Geoderma 342 (2019) 93–105

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

Farmers as data sources: Cooperative framework for mapping soil properties for permanent crops in South Tyrol (Northern Italy)

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ARTICLE INFO

Handling editor: Alex McBratney

Keywords:
Integrated farming
Soil data sourcing
Digital soil mapping
Soil texture
Soil organic matter
pH

ABSTRACT

Detailed knowledge of agricultural soil properties is a key element for high-quality food production. However, high-resolution soil data covering a large agricultural region are generally unavailable. This study explores a demand-driven cooperative framework for soil data sourcing that connects individual farmers to several stakeholders by means of a centralised database containing more than 16,000 records of soil information collected within the framework of an integrated production program for intensively managed permanent crops in the Adige/Etsch and Venosta/Vinschgau valleys in South Tyrol, Italy. Data for soil pH, soil organic matter (SOM), and soil texture were used to produce digital soil maps with a RMSE of 0.21, 1.25% and a cross-validation of 43%, respectively. Spatialisation was conducted using either regression-kriging or multinomial logistic regression. Collaboration among farmers, public administrators, and researchers provided a successful cooperative framework for digital soil mapping. The maps highlight the complex interplay of the postglacial evolution of these valleys due to the presence of a cluster of large alluvial fans and the anthropogenic influences of intense farming on pH, SOM, and soil texture. This study regarded a subset of the available soil properties, which can be dealt with using the geostatistical approaches presented herein. Thus, a long-term soil monitoring program and the combination of all available variables will allow digital assessment of the spatial patterns of nutrient availability, ecological risk assessments, change detection studies, and an overall long-term plan for soil security at larger spatial scales.

1. Introduction

Strategies to respond to the growing demands for sustainable agriculture and soil conservation, together with improved food quality, land productivity, and profitability, are present day challenges. Combining these multi-level and multi-functional demands requires action through development of agricultural policies and guidelines applicable to different stakeholders, including food retailers, land managers, and farmers (Foley et al., 2011; Robertson and Swinton, 2005; Tilman et al., 2011). Demand for sustainable foods plays a driving role for farmers to abide by strict regulations. Among the different sustainable farming practices, integrated farming is widely adopted throughout European agriculture (Edwards et al., 1993; Morris and Winter, 1999). In particular, integrated farming promotes the improvement of soil quality via guidelines for optimal soil management (Carter, 2002; Hendrickson et al., 2008). In this framework, farmers collect a large amount of valuable spatio-temporal agronomic data. As done in some citizen science projects for collecting and disseminating soil information (Rossiter et al., 2015), this framework, if properly explored, may turn farmers into a potentially valuable source of knowledge by engaging in interdisciplinary and participative collaborations with the various stakeholders (Bouma, 2015; Bouma et al., 2012). Information of soil chemical and biophysical properties and their spatial variability is a key element in soil management, providing farmers, land managers, and policy makers with valuable knowledge for the effective implementation of sustainable agriculture (Rüdisser et al., 2015; McBratney et al., 2014; Bouma et al., 2012). Moreover, soil information may be of enormous interest among retailers who can

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https://doi.org/10.1016/j.geoderma.2019.02.010
Received 19 June 2018; Received in revised form 1 February 2019; Accepted 4 February 2019

better leverage available data and explore new potential applications as well as pro-active citizens and scholars for creating awareness campaigns and digital technologies (Drakos et al., 2015; Godan, 2015; Woodard, 2016). The most relevant soil properties for optimal soil management are soil texture, soil organic matter (SOM), and pH. Soil texture influences nearly all soil processes and contributes to water, heat, and nutrient fluxes and their holding capacity (Saxton and Rawls, 2006; Grashey-Jansen, 2010). SOM affects soil–water relationships (Bot et al., 2005) and serves as a soil quality and fertility indicator (Herrick, 2000; Lal, 2009). The pH directly affects nutrient availability, nutrient uptake, and heavy metals dissolution, which may be toxic to plants. Thus, non-optimal soil pH can cause plant stress (Läuchli and Grattan, 2017). Available point-wise soil information can be extrapolated in space by means of digital soil mapping (McBratney et al., 2003; Minasny and McBratney, 2016; Robinson and Metternicht, 2006). This technique has been extensively tested by various authors (Scull et al., 2003; Hengl et al., 2004). For continuous variables, such as pH, SOM, and several other chemical soil properties, regression-kriging (RK) has been proven to have good predictive capability (Hengl et al., 2007a, 2004). In contrast, the spatial prediction of categorical variables (i.e., soil texture) can be performed by means of multinomial logistic regression (MLR) (Collard et al., 2014; Hengl et al., 2007b; Kempen et al., 2009). Developing and managing comprehensive datasets are challenging tasks; national-level soil surveying covers the medium to small scales and generates coarse soil maps (Scull et al., 2003), while large-scale soil surveying covers short-distance changes in soil properties (Corstanje et al., 2007) related to geomorphology (Schaetzl and Thompson, 2015) and land use management (Sun et al., 2003). Single institutions collect limited amounts of soil data with high-quality standards and methods, while projects with a citizen scientist approach collect large amounts of data with diverse quality and collection protocols. In the South Tyrol case study, the public administrators and farmers have established a rather interesting long tradition of collaboration. The local public research centre of agriculture and forestry has provided important services (Dalla Via and Mantinger, 2012) to local farmers. As a result, the centre has been recording soil information analysed with reliable standards and protocols for decades. In this study, a demand-driven cooperative and iterative framework for soil data sourcing and management is explored. Integrated farming guidelines address the demand for sustainable agricultural practices, which are achieved via collaborative cooperation between farmers, public administrators, and research scientists. Hence, this research study aims to (i) present a promising demand-driven framework that foresees farmers as data sources of spatial soil information in intensively managed permanent crops in South Tyrol; (ii) show the applicability of a high-density soil database to the production of accurate digital soil maps; and (iii) present and briefly discuss the produced maps of pH, SOM, and soil texture.

2. Materials and methods

2.1. Study area

This study covered the Venosta/Vinschgau and Adige/Etsch valleys in the Province of Bolzano/Bozen, South Tyrol, Italy (Fig. 1). South Tyrol lies on the southern side of the main Alpine ridge. The area has a typical continental Alpine precipitation regime, with low total annual precipitation (450–850 mm) (Hydrographic Office, South Tyrol). The prevalent soil types on hillsides are Leptosols and Cambisols, while in the valley floor they are gleyic Cambisols (partially calcaric), Fluvisols, or Gleysols (Grashey-Jansen and Schröder, 2009; IUSS Working Group WRB, 2014). South Tyrol is Europe's largest apple-growing area spreading over nearly 19,000 ha, while vineyards cover about 5500 ha. The rest of the agricultural land is covered by pastures (nearly 120,000 ha), meadows (nearly 70,000 ha), and other cultures (nearly 15,000 ha) (Agricultural Office, South Tyrol). Overall, 22.5% of the land surface is used for agriculture (Tasser et al., 2008).

2.2. Soil sample data sourcing

In South Tyrol, viticulturists do not follow specific guidelines for soil management, while apple farmers conduct integrated farming and follow precise guidelines and regulations that prescribe soil sampling every 5 years (AGRIOS, 2018). Notwithstanding, about 70% of all the farmers in South Tyrol send soil samples to the Public Research Centre of Agriculture and Forestry, Laimburg; the other 30% send them to smaller local laboratories, and thus these soil data may be difficult to access. Data used in this study is publically available upon request and registration at the Research Centre for Agriculture and Forestry, Laimburg, Bolzano/Bozen, Italy. The license agreement prevents commercial use, while consent use of the data for research, educational and dissemination purposes. Derivative and aggregated products can be published if they do not contain cadastral parcel code in order to keep farmers data anonymous. Data refer to soil properties for apple orchards and vineyards located in the Venosta/Vinschgau and Adige/Etsch valleys and analysed by the Laimburg laboratory during the period 2006–2013. Farmers collected a minimum of 15 soil subsamples from within each parcel at the same profile depth (0–20 cm) and 1 kg of mixed soil material was submitted to the laboratory. Determination of pH and chemical composition was analytical, while textural classes were defined by feel (Thien, 1979) according to the German classification (AD-HOC AG, 2005), (Table 1). Each sample was identified with a unique cadastral parcel code but not with geographical coordinates; matching with an open-source cadastral map (OpenKat, 2018) allowed us to georeference the samples using the coordinates of the centroid of the corresponding cadastral parcel. Soil samples were ignored by the study if a mismatch between the reference parcel code of the soil sample database and the cadastral maps occurred. Finally, the dataset comprised 16,139 sample points. Among many soil properties available, this research focuses on pH, SOM, and soil texture of topsoil (0–20 cm) samples (Table 1).

2.3. Spatial analysis

2.3.1. Modelling framework

For each soil sample, two types of variables were investigated: numerical (pH and SOM) and categorical (soil texture). Thus, two different interpolation methods were chosen to spatialize the studied variables: RK for pH and SOM (Hengl et al., 2007b) and MLR for soil texture classes. Because kriging estimators are sensitive to out-of-normality datasets (Lark, 2000), numerical pH and SOM variables were investigated for normality and log (Mcgill et al., 1978). The spatial analysis steps used in this paper follow the framework described in (Hengl, 2009, 2007). The GSIF R package (Hengl et al., 2016) has been used as the main tool for the spatial prediction.

2.3.2. Auxiliary variables

Several covariates were sourced and assessed for significant correlation with the selected soil properties: a digital terrain model (DTM) at 25 × 25 m grid size (Geocatalogo, 2018); Slope at 25 × 25 m grid size (Geocatalogo, 2018). Moreover, to distinguish the influence of bedrock and sediment transport, three different maps were derived from the geological map (Geocatalogo, 2018; ISPRA-Servizio Geologico, 2010), representing the topographic distance from the main geological units (i.e., sedimentary, metamorphic, and volcanic). The valley bottom maps were derived by a map of areas prone to flood events (Geocatalogo, 2018); the map clearly distinguishes the alluvial flood plain from alluvial fans. This map was converted into two binary maps. The first map showing the areas at the bottom of the valley (the alluvial plain) and the second map referring to the areas not at the bottom of the valley (alluvial fan and side slope, respectively). A detailed land use map (LISS, 2013) was converted into two binary maps distinguishing

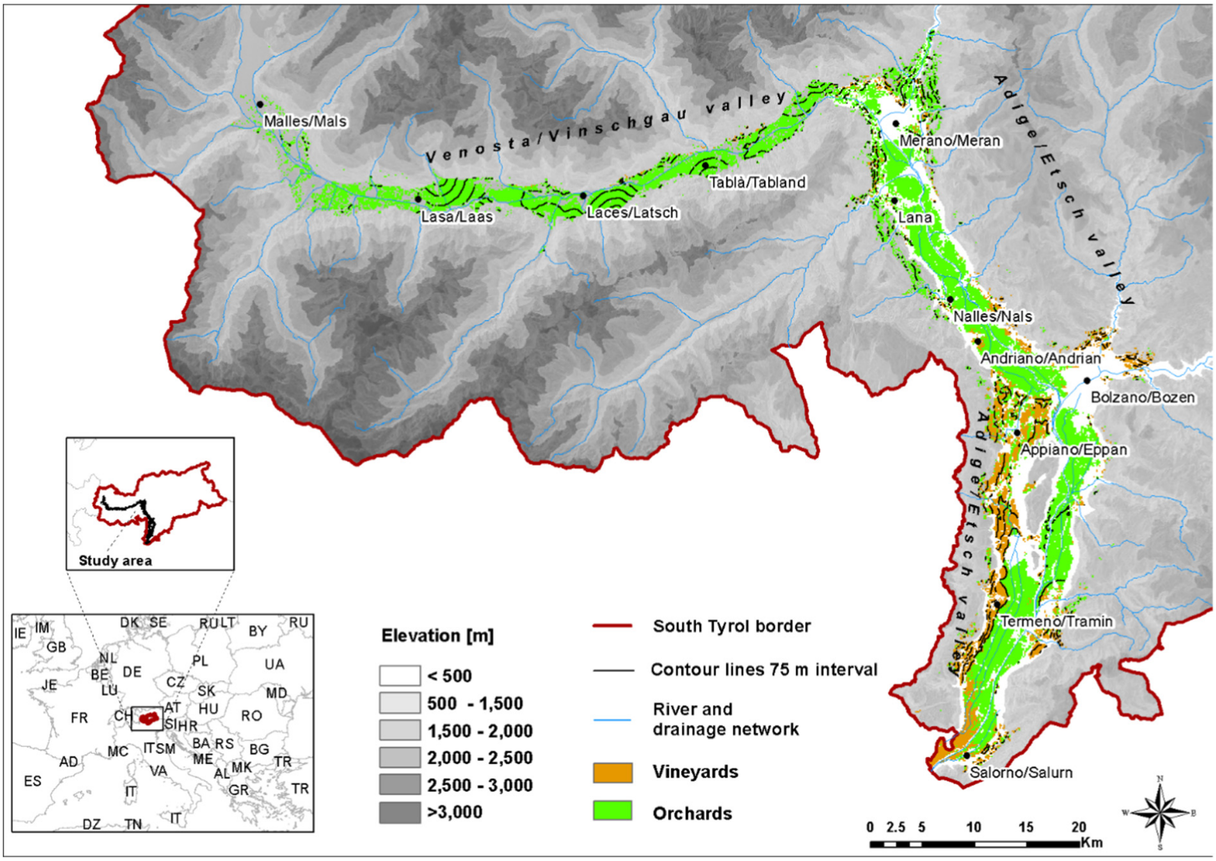

Fig. 1. Study area in the Venosta/Vinschgau and Adige/Etsch valleys in South Tyrol, Italy. Contour lines highlight topographic features such as alluvial fans and side slopes in the study area.

Table 1
Parameters measured in topsoil (0–20 cm): analysis methods (VDLUFA, 1991), units, and variable type. ICP-OES: inductively coupled plasma–optical emission spectrometry; CAL: calcium acetate-lactate; CAT: CAT method (extraction solution: 0.01 M CaCl2 + 0.002 M DTPA-solution). Textural classes were defined by feel according to the German classification (AD-HOC AG Boden, 2005). *Note that this is a comprehensive list of the variables available, as only pH, SOM, and soil texture are considered in this study.

Parameter	Analysis method	Units	Variable type
*pH	CaCl2 glass electrode	–	Numerical
*SOM	Elemental analysis	%	Numerical
*Soil texture	Feel test	Soil texture class	Categorical
P_2O_5	CAL colorimetry	mg/100 g	Numerical
K_2O	CAL flame photometry	mg/100 g	Numerical
Mg	CAT ICP-OES	mg/100 g	Numerical
Bor	CAT ICP-OES	mg/kg	Numerical
Mn	CAT ICP-OES	mg/kg	Numerical
Cu	CAT ICP-OES	mg/kg	Numerical
Zn	CAT ICP-OES	mg/kg	Numerical

between vineyards and apple orchards. Because the soil samples were sampled from apple orchards and vineyards, other reported land uses (LISS, 2013) were masked out before carrying out spatial predictions in order to produce consistent digital soil maps. To reduce the multicollinearity effect, a principal component analysis (PCA) on the covariates was performed (Jolliffe, 2011). The transformed components were used for regression predictions (Hengl, 2007). Raster covariates were first overlaid on the land use map (apple orchards and vineyards), centred on the mean, and normalised between 0 and 255. Ilwis software (Gorte et al., 1988) was used to perform both normalization and PCA computation.

2.3.3. Spatial prediction of soil properties

Values for pH and SOM were spatialized using RK. In RK, the regression modelling is combined with kriging modelling of variograms for regression residuals, which are then interpolated and added to the regression estimate (Hengl et al., 2004). A machine learning random forest algorithm was chosen for regression (Liaw and Wiener, 2014) and ordinary kriging was chosen for the interpolation of residuals (Pebesma and Wesseling, 1998). Model fitting and predictions were performed with the GSIF R package using the fit.gstatModel() and predict.gstatModel() functions (Hengl et al., 2016). Soil texture was spatialized using MLR, which is a generalization of the logistic regression analysis to multiple events/categories (Venables and Ripley, 2002). This was achieved with the function spmultinom() within the GSIF R package (Hengl et al., 2016), which uses the multinom() function from the nnet R package (Ripley and Venables, 2016). The final spatial resolution is 25 m × 25 m (Hengl, 2006). Accuracy of the digital maps of pH, SOM and soil texture was assessed by 5-fold cross-validation by means of R^2 and root-mean square error for pH and SOM and k statistic for soil texture. Misclassification of the soil texture was determined by confusion matrix. Similarly to (Rossiter et al., 2017), to assess the weight of misclassification of the soil texture classes, Euclidean distance between soil texture classes centroid was computed.

3. Results

3.1. Farmers' data sourcing and exploratory statistic

The links among demand for sustainable agriculture, agronomic guidelines, and digital soil mapping using the farmers as a data source was explored and appears to be a promising cooperative framework, as synthesized in Fig. 2. This demand-driven framework highlights the

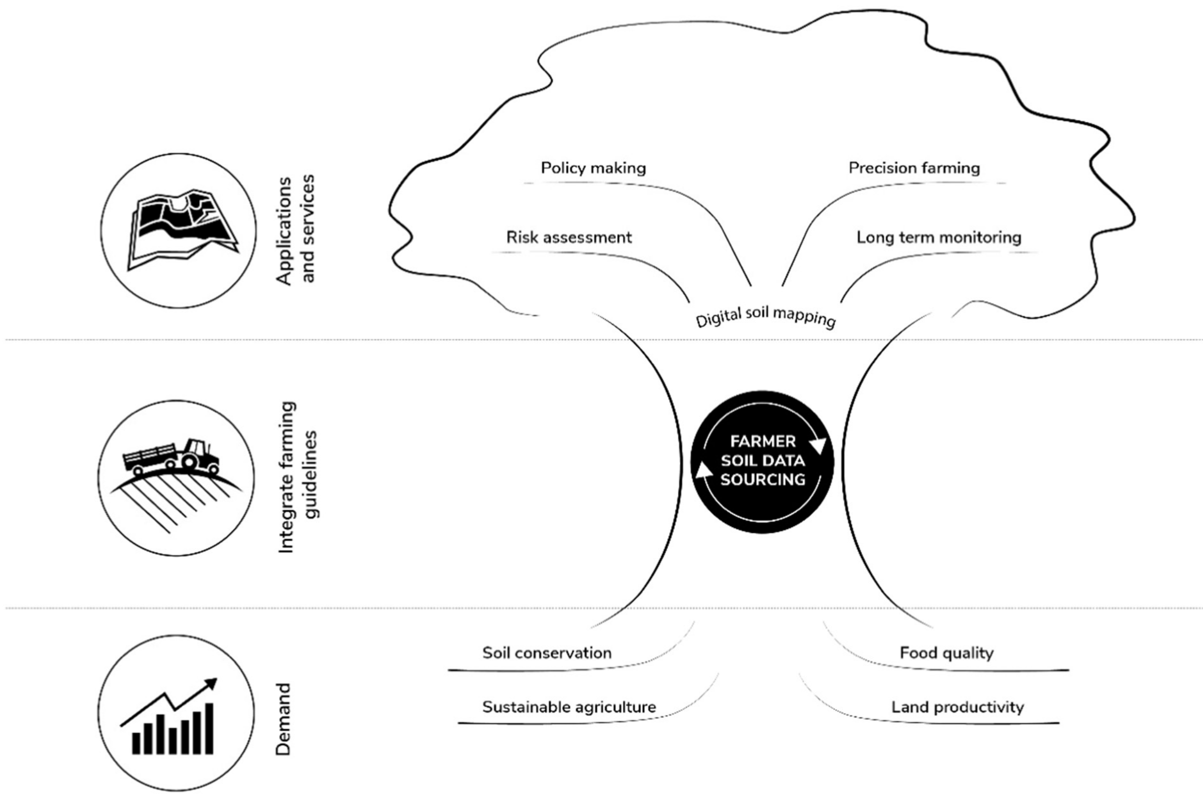

Fig. 2. Demand-driven cooperative framework. Market demand for food quality and stakeholder demand for maintaining soil functions have led to the development of sustainable agriculture regulation. Integrated farming guidelines for soil management implemented by farmers, combined with a centralised spatial data infrastructure, can provide further applications and services.

fundamental role of farmers as providers of a suite of crucial data at an optimal resolution to support decision-making and sustainable crop management.

The total number of samples was 714 (4.42%) for the vineyards and 15,425 (95.58%) for the apple orchards (Fig. 3). For the latter, the sample density ranged from 0 to 239 points/km^2 with an average of 62 points/km^2, while in vineyards, the sample density ranged from 0 to 174.3 points/km^2 with an average of 24.9 points/km^2. The mean sample density for the entire dataset is 54 points/km^2, with each single soil sample representing on average 0.5 ha with a mean distance of 136 m (Fig. 3).

None of the continuous variables were normally distributed (Table 2). Soil pH ranged from 4.2 (very acidic) to 8.1 (moderately alkaline), with a median of 6.9. Soil pH showed a low relative variability with a coefficient of variation (CV) of 7.4% and quasi-normal distribution with a moderate negative skewness of −0.93. SOM ranged from 0.2% to 45.7%, with median of 4%. The large skewness of 3.86 and high relative variability of 52.8% in SOM is due to the presence of extreme values on the far-right side of the distribution. Log-transformations of the data are represented in Table 2. The logarithm of pH (log pH) slightly increased the skewness to −1.2, while logarithm of SOM (log SOM) reduced the skewness of −0.56. Shapiro-Wilk test indicates that transformed and raw data are not normal distributed. Finally, pH and log SOM were adopted in the RK.

According to the German classification (AD-HOC AG Boden, 2005), soil texture is represented by 11 categories in the study area (Fig. 4). The most observed soil texture class is medium loamy sand (Sl3) with 35.78% followed by medium silty sand (Su3) with 19.17%, slightly loamy sand (Sl2) with 15.8%, sandy silt (Us) with 15.68%, medium clayey silt (Ut3) with 6.05%, and medium sandy loam (Ls3) with 3.40%. These six soil texture classes together cover more than 95% of all the soil samples (Table 3).

3.2. Spatial modelling

To account for multicollinearity, a PCA is computed for pH and SOM predictors prior to RK, as well as for soil texture predictors prior to LMR. PCA results for pH and SOM and for soil texture are presented in Tables X. The first three principal components (PCs) for pH and SOM and soil texture together explain 91.61% of the variance (Table 4). The PC1 distinguishes orchards at the valley bottom from vineyards on the valley sides, PC2 reflects the flood area, and PC3 takes into account geology and land use aspects.

The RK model parameters and cross-validation outcomes are reported in Table 5. The regression model explained 61% of the variance for pH and 40% of the variance for SOM. The mean of squared residuals is 0.0023 and 0.1434, respectively, indicating higher regression errors for SOM. The nugget value is small for pH and higher for SOM, while ranges are similar at 1690 m and 1230 m, respectively. Partial sill and nugget have similar values for both pH and SOM, suggesting a weak spatial autocorrelation. RK performed better for pH than for SOM given their overall accuracies of 82% and 68% (Table 5), respectively. The multinomial logistic model for soil texture returned an overall accuracy of 42.76% (Table 5). Confusion matrix between true and predicted soil texture classes are reported in Table 6, while the weight of the misclassification in terms of distance between soil texture classes are presented in Table 7. The confusion matrix highlights Sl3 and Su3 as the best predicted soil texture class with 72.6% and 52.4% accuracy, respectively, with main misclassification assigned to the most similar classes. The slightly loamy sand (Sl2), highly loamy sand (Sl4) and loamy silty sand (Slu) were entirely misclassified. Slightly loamy sand (Sl2) and highly loamy sand Sl4 were assigned to the nearest medium loamy sand (Sl3) and medium silty sand (Su3). Loamy silty sand (Slu) was entirely and largely misclassified after it was assigned to the relatively farthest classes. Sandy silty (Us) has an accuracy of 27.8% and presents a relatively large misclassification error as it is assigned mainly

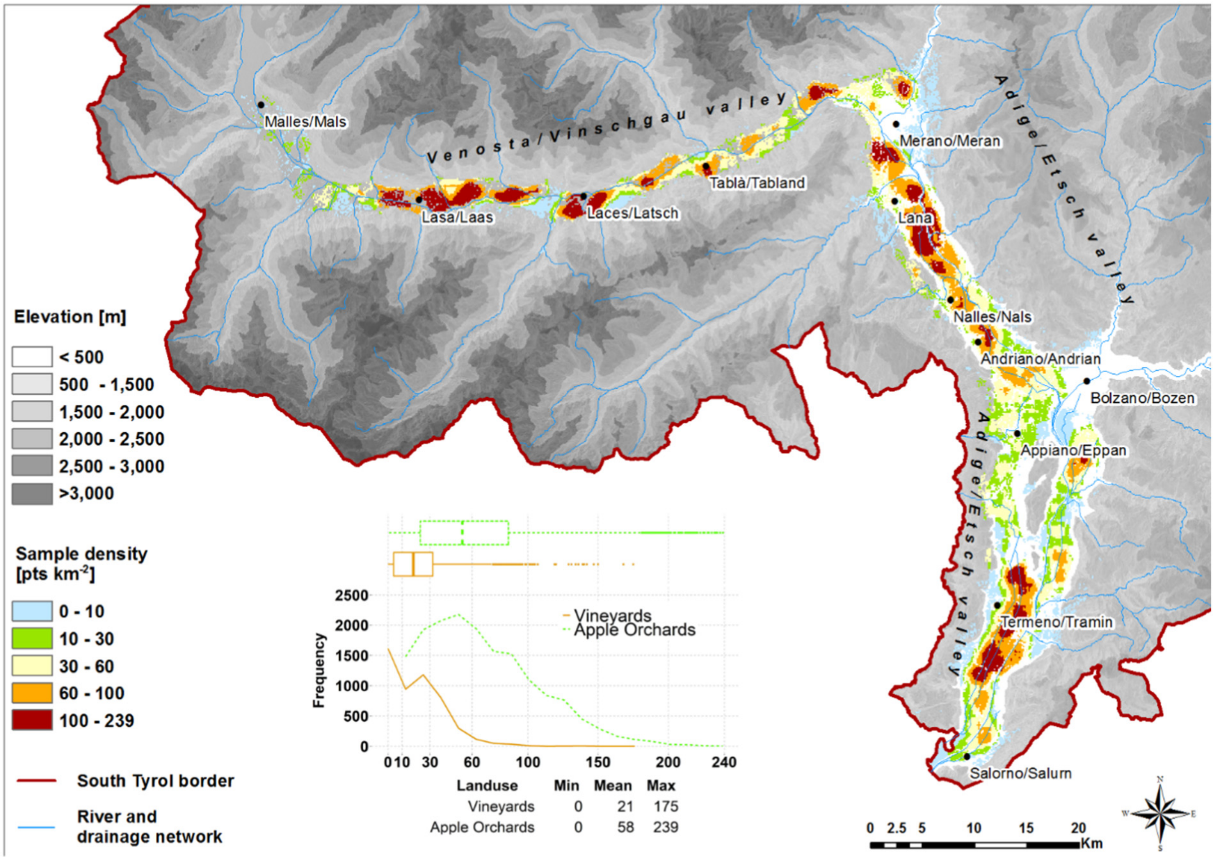

Fig. 3. Soil sample density and distribution. The samples are unevenly distributed between the two farmland uses, with orchards representing more than 95% of the total samples.

to medium silty sand (Su3) and medium loamy sand (Sl3).

3.3. Topsoil property maps

The results of the spatial prediction are the maps of pH, SOM, and soil texture shown in Figs. 5, 7, and 9, respectively. The map distribution of pH, SOM, and soil texture with respect to their predictors are presented in Figs. 6, 8, and 10, respectively.

Predicted pH values (Fig. 5) range from moderately acidic (pH 5.5–6.0) with a minimum pH of 5.16 in apple orchards, to slightly acidic (pH 6.0–6.5), neutral (6.5–7.3), and slightly alkaline (pH 7.3–7.8), with a maximum pH of 7.96. Both land uses cover the entire pH spectrum, but apple orchards show a bimodal distribution with two peaks at neutral and slightly acid values. Soil pH in vineyards shows smaller variability and a unimodal distribution with a peak at neutral values. Both vineyards and apple orchards have very similar mean pH of 6.80 and 6.77, respectively. Slightly alkaline pH is found in flat valley bottoms near calcareous metamorphic rocks, where past floods deposited carbonates (Fig. 6) and in the northwestern part of the Venosta/Vinschgau Valley in the high-altitude apple orchards. Slightly alkaline soil is also present in some small and localized hotspots in the southern part of the Adige/Etsch Valley. Neutral pH characterizes the study area among diverse altitudinal and slope ranges as well as in the valley bottoms and in some alluvial fans of the Adige/Etsch Valley (Fig. 6). The alluvial fans show slightly and moderately acid pH owing to their silicate parent materials.

The SOM spatial distribution is shown in Fig. 7. SOM spatial patterns are quite heterogeneous in the Venosta/Vinschgau Valley, while they are more defined in the Adige/Etsch Valley. SOM frequency distribution (Fig. 7) presents larger variability in apple orchards, with minimum and maximum values of 0.98% and 24.39%, respectively, than the variability in vineyards, with minimum and maximum values of 1.29% and 10.17%, respectively. Vineyards and apple orchards have similar mean values of 4.14 and 4.29%, respectively. Low SOM values between 0% and 2% are found in the southern Adige/Etsch Valley in the valley bottom along the Adige/Etsch River (Fig. 8). SOM most frequently ranged between 2% and 6% across the study area, and it was generally lower in the Adige/Etsch Valley and higher in the Venosta/

Table 2
Descriptive statistics of the original dataset (raw and log-transformed data) for pH and SOM. The table shows the statistical summary for pH and SOM. Min.: minimum value. Q1: first quartile value. Median: median value. Q3: third quartile value. Max.: maximum value. Skew.: Skewness. CV: Coefficient of variation. W: Shapiro-Wilk test. p-value: Probability value.

									Shapiro-Wilk test	
	Min.	Q1	Median	Mean	Q3	Max.	Skew.	CV	W	p-Value
pH	4.2	6.5	6.9	6.77	7.1	8.1	−0.93	7.44	0.9639	0.043
SOM [%]	0.2	3	4	4.39	5.3	45.7	3.86	52.8	0.7856	1.65e-14
Log pH	1.44	1.87	1.93	1.91	1.96	2.09	−1.2	4.07	0.9376	0.002
Log SOM [%]	−1.61	1.1	1.39	1.36	1.67	3.82	−0.56	36.17	0.9816	0.023

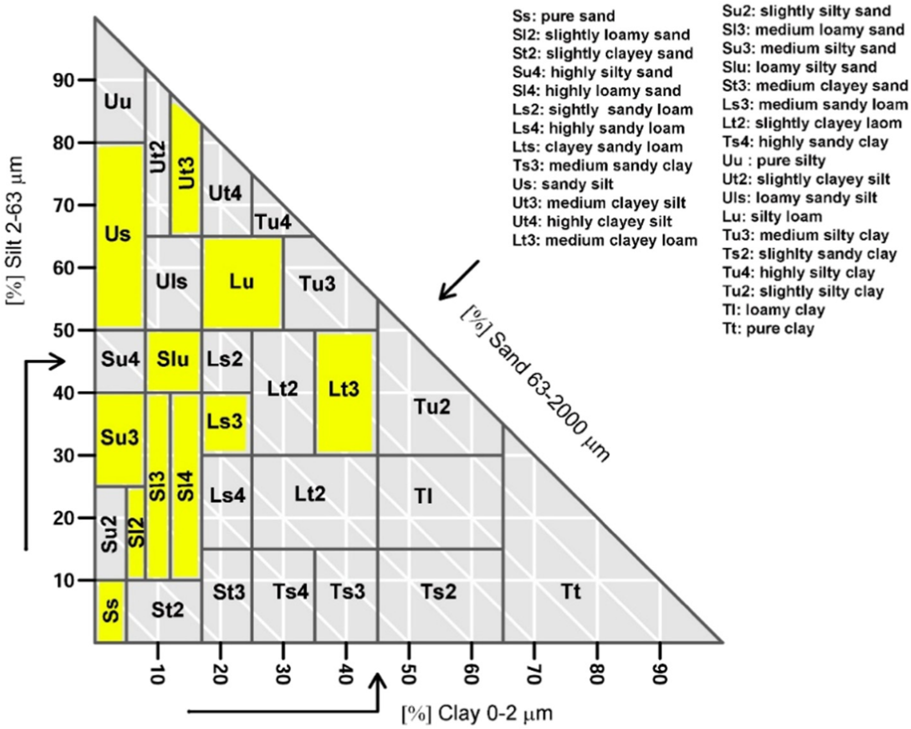

Fig. 4. Soil sample texture classes according to AD-HOC AG Boden (2005). T = Clay, S = sand, U = silt, L = loam. 2 = slight, 3 = medium, 4 = high. The soil texture classes sampled in the study area are highlighted in yellow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Percent distribution of soil sample texture classes according to AD-HOC AG Boden (2005). In the study area, 11 soil texture classes were found. Loamy sand soils (Sl3, Sl2) are the most representative, followed by silty sandy soils (Su3) and sandy silt (Us).

Soil texture classes (Ad-hoc-AG Boden)	Percent [%]	Cumulate Percent [%]
Ss - pure sand	0.01	0.01
Sl2 - slightly loamy sand	15.80	15.81
Sl3 - medium loamy sand	35.78	51.59
Su3 - medium silty sand	19.17	70.76
Sl4 - highly loamy sand	0.44	71.20
Ls3 - medium sandy loam	3.40	74.60
Slu – loamy silty sand	2.13	76.75
Lt3 - medium clayey loam	0.02	76.75
Us - sandy silt	15.68	92.43
Lu - silty loam	1.52	93.95
Ut3 - medium clayey silt	6.05	100

Vinschgau Valley. SOM between 6% and 10% was mostly located on side slopes at higher elevation in the Adige/Etsch Valley, while it was mostly located on alluvial fans in the Venosta/Vinschgau Valley (Figs. 7 and 8). Values of SOM above 10% are found at higher altitude in the upper part of the Venosta/Vinschgau Valley, mostly in the valley bottom and alluvial fans close to metamorphic rocks.

The soil texture composition changes from upstream (upper part of Fig. 9) to downstream (lower part of Fig. 9). Medium loamy sand (Sl3), medium silty sand (Su3), and sandy silt (Us) together represent more than 90% of the study area. Vineyards and apple orchards are mostly grown on medium loamy sand (Sl3) (statistics in Fig. 9). Upstream, the Venosta/Vinschgau Valley presents sandy silt (Us) soils followed downstream by medium loamy sand (Sl3) soils. The northern part of the Adige/Etsch Valley shows medium silty sand (Su3) soils in the valley bottom and medium loamy sand (Sl3) on the side slopes and alluvial fans. In the southern part of the Adige/Etsch Valley, soil classes downstream typically represent finer material, such as sandy silt (Us) and medium clayey silt (Ut3) soils. Side slopes of the southern part of the Adige/Etsch Valley present medium sandy loam (Ls3) soils. Medium loamy sand (Sl3) soils are generally closer to metamorphic and volcanic rocks and further away from sedimentary rocks (see Fig. 10). Moreover, these soils are mostly localized in the Venosta/Vinschgau Valley in the valley bottom, as well as on the large alluvial fan and in the Adige/Etsch Valley in alluvial fan areas, as well as on the Appiano/Eppan plateau above the valley bottom. Medium loamy sand (Sl3) soil is found more frequently in the Adige/Etsch Valley in the flat valley bottom close to volcanic and sedimentary rocks (Fig. 10). Medium sandy loam

Table 4
Soil predictive components for soil texture. Var. is the variance explained by each single PC, DTM is digital terrain model, Slope, Dist. from Sed. is distance from sedimentary rocks, Dist. from Met. Is distance from metamorphic rocks, Dist. from Volc. Is distance from volcanic rocks, bottom valley is a binary map that excludes side slopes and alluvial fans, and not bottom valley is a binary map that excludes flood plains. Land use orchard and vineyard are binary maps that respectively define the land use.

	Var.	DTM	Slope	Dist. from Sed.	Dist. from Met.	Dist. from Volc.	Valley bottom	Not valley bottom	Land use orchard	Land use vineyard
PC1	56	0.246	0.12	0.243	0.232	0.162	0.371	0.415	0.104	0.682
PC2	23.18	0.183	0.175	0.062	−0.051	0.022	−0.591	0.66	0.302	−0.233
PC3	12.43	0.202	−0.07	0.222	−0.544	0.139	−0.328	−0.009	−0.629	0.292
PC4	4.23	0.437	0.033	0.378	−0.35	0.403	0.277	−0.243	0.366	−0.332
PC5	1.56	0.408	−0.249	−0.382	0.48	0.552	−0.186	−0.092	−0.205	−0.074
PC6	1.24	0.292	0.758	−0.523	−0.181	−0.08	0.098	−0.109	−0.062	0.051
PC7	0.88	−0.201	0.547	0.529	0.441	0.171	−0.181	−0.208	−0.249	−0.139
PC8	0.47	0.618	−0.115	0.216	0.26	−0.672	−0.043	−0.141	−0.1	−0.084

Table 5
RK and MLR parameters and cross-validation. GoF: goodness of fit, Mean sq. res.: mean squared residuals, Var. expl.: variance explained, Psill: (partial sill) value of semivariance at which stationary trend is reached, Nugget: value of semivariance at distance zero, Range: distance at which 95% of the Psill is reached, Cross. Val.: cross validation.

	GoF		Regression model		Variogram parameters			
Variable	RMSE	R^2	Mean sq. res.	Var expl.	Model	Nugget	Psill	Range
pH	0.21	82%	0.1	61.75%	Exponential	0.05	0.07	259,443
SOM	1.25	68%	0.15	39.86%	Exponential	1.97	1.51	667
	Cross. Val.							
Soil texture	42%							

(Ls3) is localized in the southern part of the Adige/Etsch Valley on higher side slopes, near sedimentary and volcanic rocks. Sandy silt (Us) is located in the flat valley bottom of two distinct regions of the study area, that is, the northern-west part of the Venosta/Vinschgau Valley and the southern part of the Adige/Etsch Valley.

The spatial distribution of pH, SOM, and soil texture in the study area are the result of the complex interplay between its postglacial evolution, geomorphology, geology, and the more recent impact of intensive agriculture. To better depict common patterns and relations, the three maps in Fig. 11 were synthesized. Neutral pH (6.5–7.3) covers 72.2% of the total area, generally in the valley bottom, and is represented for 41% by SOM 2–4%, 23.9% by SOM 4–6%, and 5.6% by SOM 6–8%. Neutral pH is mostly on medium silty sand (Su3) and medium loamy sand (Sl3) (Fig. 11g, m, and q). Slightly acidic (pH 6.0–6.5) and moderately acidic (pH 5.5–6) soils cover 23.82% and 1.40% of the total area, respectively, and they are associated with alluvial fans owing to the respective silicate parent material. Similarly to neutral pH, slightly acid and moderately acid pH soils have SOM content ranging from 2% to 8% with soil texture being medium loamy sand (Sl3) (Fig. 11f, l, and p). Moderately acidic soils are absent at the lowest and highest SOM class and are found on medium loamy sand soils and marginally on medium silty sand (Fig. 11a and z). Slightly alkaline pH soils cover 2.49% of the total surface on sandy silt (Us) soils with SOM content being mostly 2–6% (Fig. 11h and n). Finally, 93.4% of the total study area refers to SOM classes between 2% and 8% with neutral or slightly acidic soils with texture classes being comprehensively represented (Fig. 11f, g, l, m, p, and q).

4. Discussion

4.1. Farmer data sourcing

Soil science research produces large knowledge bases that sometimes are disconnected from real practices in farming fields. Knowledge and data collected by farmers during their agronomic practices are often not shared between "neighbours." Demands by regulatory bodies for sustainable agriculture and their sustainable management guidelines can operate as interlinks and driving forces for fruitful cooperation between farmers (as data sources) and soil scientists (Bouma, 2001). This cooperation can be realized through a centralised database for soil information and can promote a successful framework for extensive and long-term soil monitoring in agricultural areas. The framework would allow studies of spatial patterns and trends, which are much more valuable than disentangled point-wise knowledge. Moreover, coupling this demand-driven cooperative framework with participatory approaches would eventually raise awareness and stress the importance of the role of each stakeholder toward sustainable agriculture (Bouma et al., 2012). However, the soil data used in this study were available only thanks to an ad-hoc agreement, hence, is not publicly available. In this context, the authors intend to proactively stimulate the debate on this issue and promote opportunities for data sharing among various stakeholders (Bouma, 2001). This study highlights that the framework allowed the management of a large dataset of soil properties, with an average density of about 50 soil samples/km^2. Moreover, the relative sample density will increase over time, and so will map accuracy as a consequence. Nevertheless, the highest sample density was in apple orchards, while vineyards had generally lower sample density. This is due to the soil management guidelines for

Table 7
Normalised Euclidean distance of soil texture classes by means of their particle size fraction centroid.

	Normalised Euclidean distance								
	Sl2	Sl3	Su3	Sl4	Ls3	Slu	Us	Lu	Ut3
Sl2	0	0.16	0.22	0.23	0.45	0.50	0.74	0.82	1.00
Sl3	0.16	0	0.11	0.08	0.30	0.34	0.60	0.66	0.85
Su3	0.22	0.11	0	0.16	0.30	0.30	0.52	0.63	0.79
Sl4	0.23	0.08	0.16	0	0.23	0.30	0.57	0.60	0.80
Ls3	0.45	0.30	0.30	0.23	0	0.15	0.42	0.38	0.60
Slu	0.50	0.34	0.30	0.30	0.15	0	0.28	0.33	0.50
Us	0.74	0.60	0.52	0.57	0.42	0.28	0	0.28	0.30
Lu	0.82	0.66	0.63	0.60	0.38	0.33	0.28	0	0.24
Ut3	1.00	0.85	0.79	0.80	0.60	0.50	0.30	0.24	0

Table 6
Confusion matrix expressed in percent between true and predicted soil texture classes.

		True								
		Sl2	Sl3	Su3	Sl4	Ls3	Slu	Us	Lu	Ut3
Predicted	Sl2	**0.0%**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Sl3	60.7%	**72.6%**	28.6%	64.3%	61.3%	47.0%	25.4%	14.0%	9.6%
	Su3	29.2%	19.3%	**52.4%**	21.4%	11.3%	25.8%	39.2%	36.0%	47.5%
	Sl4	0.0%	0.0%	0.0%	**0.0%**	0.0%	0.0%	0.0%	0.0%	0.0%
	Ls3	0.2%	1.3%	0.3%	0.0%	**9.4%**	7.6%	0.4%	16.0%	1.0%
	Slu	0.0%	0.0%	0.0%	0.0%	0.0%	**0.0%**	0.0%	0.0%	0.0%
	Us	8.1%	6.4%	13.6%	14.3%	16.0%	15.2%	**27.8%**	12.0%	33.8%
	Lu	0.0%	0.1%	0.0%	0.0%	0.0%	1.5%	0.2%	**6.0%**	0.5%
	Ut3	1.8%	0.4%	5.1%	0.0%	1.9%	3.0%	7.1%	16.0%	**7.6%**

The values in bold represent the percentage of the soil texture classes correctly predicted.

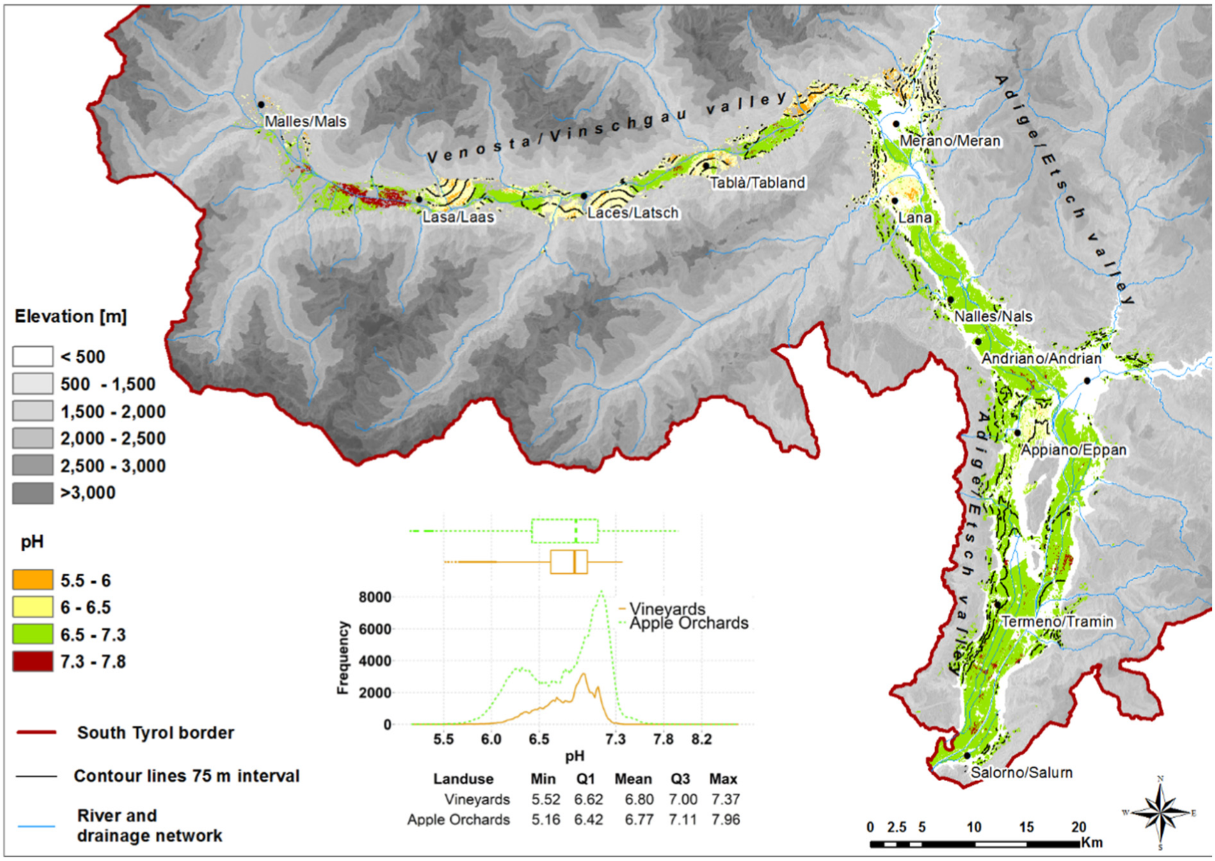

Fig. 5. Topsoil pH map. The lower part of the map shows the frequency distribution subdivided by land use. Contour lines highlight topographic features such as alluvial fans and side slopes in the study area.

integrated fruit production (AGRIOS, 2018). Adopting similar guidelines for vineyards would greatly improve data amount and spatial distribution, hence improving soil mapping spatial prediction. However, apple orchards still represent 80% of the permanent crop fields in South Tyrol. Soil sampling repetition and analyses, which occur on a 5 yearly basis, are an ideal framework for long-term soil monitoring (Morvan et al., 2008; Nerger et al., 2016). The systematic monitoring of all the available soil variables is fundamental for detection of changes in soil physical and chemical properties, hence soil quality (Bünemann et al., 2018). Detection of changes in soil quality will promote design of specific policy measures for a sustainable use of soil.

4.2. Spatial analysis

Regression models can be used for spatial prediction if independent variables, called predictors, are available, and a correlation between dependent and independent variables is found. The predictors selected in this study proved to be reliable and their PCs adequately identified environmental characteristics such geomorphology, geology, and fluvial transport. On the one hand, MLR is a form of regression equation predicting the probability of category membership on a dependent variable based on multiple independent variables (Kwak and Clayton-Matthews, 2002). On the other hand, RK intermixes regression with spatial autocorrelation of the variable to be interpolated (Hengl et al., 2004). This approach worked best in this research with numerical variables, where correlations between the chosen predictors and pH and SOM were found, though random patterns were still present. Kriging interpolation of residuals improved regression performance for both pH and SOM despite regression residuals having a weak autocorrelation; therefore, kriging helps us deal with spatial stochasticity. The accuracy of kriging models requires a sound sample design in terms of quality, number, and spatial distribution (Hengl et al., 2007a). The high sample number and density in this study ensure satisfactory performance of the interpolation models (Stahl et al., 2006; Webster and

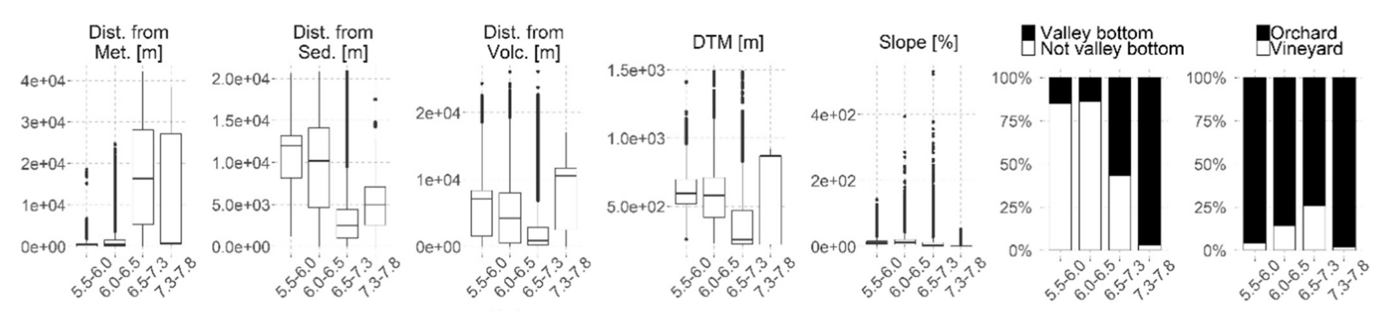

Fig. 6. Synthesis of how the pH soil property map is distributed among the different predictors.

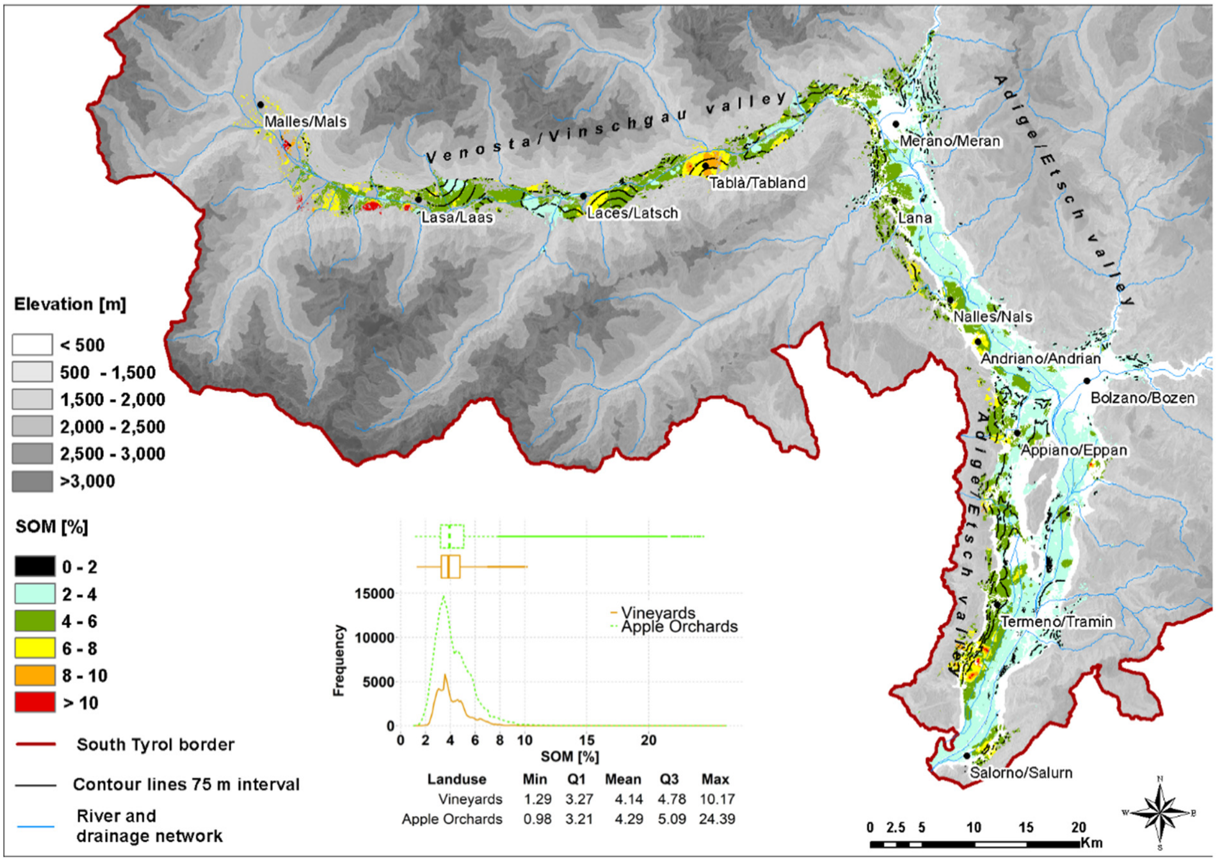

Fig. 7. Topsoil map of SOM (%).The lower left portion maps the frequency distribution according to land use. Contour lines highlight topographic features such as alluvial fans and side slopes in the study area.

Oliver, 1992). RK and MLR could lead to artefacts when predictors and their PCAs show unreliable patterns (Hengl et al., 2007a), but the quality of the selected predictors avoided such issues. For pH and SOM maps, performance of RK proved to be comparable with that of previous studies (Kumar et al., 2012; Zhu and Lin, 2010). MLR was biased by unbalanced proportion of samples (Debella-gilo and Etzelmüller, 2009; Real et al., 2006). That could be the reason for the higher prediction performance on classes with a higher number of samples. MLR assigned the Sl2 (slightly loamy sand) texture class almost entirely to the Sl3 (medium loam sand) class. These two classes represent 15.80% and 35.78% of the survey's samples, respectively. As a result, the Sl2 class is excluded from the final map and its accuracy is computed as zero, also affecting the overall accuracy of the map. For these reasons, soil texture spatial prediction showed a lower accuracy in comparison with what is generally presented in the literature (Hengl et al., 2007b).

4.3. Soil property maps

The results presented in this work show the complex interplay of postglacial evolution, geomorphological processes, and anthropogenic influences on the variability of pH, SOM, and soil texture in the study area. The large number of samples combined with good spatial distribution and proper predictors have contributed to the robust estimation of soil pH and SOM patterns, while the overall accuracy of the predicted soil texture map is less satisfactory. The feel test for soil texture classification, despite being an empirical method, proved to be sufficiently accurate and could replace laboratory analysis for soil mapping purposes (Vos et al., 2016). Moreover, while chemical properties change over time, in dam-regulated networks like the Adige/Etsch River, soil texture generally maintains its properties. Since soil texture data almost doubles in quantity every 5 years, the accuracy of future soil texture spatial predictions is expected to improve. A general limitation of the presented results is that they refer only to the topsoil.

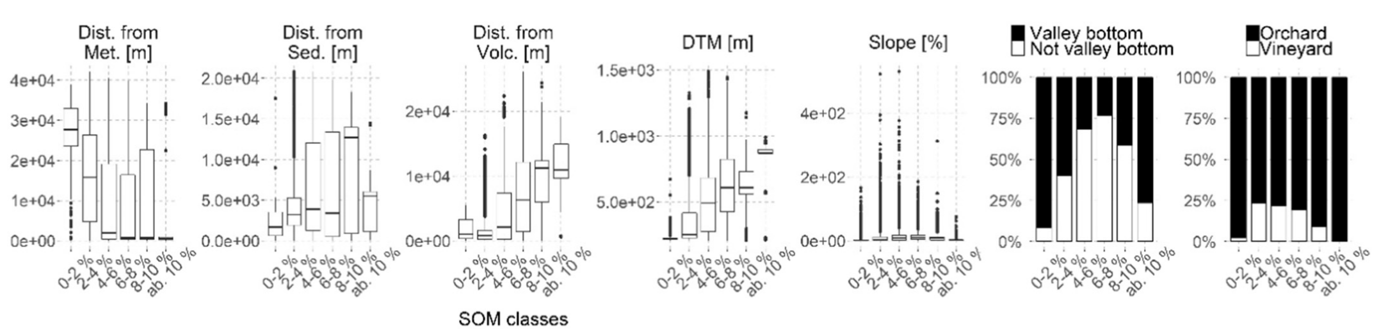

Fig. 8. Synthesis of how SOM is distributed among the different predictors.

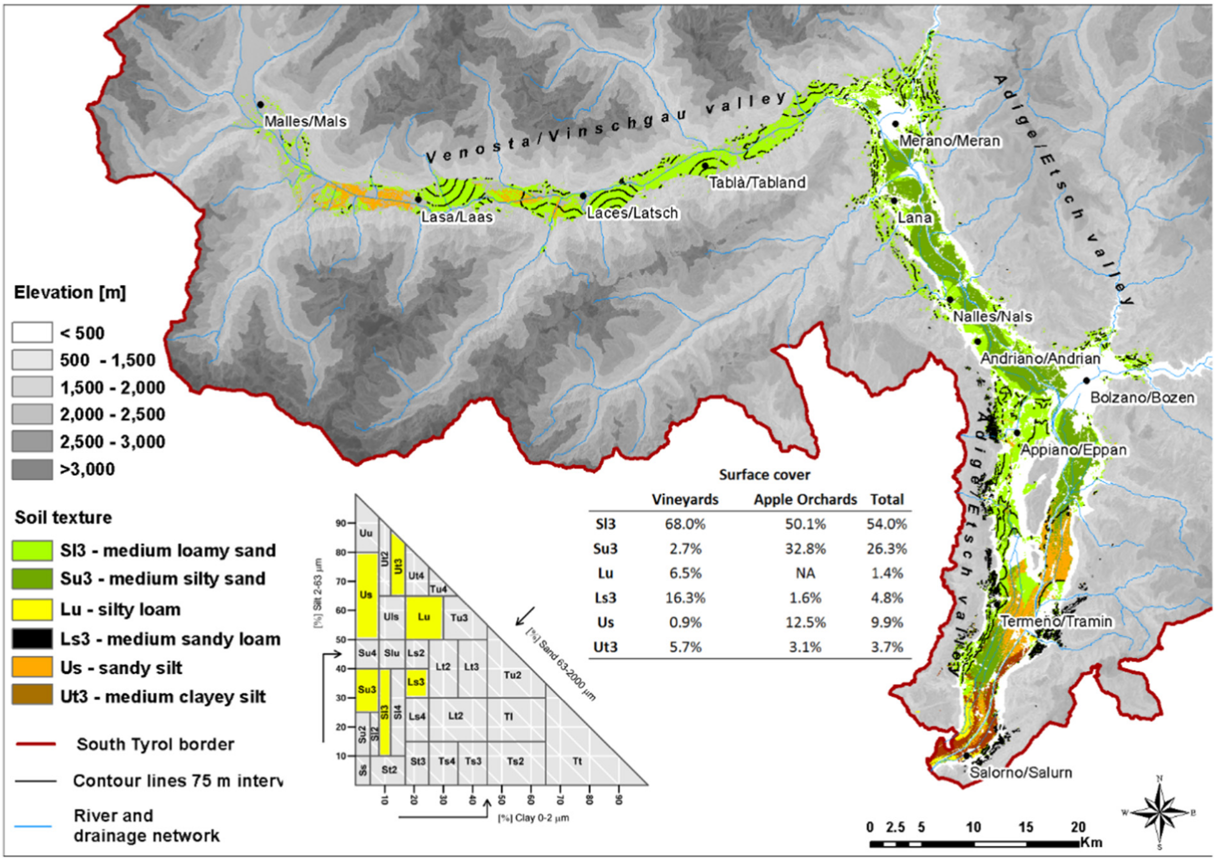

Fig. 9. Topsoil textural classes predicted by the MLR, German classification according to AD-HOC AG Boden (2005). In the soil texture triangle, yellow highlights the six classes after spatial interpolation. Note that the class Lu – silty loam (Lu) is barely visible in the southern part of the Adige/Etsch Valley owing to the very low coverage. Contour lines highlight topographic features such as alluvial fans and side slopes in the study area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

However, the topsoil is relevant in agriculture, as this is where organic matter and microorganism biological activity are concentrated (Nair, 2016). Data on subsurface soil (20–40 cm) and other agricultural land uses exist in the adopted database, but with a 10-fold lower sampling density. Therefore, spatial prediction of subsoil physical and chemical properties might not be accurate. However, with the amount of data increasing over time, subsoil texture spatial prediction will become possible. Moreover, a detailed laboratory particle-size analysis would allow the estimation of the exact percent fraction distribution for a more detailed soil texture classification and hydraulic property estimation (Clapp and Hornberger, 1978; van Genuchten, 1980). Grashey-Jansen (2014) investigated the soil water dynamics in the Venosta/Vinschgau Valley, highlighting the importance of knowing the soil texture particle size fraction to assess plant water availability. This is particularly valuable in the valley bottom, where heavy soils and shallow groundwater directly impact the magnitude of the potential capillarity rise of groundwater (Grashey-Jansen, 2010). Despite the overall poor accuracy of the topsoil texture map, more than 80% of the predicted soil texture classes belong to medium loamy sand (Sl3) and medium silty sand (Su3) soils, which do not largely differ in particle size fraction. Therefore, prediction errors do not substantially affect the spatial pattern of soil texture, which is scientifically sound and clearly shows the interplay of past river floods as finer material is at the valley bottom and increases in fraction from upstream to downstream. Moreover, the presence of postglacial mega alluvial fans (Cavalli et al., 2013) affected debris flow and thus sedimentation in the north eastern part of the Venosta/Vinschgau Valley (Brardinoni et al., 2018). The alluvial fans in the Adige/Etsch Valley were unaffected by floods and thus show medium loamy sand (Sl3) soils. Downstream in the Adige/Etsch Valley near the city of Bolzano/Bozen, soil becomes finer and

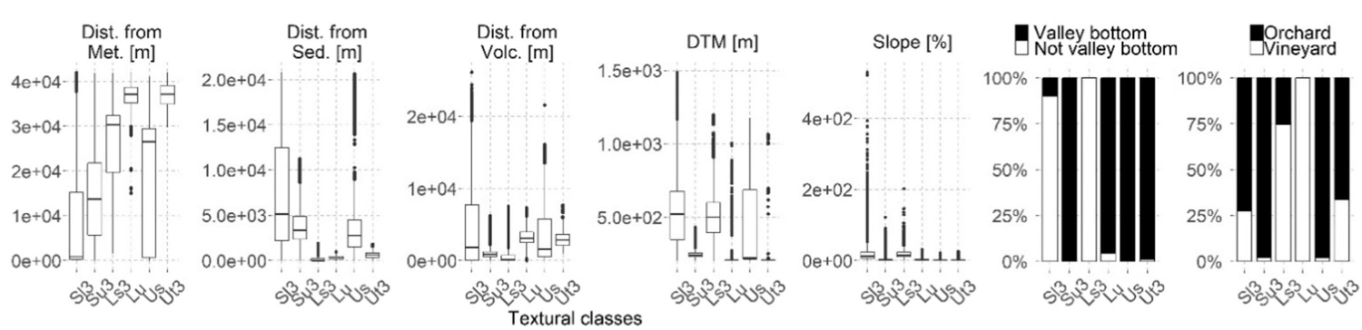

Fig. 10. Synthesis of how the SOM soil property map is distributed among the different predictors.

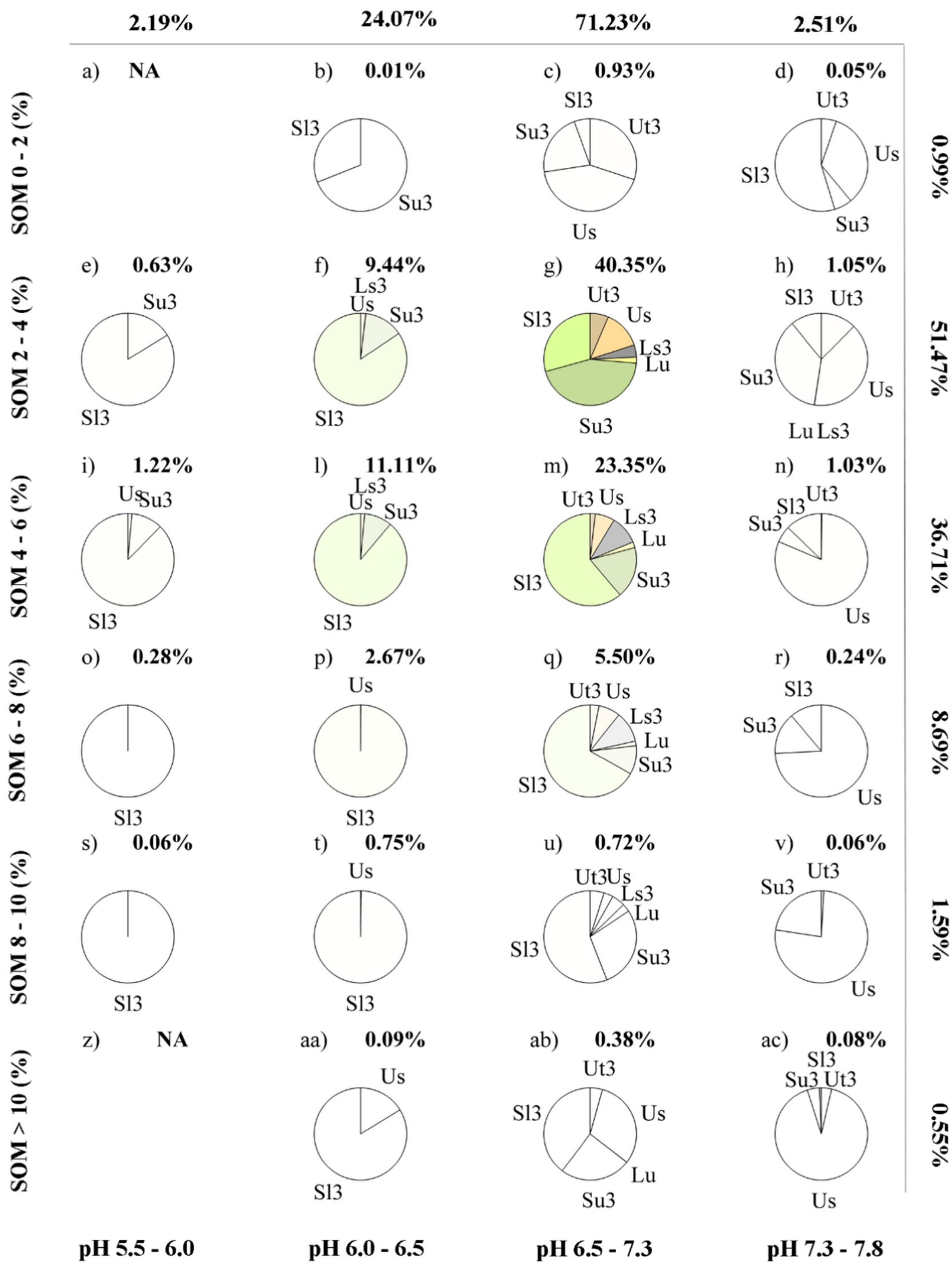

Fig. 11. Pie charts representing the soil property maps classified and combined to assess the different relations. The percentage of pixels falling within each combination of pH and SOM is explicitly reported and highlighted as layer transparency relative to each pie chart. Total percentage for each class of pH and SOM is also reported. Abbreviations for the soil texture classes can be found in Table 3 and Fig. 4.

heavier due to the different dynamics after the confluence of the eastern and western watersheds. Spatial distribution of pH reflects the anthropogenic impact of intensive agriculture, geomorphology, and the surrounding geology. Soil pH had an overall low variability, indicating soil conditioning through liming by farming activity (Bogunovic et al., 2017). The Venosta/Vinschgau Valley shows a larger variability in pH compared with the Adige/Etsch Valley owing to the presence of a cluster of large alluvial fans where pH is dominated by the silicate parent material. The slightly alkaline sandy silt (Us) soils with high SOM content, in the northern west part of the Venosta/Vinschgau Valley, is linked to its postglacial evolution. The presence of the largest alluvial fan in the Alps (Cavalli et al., 2013) dammed the course of the Adige River, thus depositing metamorphic calcareous sediments of the Ortles/Ortler Mountain (Maraio et al., 2018). The higher heterogeneity and overall higher values of SOM spatial distribution are located in the Venosta/Vinschgau Valley, with very high SOM content located in former lacustrine and swampy zones created by alluvial fans (Brardinoni et al., 2018; Cavalli et al., 2013). Moreover, in the Venosta/Vinschgau Valley, rates of SOM degradation are influenced by the colder climate and more recent intensive farming land use in the upper part of the valley (Pulleman et al., 2000). A relatively lower variability of SOM is found in the lower part of the Adige/Etsch Valley bottom and on southwest-exposed slopes. This might be explained by a combination of climatic, topographic, and anthropogenic factors. The Adige/Etsch Valley is climatically warmer due to the lower altitude. Moreover, the western-southwestern exposed side of the valley is generally warmer, which can affect the mineralization of SOM mineralization. Finally, the Adige/Etsch Valley has a longer tradition of intensive agricultural practices where organic matter degradation processes may occur, resulting in relatively greater decomposition (Bogunovic et al., 2017; Paltineanu et al., 2016). Nevertheless, patterns of SOM require further investigation because high SOM is also found on northern-exposed alluvial fan in the Venosta/Vinschgau Valley, as well as on the eastern-exposed slopes of the Adige/Etsch Valley. Moreover, South Tyrol vineyards and apple orchards have traditionally had grasses between planting rows. Hence, organic matter losses should be very limited (Atucha et al., 2011; Mcgourty and Reganold, 2005). Finally, the integration of soil texture, SOM, and pH data with the existing soil chemical data not analysed in this study can provide further information for estimating the spatial availability of specific nutrients (Fageria et al., 2002; Singh, 1994), estimating plant water availability (Saxton and Rawls, 2006), estimating soil water hydraulic properties for hydrological and hydropedological application (Thompson et al., 2012), designing fertilisation management (Grant, 2016), carrying out ecological risk assessments (Suter II, 2016), and improving overall soil security (McBratney et al., 2014).

5. Conclusions and outlook

Demand for sustainable agriculture by regulatory bodies and their sustainable management guidelines can operate as interlinks and driving forces for a fruitful cooperation between farmers, who provide data, and scientists, who can enhance the current understanding of agricultural systems and help formulate sustainable agricultural program policy. Indeed, public administrators can make informed decisions and promote a promising framework for extensive and long-term soil monitoring in agricultural areas. Linking all individual farmers' agronomic practices can potentiate soil knowledge to address issues beyond the individual farmer's agronomic production. The resulting maps of pH, SOM, and soil texture provide further insights to characterize the dynamics of mountain valleys shaped by the complex interplay of postglacial evolution, geomorphological processes, and anthropogenic influences. These results can be used to optimize land management at large spatial scales. This study presents only a few of the available variables; further studies should consider the rest of the data to digitally assess spatial patterns of nutrient availability and carry out ecological risk assessments for sustainable agriculture. An integrated farming long-term data collection program over time will enhance the reliability of the produced maps and the estimated trends and changes in physical-chemical soil properties. This would open new paths toward comprehensive monitoring in the field of sustainable agriculture and creation of long-term plans for soil security.

Acknowledgments

This work was supported by the research grant 'MONALISA' of the Department of Innovation, Research and University of the Autonomous Province of Bozen/Bolzano, Italy. The authors thanks the Department of Innovation, Research and University of the Autonomous Province of Bozen/Bolzano, Italy, for covering the Open Access publication costs. We would like to thank Aldo Matteazzi, Office of Agricultural Chemistry, Research Centre for Agriculture and Forestry, Laimburg, for support and providing the laboratory data. We thank Rachele Carloni for graphical design. Finally, we would like to express our gratitude to all the farmers whose soil sampling work permitted this research.

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