improvement of the internal drainage and cation lixiviation, accompanied by the increase of SOM and LOC content (e.g., by a higher mass of crop residue left on the field), might be the best soil management strategy. Contrastingly, in acid soils, only the correlation of the "presence of a tillage pan" with pH was statistically significant; SOM and LOC content were dominant properties affecting the scores of the other indicators. Thus, maintaining an adequate mass of plant residues on the fields may lead to better scores of these indicators. Liming to correct soil reaction could be advisable, but only the "presence of a tillage pan" seems to benefit from this practice. However, soil liming may be justifiable if the microbial activity, nutrient cycling, plant nutrient uptake, and toxicity of some metals are issues. Regarding climate effects on the scores of the visual indicators, the positive correlations with P, AI, and NPP and negative correlations with T and PET, within both soil reaction groups, would suggest that practices such as mulching in drier and hotter climates would contribute to better scores (at least for those indicators that had statistically significant correlations with those variables); see [25]. However, as discussed before, the significances of some climate variables explaining the scores of some indicators depend on the values of other variables (i.e., there are interactions). Moreover, the interactions are not limited to climate variables; there are interactions between climate variables and soil properties. The overall effects of the different variables and interactions on the scores of the visual indicators must be modelled. Only then, the unique contributions of each variable can be assessed.

5. Conclusions

We showed with this study that dominance analysis is adequate and meaningful for ranking the explanatory variables of the New Zealand visual indicators (for variable preselection for modelling the scores with, for example, logistic regression). In alkaline soils, soil pH dominated other soil properties for most visual indicators. In acid soils, pH dominated the other variables only for the "presence of a tillage pan"; for most of the other visual indicators, SOM and LOC dominated. For the other soil properties and the climate variables, the magnitudes—or directions or both—of the correlations between variables and between the variables and the scores of the visual indicators were different in acid and alkaline soils. Thus, modelling the scores of the visual soil quality indicators, or simply interpreting the scores, must be in light of soil reaction.

This study covered only a relatively small set of variables that potentially affect the scores of the visual indicators. Thus, other candidate variables should be measured, and their correlations with the visual indicators should be determined, including fractions of the soil organic matter or compounds such as glomalin, climate indices, etc.

Future work will consider the quantification of the effects of the variables on the scores of the visual soil quality indicators, including the long-term effects of the soil management practices.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The author declares no conflict of interest.

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Supplementary

Supplemental Materials: figures and tables.