

Farmer's data sourcing: A best practise example for mapping soil properties in permanent crops in South Tyrol (northern Italy)

Stefano Della Chiesa^{1*}, Daniele la Cecilia², Giulio Genova¹, Andrea Balotti¹, Martin Thalheimer³,
Ulrike Tappeiner^{1,4}, Georg Niedrist¹

¹eurac research, Institute for Alpine Environment, Bolzano/Bozen, Italy

²School of Civil Engineering, University of Sydney, Sydney 2006 NSW, Australia

³Research Centre for Agriculture and Forestry, Laimburg, Bolzano/Bozen, Italy

⁴University of Innsbruck Department of Ecology, Innsbruck, Austria

**Corresponding author at: eurac research, Institute for Alpine Environment, I-39100, Bolzano/Bozen, Italy.*

E-mail address: stefano.dellachiesa@eurac.edu

Abstract

In agriculture, detailed knowledge of soil properties is a key element for high-quality food production. However, soil data at a single parcel scale are generally unavailable. In this study, a best practice framework is presented where, through an operational chain from an individual farmer through a centralised database and with a geostatistical approach, new knowledge has been generated that enables application far beyond a single soil sample at the parcel scale. This study was carried out in intensively managed permanent crops in South

Tyrol, Italy, where 16,000 soil samples taken in the framework of an integrated production program have been used to show the capability to predict accurate soil property maps. Geospatialisation was conducted using Kriging interpolation. Finally, the resulting maps of soil texture, soil organic matter (SOM), and pH are shown and discussed. The results showed that combining agricultural production guidelines, a long-term data collection program, farmers, public administration services, and scientific analysis can provide a successful framework for digital soil mapping. The large number of samples combined with their spatial distribution has contributed to the robust estimation of the soil texture, pH, and SOM prediction. The maps show the complex interplay of fluvial processes, topography, and anthropogenic influences on the variability of soil texture, pH, and SOM. Finally, this study was focused on a fixed time span and a subset of the available agronomic variables. Thus, the long-term soil monitoring program and the combination of all the 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.

1. Introduction

Knowledge of soil chemical and biophysical properties and their spatial variability is a key element in soil management, providing farmers, land managers, and policy makers valuable information for the implementation of effective management strategies and sustainable agriculture (Alliaume et al., 2010; Rüdiger et al., 2015, McBratney et al., 2014; Plant, 2001). To maintain profitability and deliver high-quality food whilst maintaining and enhancing sustainable agriculture, integrated farming regulations are widely adopted throughout European agriculture (Edwards et al., 1993; Morris and Winter, 1999). Particularly, the

integrated farming program aids in the improvement of soil quality via a guideline for soil management (Hendrickson et al., 2008). In this framework, farmers using these management practices 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), farmers are performing valuable data sourcing by engaging in interdisciplinary collaborations with the various stakeholders (Bouma, 2015). Promoting the public availability of soil information from agricultural fields generates enormous interest among retailers interested in better leveraging data and exploring new potential applications (Drakos et al., 2015; GODAN, 2015; Woodard, 2016).

Throughout their agronomic practices and implementation of integrated agriculture guidelines, farmers regularly monitor several chemical-physical properties of soil. Among these, soil texture, soil organic matter (SOM), and pH are the most relevant. Soil texture influences nearly all soil processes and contributes to water, heat, and nutrient fluxes and holding capacity (Saxton et al., 1986; Sinowski et al., 1997; Grashey-Jansen, 2010). SOM affects soil–water relationships (Bot and Benites, 2005; Lal, 2007) and is a soil fertility indicator (Herrick, 2000). The pH directly affects nutrient availability, nutrient uptake, and heavy metal dissolution, which may be toxic to plants. Thus, non-optimal soil pH can cause plant stress (Läuchli and Grattan, 2017).

Digital soil mapping allows pointwise soil information to be extrapolated and soil properties in space to be predicted through a robust interpolation method (Minasny and McBratney, 2016; Robinson and Metternicht, 2006). These techniques have been extensively tested by various authors (Scull et al., 2003; Hengl et al., 2004). The most advanced techniques usually employed are the geostatistical methods for data interpolation by means

of Kriging. For continuous variables such as pH, SOM, and several other chemical soil properties, Kriging has been proven to have good predictive capability (Hengl et al., 2004; Vieira et al. 1983). Meanwhile, the spatial prediction of compositional data such as soil texture can be estimated by means of compositional Kriging (De Gruijter et al., 1997; Kerry and Oliver, 2007; Zhang et al., 2013).

Collecting comprehensive datasets is a challenging task; national-level soil surveying covers medium- to large-scale and generates coarse-scale soil maps (Scull et al., 2003). Small-scale soil surveying covers short-distance changes in soil properties (Corstanje et al., 2007) related to topography (Schaetzl and Anderson, 2005) and land use management (Barrios et al., 2015; Sun et al., 2003). Single institutions collect limited amounts of soil data with high-quality standards and methods generally used for larger areas, while projects with a citizen scientist approach collect large amounts of data with diverse quality and collection protocols. In the South Tyrol case study, farmers, private stakeholders, and the public administration have established a rather unique and long tradition of collaboration. The local public research centre of agriculture and forestry provides important services (Dalla Via and Mantinger, 2012) to local farmers. It has also stored decades of soil data with reliable protocols and standards.

In this study, a best practice framework is presented, linking individual farmers' agronomic practices with a centralised soil database and a geostatistical approach, providing further insights into spatial soil properties, knowledge of which can be used to address issues beyond the single parcel of land. This contribution aims for the following objectives: (i) to present the best practice framework for farmer data sourcing of spatial soil information in intensively managed permanent crops in South Tyrol; (ii) to show the capability of a high-

density soil database to predict accurate soil property maps; (iii) to briefly discuss the maps produced of soil texture, SOM, and pH.

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 (Figure 1). South Tyrol lies on the southern side of the main alpine ridge, and the area has a typical continental alpine precipitation regime, with low total annual precipitation (450–850 mm), a summer characterised by convective rainfall events, and a relatively cold winter with weak Atlantic frontal systems and little precipitation ([Hydrographic office South Tyrol](#)). The prevalent soil types on hillsides are Leptosols and Cambisols, while in the valley floor they are gleyic Cambisols (partially calcareic) Fluvisols or Gleysols ([Grashey-Jansen, 2010](#);). South Tyrol is Europe's largest apple-growing area, at ca. 19,000 ha. The production is sold at about 50% within Italy, 15% to the rest of Europe, and 2% worldwide outside of Europe ([Dalla Via and Mantinger, 2012](#)). Vineyards cover about 5500 ha, representing ca. 1% of Italian production (49% regional consumption, 18% rest of Italy, 26% Europe, 7% worldwide). The rest of the agricultural land is covered by pastures of ca. 120,000 ha, meadows of ca. 70,000 ha, and other cultures of ca. 15,000 ha ([Agricultural office, South Tyrol](#)). Overall, 22.5% of the land surface is used for agriculture ([Tasser et al., 2008](#)).

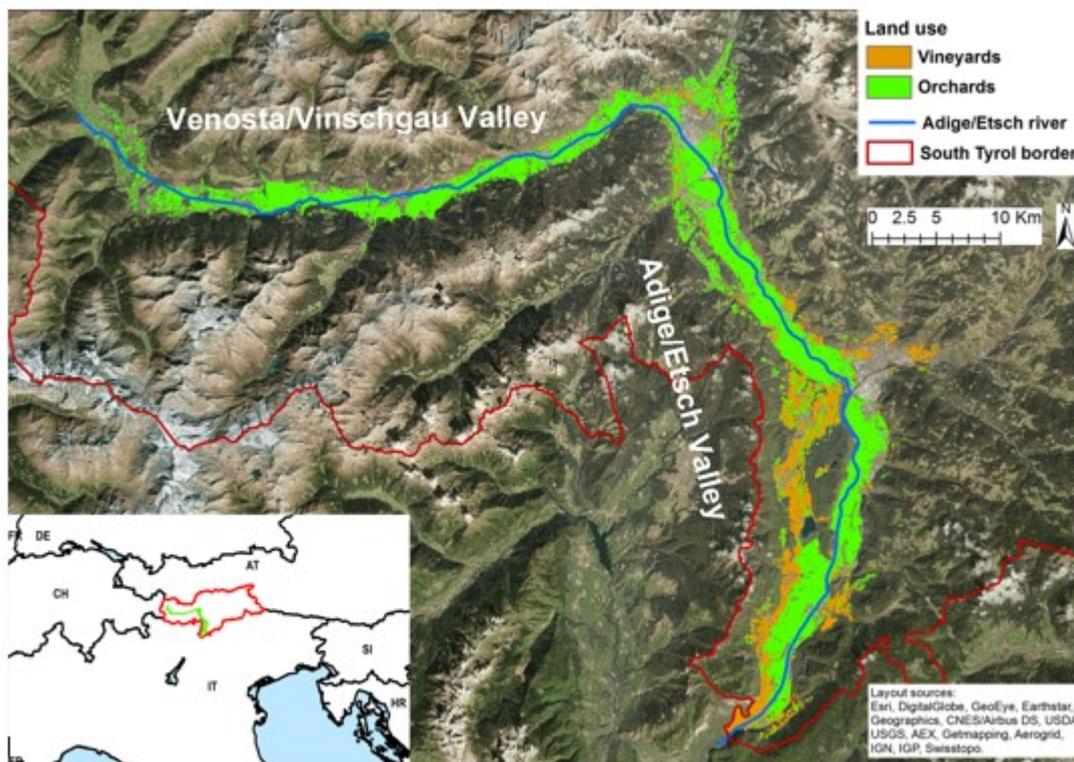


Figure 1. Study area in the Venosta/Vinschgau and Adige/Etsch Valleys (green area) in South Tyrol (red boundary), Italy.

2.2. Soil sample data sourcing

In South Tyrol, viticulturists do not follow specific guidelines for soil management, while apple farmers conduct integrated farming with precise guidelines and regulations that prescribe soil sampling repetition every 5 years (AGRIOS, 2017). About 70% of 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 the data is inaccessible. Thus, the current study focuses on data collected by the Laimburg laboratory during 2006–2013 with a dataset coming from apple orchards and vineyards located in the Venosta/Vinschgau and Adige/Etsch Valley. For each orchard or vineyard parcel, a minimum of 15 soil subsamples were taken in different locations at the same profile depth (0-20 cm) by each individual farmer. Samples from the same profile depth were mixed, and 1 kg of soil material was submitted to the laboratory. It was analysed to determine pH and chemical compositions, and textural soil classes were defined by a feel test (Thien, 1979 (Table 1). Each sample was assigned a unique cadastral parcel code and was joined to the cadastral map, with the sample point position selected as a random location within each cadastral parcel to avoid spatial artefacts caused by parcel geometry. Because of several mismatches between the reference parcel code in the soil sample database and the cadastral maps of some municipalities, it was not

possible to georeference all the available soil samples. Finally, the dataset comprised ca. 16,139 sample points. For analysis only, the soil texture, pH and SOM are considered in this study (

Table 1).

Parameter	Analysis method	Units	Variable type
*SOM	Elemental analysis	%	Numerical
*pH	CaCl ₂ glass electrode	-	Numerical
*Soil texture	Feel test	Soil texture class	Categorical
P ₂ O ₅	CAL colorimetry	mg / 100 g	Numerical
K ₂ O	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

Table 1. Measured parameters, 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). *Note that this is a comprehensive list of the variables available, as only the organic content, pH and soil texture are considered in this study.

2.3. Model calibration and validation

For each soil sample, two types of variables were generated: categorical (soil texture classes) and numerical (chemical analyses). Thus, two different geostatistical

methods were chosen to spatialise the studied variables: compositional Kriging ([Gruijter et al. 1997](#), [Walvoort and de Gruijter 2001](#)) for soil texture classes and ordinary local Kriging for pH and SOM. Although the kriging estimator does not depend on any distribution assumption, if the empirical distribution of the data is skewed then the kriging estimators are sensitive to outliers ([Lark, 2000](#)). Thus, for pH and SOM, to properly estimate the patterns of dominant processes with minimal influence of spurious points indicating polluted data, the outliers were investigated before spatial interpolation, and if they exceeded the 1.5 interquartile range ([Mcgill et al., 1978](#)) they were excluded from further spatial analysis.

The optimal parameters for the interpolator in both methods were estimated using auto-calibration, which consists of running the geospatialisation function *n* times (i.e., compositional kriging/ordinary local kriging) for a range of input parameters and selecting the parameter combination that returns the best goodness of fit (GOF). The hydroPSO package ([Zambrano-Bigiarini and Rojas 2014](#)) within the R software was used for auto-calibration. For the numerical variables, the set of parameters that returned the lowest root mean square error (RMSE) was selected for the validation and final interpolation. Meanwhile, for the categorical variable, the best parameter set was chosen by selecting the iteration with the highest percentage of correspondence between the estimated and observed texture class. To verify the model's performance, a 5-fold cross-validation approach was adopted to determine the accuracy and uncertainty for both methods. This approach randomly divides the observed data into five datasets and then trains the model

using all except one subset (Hastie et al., 2009). The subset left aside is used for model validation (i.e., GOF estimation).

2.4. Spatial interpolation of soil properties

Georeferenced soil samples of pH and SOM were spatialised using ordinary local kriging (OLK) in the R environment (Gräler et al., 2016; Pebesma, 2004). OLK computes the spatial continuity of the dataset by variogram analysis. The model training process consists of computing an experimental variogram on a training dataset and then fitting a variogram model on the experimental one to obtain the model parameters. In this case, the exponential model showed better performance. The model parameters are then passed to the kriging estimator for interpolation. A comprehensive description of the Kriging method can be found in (D. G. Krige, 1951; Matheron, 1963). The interpolated values are checked against a validation dataset, and the RMSE is computed to assess the accuracy of the interpolation. This process (auto-calibration) is repeated n times, changing the input parameters of the experimental variogram to find the best possible accuracy.

Soil texture classes were derived by feel test; thus, for each reference soil class, the average soil composition in terms of sand, silt, and clay percentage content was assigned using the USDA classification (FAO, 1990; HG, 1937). Soil texture is a compositional variable characterised by particle size fractions that are positive-definite and sum to a constant, which usually equals 100% (Walvoort and Gruijter, 2001). A change in one component, therefore, results in a shift in all other components. (Pawlowsky, 1984). Therefore, soil texture classes, after

characterisation by composition of sand, silt, and clay, were spatialised using compositional kriging in R (Pawłowsky-Glahn and Olea, 2004; Tolosana-Delgado et al., 2009). Compositional kriging is a straightforward extension of ordinary kriging, and its description can be found in (Walvoort and Gruijter, 2001). The spatialised soil components were finally aggregated into USDA soil texture classes. The original eight classes of the German soil texture classification (Ad-Hoc-AG, 2005) were aggregated to five classes according to the USDA texture (Soil Survey Staff, 1999) classification (Figure 2 and Table 2), which were cross-validated against the validation dataset to quantify accuracy. A raster mask using the Corine Land Cover 2012 was adopted to constrain the interpolation to only agricultural fields in the valley bottom. The final spatial resolution is 100 m × 100 m.

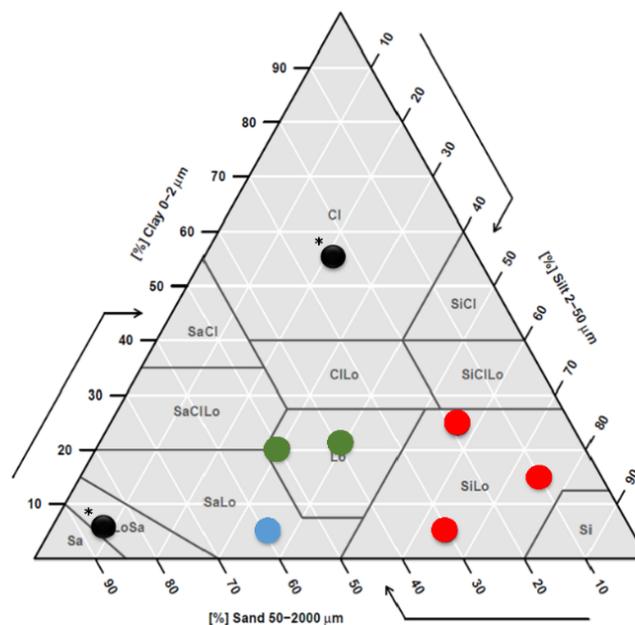


Figure 2. USDA soil textural triangle. We reclassified the German Ad-hoc AG Boden (German Ad-hoc-AG Boden, 2005) into USDA classes. We assigned average particle size fractions of the USDA classes. The USDA soil classification highlights a

rather large heterogeneity of soil types in the Venosta/Vinschgau and Adige/Etsch Valley, including loamy sand, silty loam and sandy loam. *Classes discarded from the map layout owing to low coverage.

Ad-hoc AG Boden textural class	USDA textural class	Area	Sand	Silt	Clay
		%	%	%	%
lehmiger Sand	Loam	61.24%	50	30	20
sandiger Lehm	Loam	6.34%	40	40	20
schluffiger Sand	Sandy loam	17.32%	60	35	5
sandiger Schluff	Silty loam	10.17%	30	65	5
schluffiger Lehm	Silty loam	1.53%	18	57	25
toniger Schluff	Silty loam	3.13%	10	75	15
toniger Lehm *	Clay*	0.24%	25	20	55
Sand *	Sand*	0.03%	85	10	5

Table 2. Reclassification of the original eight German soil texture classification (German Ad-hoc-AG Boden, 2005) soil textural classes into five classes according to the USDA soil textural triangle. *Classes discarded from the map layout owing to low coverage.

3. Results

3.1. Farmer data sourcing and spatial analysis

The two main farm land uses resulted in an uneven sample distribution (Figure 3). The total number of samples was 714 (4.42%) for the vineyards and 15,425 (95.58%) for the apple orchards. For the latter, the sample density ranged from 0 to 236.3 points per km² with an average of 62 points per km², while in vineyards, the sample density ranged from 0 to 174.3

points per km² with an average of 24.9 points per km². The mean sample density for the entire dataset is 54 with an average sample distance of 136 m (Figure 3).

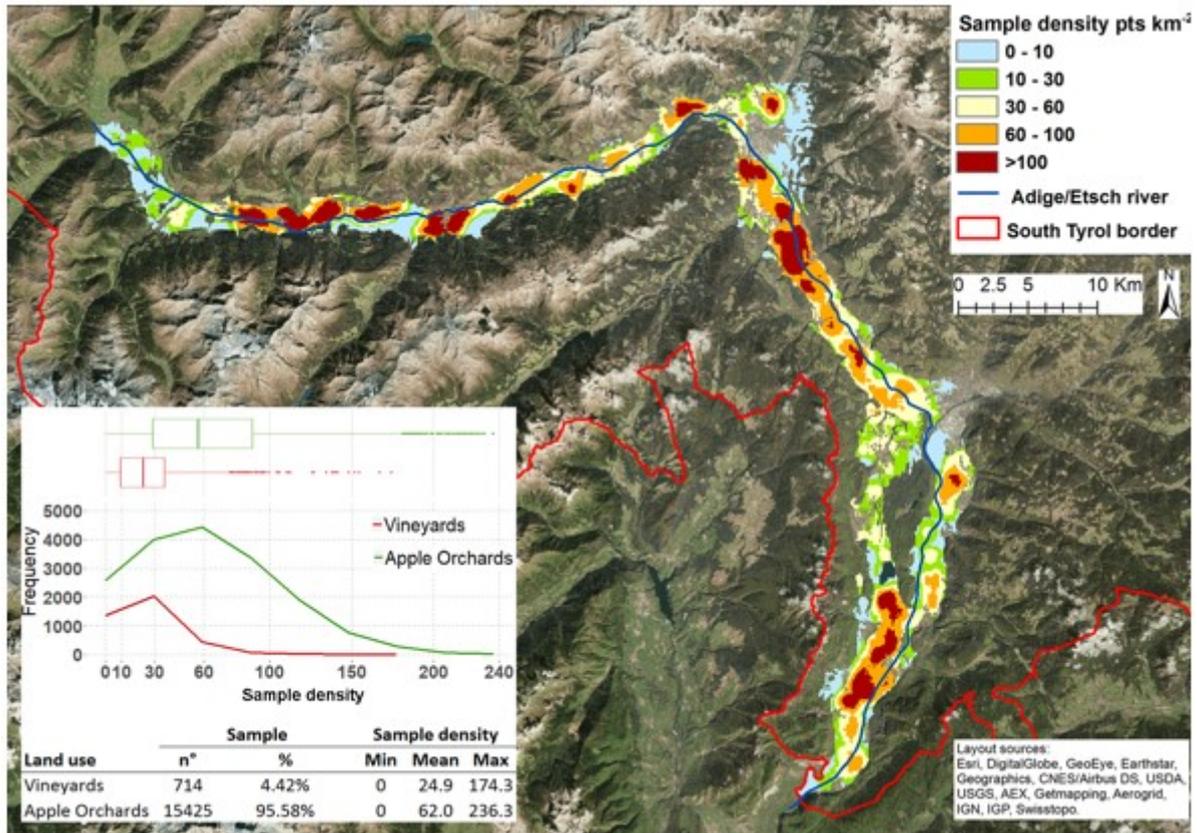


Figure 3. Soil sample density and distribution. The samples are unevenly distributed between the two farm land uses, with orchards representing more than 95% of the total samples.

None of the continuous variables is normally distributed (Figure 4). The raw data highlighted that several outliers might influence the magnitude of the skewness (see box plot in Figure 4). Soil pH ranged from very acidic (pH 4.09) to moderately alkaline (pH 7.93), with a median of pH 6.94 and standard deviation of ± 0.43 . pH showed a low relative variability

with CV of 6.3% and quasi-normal distribution with a moderate negative skewness of -0.73. Soil SOM ranged from 0.59% to 44% with median of 3.89% and standard deviation of ± 2.12 . The large skewness of 4.83 and high relative variability of 49.2% in SOM is due to the presence of extreme values on the far-right side of the distribution. Log transformation of the data was performed, and outliers exceeding the 1.5 interquartile ranges were excluded from the geostatistical analysis to overcome issues due to skewness.

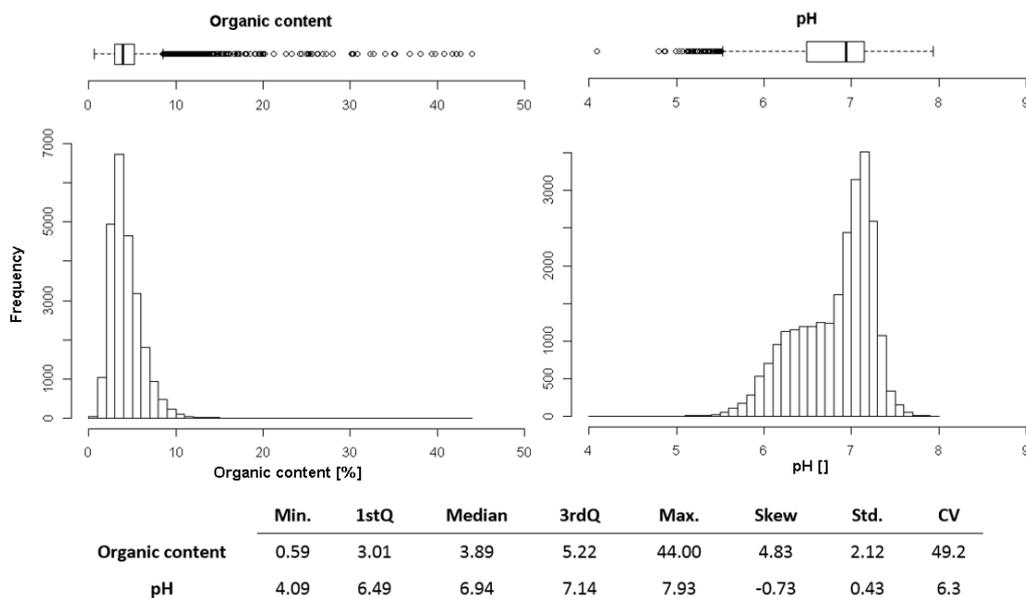


Figure 4. Frequency distribution histogram and box plot for pH (right panel) and SOM (left panel) of the original dataset.

The table shows the statistical summary for SOM and pH. Min.: minimum value. 1stQ: first quartile value. Median: median value. 3rdQ: third quartile value. Max.: maximum value. Skew: skewness value. Std.: Standard deviation. CV: Coefficient of variation.

During spatial interpolation, urban areas, industrial sites and forests were masked out to avoid inaccurate and unvalidated spatial prediction for these land uses. Thus, overall, the large data set combined with an extensive calibration and validation approach created robust estimates of spatially distributed soil properties.

Table 3 presents the parameters for the OLK and compositional model and the overall cross-validation. The exponential model performed better for pH and SOM, while the spherical model provided better performance for soil texture. The nugget value is very small for all the variables. SOM and soil texture have the lowest values, at 90.79 m and 96.35 m, respectively, while pH shows the highest value of 106.15 m. The soil texture prediction showed an accuracy of about 60%. pH spatial prediction was satisfactory with 76% accuracy and RMSE of 0.22%. SOM spatial prediction showed a lower accuracy at 57% with RMSE of about 1.26%.

Variable	Model fit parameters				OLK Parameters				Gof	
	Model	psill	Nugget	Range	Radius	nmax	nmin	omax	RMSE	r ²
				(m)	(m)					
SOM	Exponential	0.11	0.03	90.79	752.02	44.58	1.00	11.21	1.20	0.57
pH	Exponential	0.00	0.00	106.15	719.20	42.18	1.00	8.32	0.22	0.76
									cross val.	
Texture	Spherical	0.44	0.06	96.35	678.65	59.15	1	12.32	0.60	

Table 3. Semivariogram parameters for the soil texture map and overall accuracy with 5-fold validation. 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. Radius: maximum distance where interpolation is computed. nmax: number of points inside the radius used for prediction. nmin: minimum number of points inside the radius to compute interpolation. omax: maximum number of points inside each quadrant within the radius.

3.2. Soil property maps

The topsoil map of USDA textural classes is presented in Figure 5. The soil texture composition due to sediment deposition changes from upstream (upper part of Figure 5) to downstream (lower part of Fig. 5). Soil classes downstream refer typically to finer and less dense material transported by the river and deposited in the floodplain during historic floods. The most representative classes were loam, sandy loam and silty loam covering up to the 99.73% of the area (see statistics in Figure 5). The remaining 0.24% (clay) and 0.03% (sand) were discarded from the map layout. Loam top soil is typically found in alluvial cone areas as well as on the Eppan/Appiano plateau above the valley bottom. Silty loam is more frequently distributed in topographically depressed zones where floods were more frequent in the past. The rest of the valley bottom is characterised by a sandy loam texture.

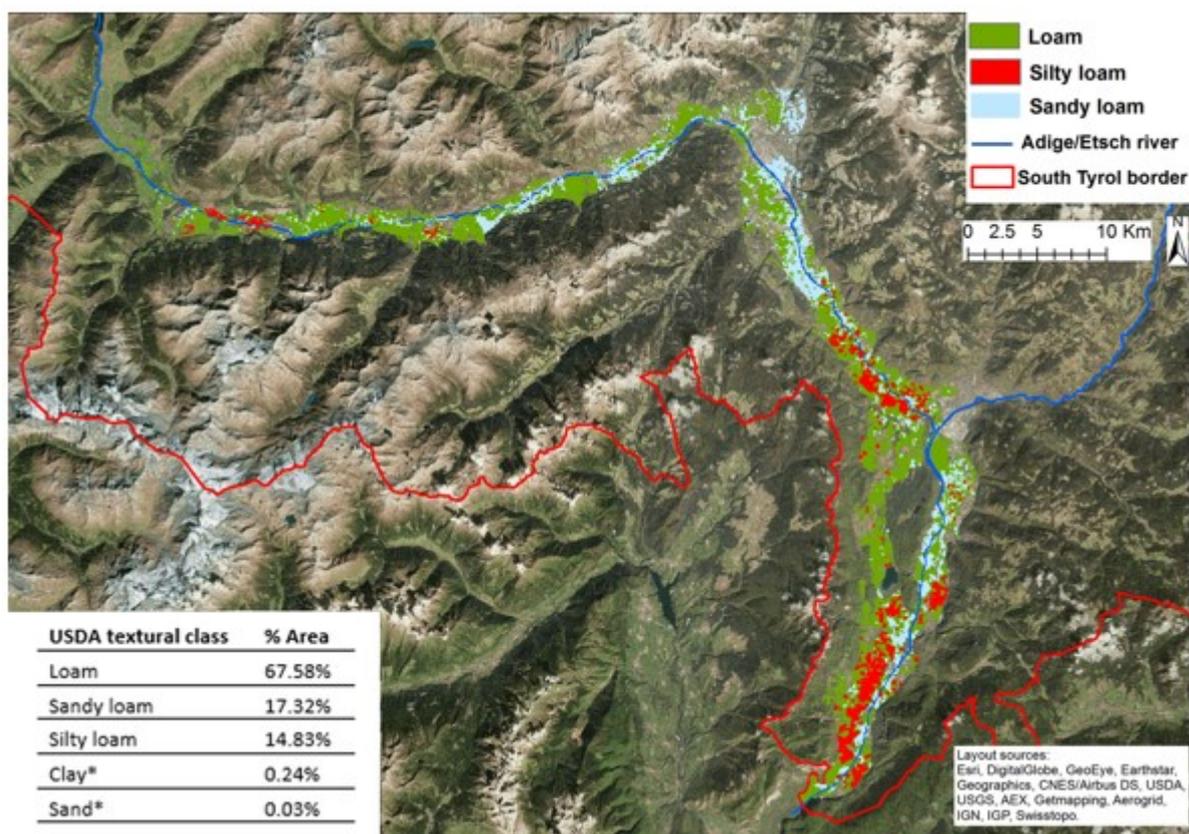


Figure 5. Topsoil map of USDA textural classes. Note that clay and sand classes are not shown in the map owing to the low coverage.

Spatial distribution of pH (Figure 6) reflects both the anthropogenic impact of intensive agriculture and the surrounding geology. Most of the areas range between moderately acidic with a minimum pH of 5.7 to slightly alkaline with a maximum pH of 7.8 owing to the presence of both silicate and dolomite bedrock in the catchment. Generally, neutral and slightly alkaline pH is found in the flat valley bottom where past floods deposited carbonates, especially in the northwestern part of the Venosta/Vinschgau Valley and in some smaller sites in the southern part of the Adige/Etsch. The alluvial cones remained unaffected by floods and show moderately acid soils owing to the respective silicate parent material. However, the decadal anthropogenic effect of intensive agriculture and liming practices has reduced the pH variability. pH density distribution (lower left panel of Figure 6) for both land uses showed a similar distribution with peaks at neutral and slightly acidic. Apple orchard fields show a larger pH relative variability of 5.5%, mean pH of 6.8 and slight negative skewness of -0.4. Vineyard fields have a lower relative variability of 4.3%, mean pH of 6.9 and relatively more skewed distribution of -0.7.

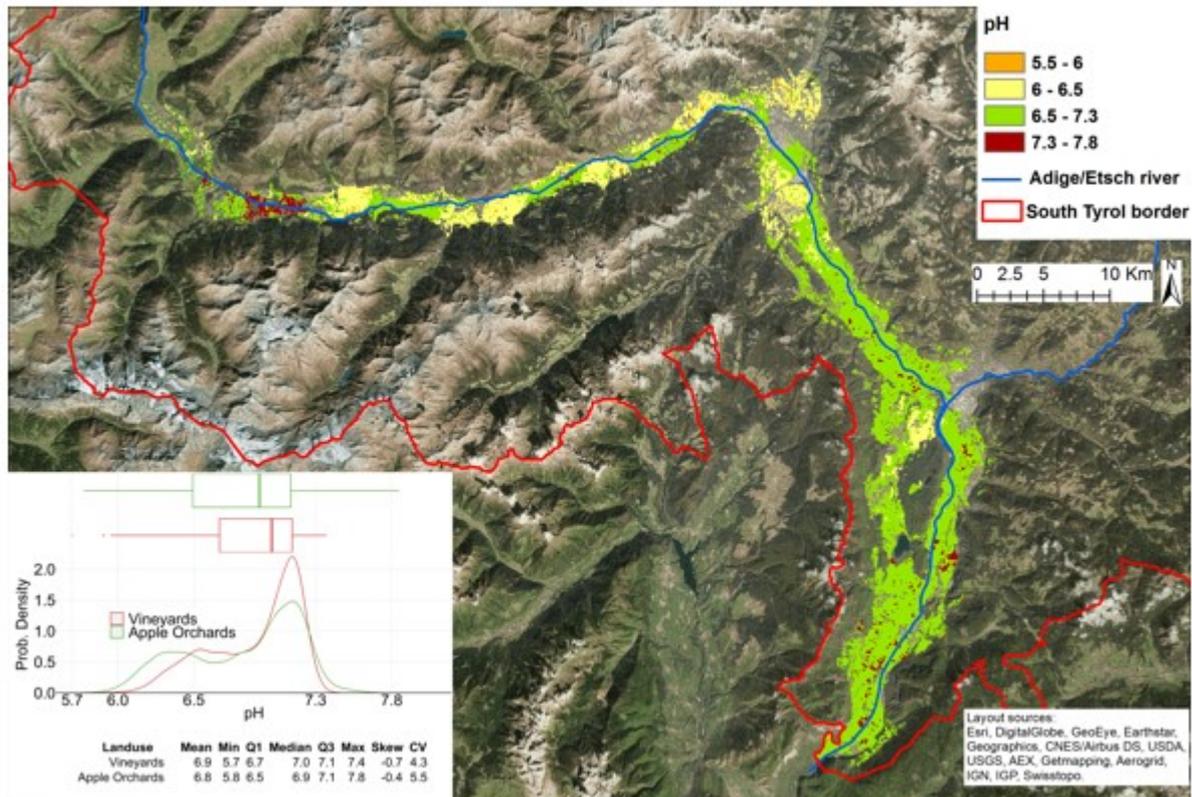


Figure 6. pH topsoil map. On the lower left is the map frequency distribution (outliers were discarded before spatial interpolation).

The SOM spatial distribution is shown in Figure 7. SOM spatial patterns are relatively heterogeneous. Higher SOM (6-8% and 8-10%) is found in the upper part of the Venosta/Vinschgau Valley, particularly on alluvial cones and former grassland fields recently turned into apple orchards. In the lower part of the Adige/Etsch Valley are areas with high SOM related to former and current peat bogs. SOM below 2% is found in a few apple orchards in the lower part of the Adige/Etsch Valley. SOM between 2% and 6% is mostly located in the valley bottom. Density distribution (lower left panel of Figure 7) shows a quasi-normal distribution for both land uses. Apple orchards show a larger SOM relative variability of 31.9%, mean of 4.2% and

positive skewness of 0.9. Vineyards have a lower relative variability of 24.2%, mean of 4.1% and skewness of 0.4, indicating almost normal data distribution.

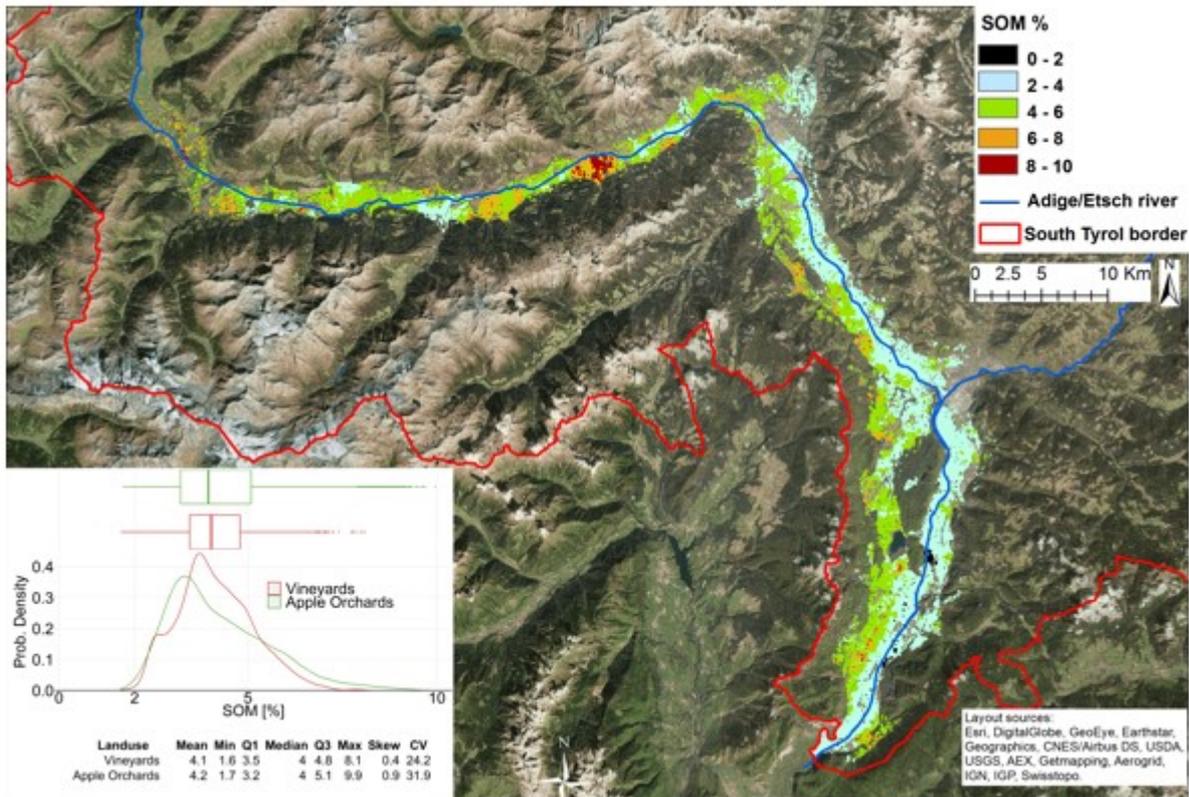


Figure 7. Topsoil map of SOM [%]. On the lower left is the map frequency distribution (outliers were discarded before spatial interpolation).

4. Discussion

4.1. Farmer data sourcing

The synergies between farmers as data providers, regulatory bodies for integrated farming, soil management, and a centralised database indicate a successful best practice for extensive and long-term soil surveying and monitoring in agricultural areas (Figure 8). Linking soil management by means of collecting time series of soil property data in a centralised database can provide information, spatial patterns and trends that are more valuable than disentangled

point-wise analysis ([“ISRIC — World Soil Information,” 2014](#)). Furthermore, the large number of samples with an average density of about 50 points per km² allow a good characterisation of soils in mountainous areas. This is due to the interplay of river floods, complex topography and geology, debris flow and glacier retreatment ([Geitner, 2007](#); [Grashey-Jansen and Schröder, 2009](#)). Moreover, the relative sample density indicates the possibility to largely increase sample density and map accuracy. Nevertheless, the highest sample density was in apple orchard fields while vineyards had generally lower sample density. This is due to the soil management guidelines for integrated fruit production ([AGRIOS, 2017](#)). These results highlight how apple orchard production guidelines, prescribing precise soil management practices, have allowed the collection of a large amount of soil information. Adopting similar guidelines in vineyards would greatly improve data availability 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 creates a robust time series for long-term monitoring of physical and chemical properties for tracking fertility changes over time ([Havlin et al., 2005](#)).

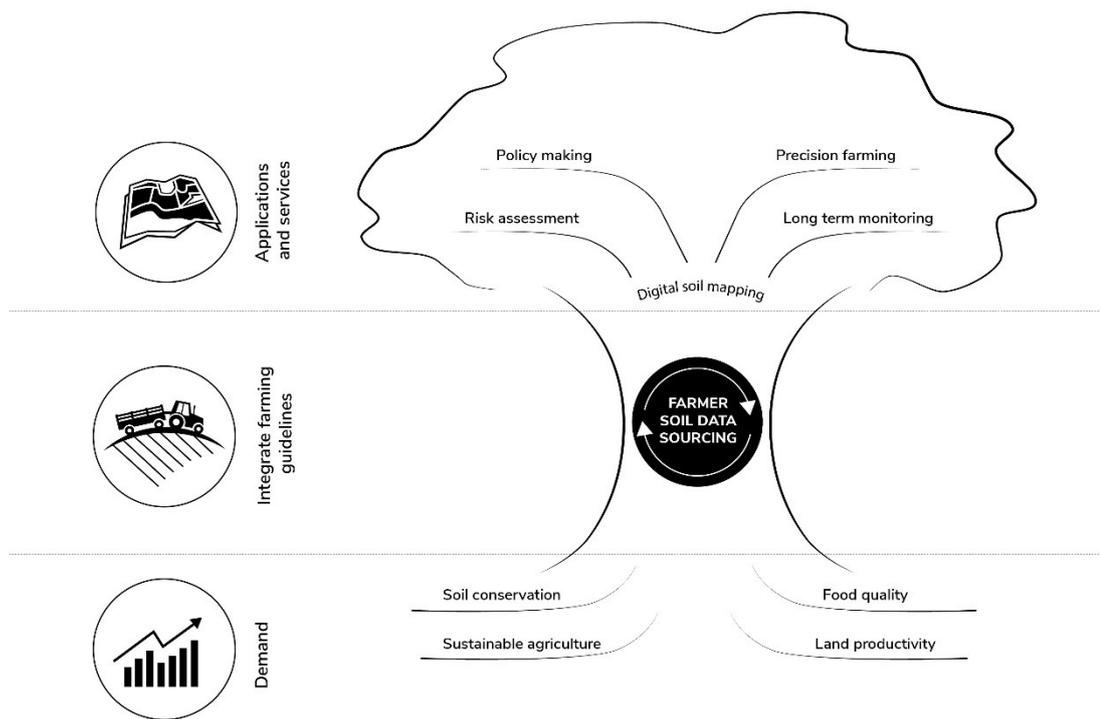


Figure 8. Farmer soil data sourcing best practice framework. Market demand for food quality, and stakeholder demand in maintaining soil function led the development of sustainable agriculture regulation. Integrate farming guidelines for soil management implemented by farmers, combined with a centralised spatial data infrastructure, can provide unexplored application and services, that are more valuable than disentangled point-wise analysis.

4.2. Spatial analysis

Despite the large number of georeferenced soil samples, still 10% of the utilised data could not be georeferenced owing to mismatching between the soil sample associated parcel code and the local cadastral map. The development of an up-to-date and common spatial data infrastructure is currently ongoing to automate data ingestion and to prevent loss of data. Auto calibration of the variogram fitting model and local kriging parameters permitted a

robust selection of the optimal parameters with the best estimate performance. Generally, with more than 10,000 samples, validation can be carried out using simple fold cross-validation; 10-20% of the data are randomly selected for validation, and the remaining 80-90% for training, respectively. However, a 5-fold cross-validation was preferred in favour of a more robust validation. The high sample number and density in this study ensure satisfactory performance of the interpolation models (Stahl et al., 2006; Webster and Oliver, 1992). The low nugget value indicates an adequate sample number and spatial variability of the studied variables. Nevertheless, the ranges for all the variables were lower than the corresponding mean sampling distances, indicating irregular sample distribution. Thus, it should be noted that the accuracy of Kriging models requires a sound sample design in terms of quality, number, and spatial distribution (Hengl et al., 2007a). For pH and SOM maps, the best fitting models were as found in similar studies (Bogunovic et. al., 2017; Mousavifard et al. 2013; Reza et al. 2016). Soil texture spatial prediction showed an accuracy comparable to what is generally presented in the literature (Hengl et al., 2007b). Moreover, with soil texture data almost doubling in quantity every 5 years, future soil texture spatial prediction will improve in accuracy.

4.3. Soil property maps

The results presented in this work show the complex interplay of fluvial processes as well as anthropogenic influences on the variability of soil texture, pH and SOM. The large number of samples combined with the even spatial distribution have contributed to the robust estimation of the soil texture, pH and SOM patterns. The feel test for soil texture classification, despite being an empirical soil texture estimation 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. Thus, soil texture samples that cover a longer time span can be used to improve future soil spatial prediction. A general limitation of the presented results is that they refer only to the topsoil; this is, however, relevant in agriculture as this is where organic matter and microorganism biological activity are concentrated (Nair, 2016). Data on subsurface soil (20 - 40 cm) as well as other agricultural land uses exist, but with a 10-fold lower sampling density. Therefore, spatial prediction of subsoil physical and chemical properties cannot be accurate. However, with the data growing over time, subsoil texture spatial prediction will become doable. 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 soil texture knowledge to assess plant water availability. This is 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). Soil pH had an overall low variability, indicating soil conditioning through liming by farming activity (Li et al. 2016) and carbonate deposits. However, the Venosta/Vinschgau Valley shows a larger variability in pH compared with the Adige/Etsch Valley owing to the presence of several alluvial cones where pH is dominated by the silicate parent material. The higher heterogeneity and overall higher values of SOM spatial distribution are located in the Venosta/Vinschgau valley, where 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. This might be explained by a combination of different factors such as a warmer climate and longer intensive agricultural practices where organic matter degradation processes may occur, resulting in relatively greater decomposition (Salome et al. 2014; Paltineanu et al. 2016). Nevertheless, South Tyrol vineyards and apple orchard fields have traditionally had grass 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), predicting plant water availability (Saxton and Rawls, 2006), estimating soil water hydraulic properties for hydrological and hydro-pedological application (Thompson et al., 2012), fertilisation management (Grant, 2016) and carrying out ecological risk assessments (Suter II, 2016).

Conclusions and outlook

The synergies between farmers as data source, farming guidelines and the public administration as in South Tyrol provide 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 production of detailed maps of soil properties is a crucial step in precision agriculture and helps in monitoring the use of agricultural compounds for pest management and fertilisation as well as to improve water use efficiency. These results can be used to make recommendations for best management practices within the local agriculture consultancy and public authorities. This study presents few of the available variables; further studies

should consider the rest of the data, paving the way to digitally assess spatial patterns of nutrient availability and carrying out ecological risk assessments for sustainable agriculture and overall soil security. The integrated farming long-term data collection program will enhance the reliability of the produced maps over time and the estimated trends and changes in physical-chemical soil properties. This would open new paths toward accurate monitoring in the field of sustainable agriculture and creating long-term plans for soil security.

Acknowledgments

This work was supported by the research grant 'MONALISA' of the Provincia Autonoma di Bolzano, Alto Adige, Ripartizione Diritto allo studio, Università e ricerca scientifica.

The computational results presented here have been obtained using the Vienna Scientific Cluster (VSC), Project 70864. We are grateful to Samuel Senorer, Eurac Research, for the IT support. We would like to thank Dr. Aldo Matteazzi, Office of Agricultural Chemistry, Research Centre for Agriculture and Forestry, Laimburg, for support and providing the laboratory data. Finally, we would like to express our gratitude to all the farmers whose soil sampling work permitted this research.

References

Ad-Hoc-AG, B., 2005. Bodenkundliche Kartieranleitung.

AGRIOS, 2017. Guidelines for Integrated Pome Cultivation 1–47.

Atucha, A., Merwin, I.A., Brown, M.G., 2011. Long-term effects of four groundcover

management systems in an apple orchard. *HortScience* 46, 1176–1183.

Bogunovic, I., Kistic, I., Mesic, M., Percin, A., Zgorelec, Z., Bilandžija, D., Jonjic, A., Pereira, P., 2017. Reducing sampling intensity in order to investigate spatial variability of soil pH, organic matter and available phosphorus using co-kriging techniques. A case study of acid soils in Eastern Croatia. *Arch. Agron. Soil Sci.* 0, 03650340.2017.1311013.
doi:10.1080/03650340.2017.1311013

Bouma, J., 2015. Engaging Soil Science in Transdisciplinary Research Facing “Wicked” Problems in the Information Society. *Soil Sci. Soc. Am. J.* 79, 454–458.
doi:10.2136/sssaj2014.11.0470

Carter, M.R., 2002. Soil Quality for Sustainable Land Management . *Agron. J.* 94, 38–47.
doi:10.2134/agronj2002.3800

Clapp, R.B., Hornberger, G.M., 1978. Empirical equations for some soil hydraulic properties. *Water Resour. Res.* 14, 601–604. doi:10.1029/WR014i004p00601

D. G. Krige, 1951. *Journal of the Chemical Metallurgical & Mining Society of South Africa*. *J. Chem. Metall. Soc. South Min. Africa* 52, 119–139.

Dalla Via, J., Mantinger, H., 2012. Agricultural Research in the Field of Fruit Growing in South Tyrol. *Erwerbs-Obstbau* 54, 83–115.

De Gruijter, J.J., Walvoort, D.J.J., Van Gaans, P.F.M., 1997. Continuous soil maps - A fuzzy set approach to bridge the gap between aggregation levels of process and distribution models. *Geoderma* 77, 169–195. doi:10.1016/S0016-7061(97)00021-9

Drakos, A., Protonotarios, V., Manouselis, N., 2015. agINFRA: a research data hub for agriculture, food and the environment. *F1000Research* 4, 127.

doi:10.12688/f1000research.6349.2

Edwards, C.A., Grove, T.L., Harwood, R.R., Pierce Colfer, C.J., 1993. The role of agroecology and integrated farming systems in agricultural sustainability. *Agric. Ecosyst. Environ.* 46, 99–121. doi:10.1016/0167-8809(93)90017-J

Fageria, N.K., Baligar, V.C., Clark, R.B., 2002. Micronutrients in Crop Production, in: Agronomy, D.L.S.B.T.-A. in (Ed.), *Advances in Agronomy*. Academic Press, pp. 185–268. doi:http://dx.doi.org/10.1016/S0065-2113(02)77015-6

FAO, 1990. *Guidelines for soil description*, 3rd edn. ed.

GODAN, 2015. How can we improve agriculture, food and nutrition with open data? 34.

Gräler, B., Pebesma, E., Heuvelink, G., 2016. Spatio-Temporal Interpolation using gstat. *R J.* 8, 204–218.

Grant, C.A., 2016. Soil Fertility and Management, in: *International Encyclopedia of Geography: People, the Earth, Environment and Technology*. John Wiley & Sons, Ltd. doi:10.1002/9781118786352.wbieg0404

Grashey-Jansen, S., 2014. Optimizing irrigation efficiency through the consideration of soil hydrological properties – examples and simulation approaches. *Erdkunde* 68, 33–48. doi:10.3112/erdkunde.2014.01.04

Grashey-Jansen, S., 2010. Pedohydrological case study of two apple-growing locations in South Tyrol (Italy). *Agric. Water Manag.* 98, 234–240. doi:10.1016/j.agwat.2010.08.012

Grashey-Jansen, S., Schröder, L., 2009. The physical geography of Val Venosta(orig.: Zur Physiogeographie des Vinschgaus), *Der Schlern*.

- Hastie, T., Tibshirani, R., Friedman, J., 2009. *The Elements of Statistical Learning Data Mining, Inference, and Prediction*, Second Ed. ed. Springer, Heidelberg.
doi:10.1007/978-0-387-84858-7
- Havlin, J.L., Beaton, J.D., Nelson, W.L., Tisdale, S.L., 2005. *Soil fertility and fertilizers: An introduction to nutrient management*. Pearson Prentice Hall Upper Saddle River, NJ.
- Hendrickson, J.R., Hanson, J.D., Tanaka, D.L., Sassenrath, G., 2008. Principles of integrated agricultural systems: Introduction to processes and definition. *Renew. Agric. Food Syst.* 23, 265–271. doi:10.1017/S1742170507001718
- Hengl, T., Heuvelink, G.B.M., Rossiter, D.G., 2007a. About regression-kriging: From equations to case studies. *Comput. Geosci.* 33, 1301–1315.
doi:10.1016/j.cageo.2007.05.001
- Hengl, T., Heuvelink, G.B.M., Stein, A., 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma* 120, 75–93.
doi:10.1016/j.geoderma.2003.08.018
- Hengl, T., Toomanian, N., Reuter, H.I., Malakouti, M.J., 2007b. Methods to interpolate soil categorical variables from profile observations: Lessons from Iran. *Geoderma* 140, 417–427. doi:10.1016/j.geoderma.2007.04.022
- Herrick, J.E., 2000. Soil quality: An indicator of sustainable land management? *Appl. Soil Ecol.* 15, 75–83. doi:10.1016/S0929-1393(00)00073-1
- HG, K., 1937. New size limits for silt and clay, in: *Soil Science Society of America Proceedings*. p. 2, 592.
- ISRIC — World Soil Information, 2014.

- Kerry, R., Oliver, M. a., 2007. The analysis of ranked observations of soil structure using indicator geostatistics. *Geoderma* 140, 397–416. doi:10.1016/j.geoderma.2007.04.020
- Lark, R.M., 2000. A comparison of some robust estimators of the variogram for use in soil survey. *Eur. J. Soil Sci.* 51, 137–157. doi:10.1046/j.1365-2389.2000.00280.x
- Läuchli, A., Grattan, S.R., 2017. 8 Plant Stress under Non-optimal Soil pH. *Plant Stress Physiol.* 201.
- Matheron, G., 1963. Principles of geostatistics. *Econ. Geol.* 58, 1246–1266. doi:10.2113/gsecongeo.58.8.1246
- Mcgill, R., Tukey, J.W., Larsen, W.A., 1978. Variations of Box Plots. *Am. Stat.* 32, 12–16. doi:10.1080/00031305.1978.10479236
- McGourty, B.G., Reganold, J., 2005. Managing vineyard soil organic matter with cover crops. *Society* 4–5.
- Minasny, B., McBratney, A.B., 2016. Digital soil mapping: A brief history and some lessons. *Geoderma* 264, 301–311. doi:10.1016/j.geoderma.2015.07.017
- Morris, C., Winter, M., 1999. Integrated farming systems: The third way for European agriculture? *Land use policy* 16, 193–205. doi:10.1016/S0264-8377(99)00020-4
- Nair, P., 2016. Evaluation of Soil Biological Agents as Indicators of Soil Health.
- Pawlowsky-Glahn, V., Olea, R.A., 2004. *Geostatistical analysis of compositional data.* Oxford University Press.
- Pawlowsky, V., 1984. On spurious spatial covariance between variables of constant sum. *Sci. la Terre Inf. Geol* 21, 107–113.

- Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. *Comput. Geosci.* 30, 683–691.
- Pulleman, M.M., Bouma, J., van, E.E.A., Meijles, E.W., 2000. Soil organic matter content as a function of different land use history. *Soil Sci. Soc. Am. J.* 64, 689–693.
- Robinson, T.P., Metternicht, G., 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. *Comput. Electron. Agric.* 50, 97–108.
doi:10.1016/j.compag.2005.07.003
- Rossiter, D.G., Liu, J., Carlisle, S., Zhu, A.-X., 2015. Can citizen science assist digital soil mapping? *Geoderma* 259–260, 71–80. doi:10.1016/j.geoderma.2015.05.006
- Rüdiger, J., Tasser, E., Peham, T., Meyer, E., Tappeiner, U., 2015. The dark side of biodiversity: Spatial application of the biological soil quality indicator (BSQ). *Ecol. Indic.* 53, 240–246. doi:10.1016/j.ecolind.2015.02.006
- Saxton, K., Rawls, W., 2006. Soil Water Characteristic Estimates by Texture and Organic Matter for Hydrologic Solutions. *Soil Sci. Soc. Am. J.* 70, 1569–1578.
doi:10.2136/sssaj2005.0117
- Scull, P., Franklin, J., Chadwick, O.A., McArthur, D., 2003. Predictive soil mapping: a review. *Prog. Phys. Geogr.* 27, 171–197. doi:10.1191/0309133303pp366ra
- Singh, B.R., 1994. Trace element availability to plants in agricultural soils, with special emphasis on fertilizer inputs. *Environ. Rev.* 2, 133–146. doi:10.1139/a94-009
- Soil Survey Staff, 1999. 'Soil taxonomy: A basic system of soil classification for making and interpreting soil surveys', *Agricultur. ed.* doi:10.1017/S0016756800045489

- Stahl, K., Moore, R.D., Floyer, J. a., Asplin, M.G., McKendry, I.G., 2006. Comparison of approaches for spatial interpolation of daily air temperature in a large region with complex topography and highly variable station density. *Agric. For. Meteorol.* 139, 224–236. doi:10.1016/j.agrformet.2006.07.004
- Suter II, G.W., 2016. *Ecological risk assessment*. CRC press.
- Tasser, E., Sternbach, E., Tappeiner, U., 2008. Biodiversity indicators for sustainability monitoring at municipality level: An example of implementation in an alpine region. *Ecol. Indic.* 8, 204–223. doi:10.1016/j.ecolind.2007.01.005
- Thien, S.J., 1979. A flow diagram for teaching texture-by-feel analysis. *J. Agron. Educ.* 8, 54–55.
- Thompson, J.A., Roecker, S., Grunwald, S., Owens, P.R., 2012. *Digital Soil Mapping: Interactions with and Applications for Hydropedology*, Hydropedology. Elsevier B.V. doi:10.1016/B978-0-12-386941-8.00021-6
- Tolosana-Delgado, R., van den Boogaart, K.G., Pawlowsky-Glahn, V., 2009. Estimating and modeling variograms of compositional data with occasional missing variables in R, in: *StatGIS'09, Geoinformatics for Environmental Surveillance Workshop*. pp. 17–19.
- van Genuchten, M.T., 1980. A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils¹. *Soil Sci. Soc. Am. J.* doi:10.2136/sssaj1980.03615995004400050002x
- VDLUFA, 1991. *Methodenbuch, Band I: Die Untersuchung der Böden*.
- Vos, C., Don, A., Prietz, R., Heidkamp, A., Freibauer, A., 2016. Field-based soil-texture estimates could replace laboratory analysis. *Geoderma* 267, 215–219.

doi:10.1016/j.geoderma.2015.12.022

Walvoort, D., Gruijter, J. De, 2001. Compositional Kriging : A Spatial Interpolation Method for Compositional Data. *Math. Geol.* 33, 951–966. doi:10.1023/A:1012250107121

Webster, R., Oliver, M.A., 1992. Sample adequately to estimate variograms of soil properties. *J. Soil Sci.* 43, 177–192.

Woodard, J.D., 2016. Data science and management for large scale empirical applications in agricultural and applied economics research. *Appl. Econ. Perspect. Policy* 38, 373–388. doi:10.1093/aepp/ppw009

Zhang, S. wen, Shen, C. yang, Chen, X. yang, Ye, H. chun, Huang, Y. fang, Lai, S., 2013. Spatial Interpolation of Soil Texture Using Compositional Kriging and Regression Kriging with Consideration of the Characteristics of Compositional Data and Environment Variables. *J. Integr. Agric.* 12, 1673–1683. doi:10.1016/S2095-3119(13)60395-0