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Phytoavailable phosphorus (P_2O_5) and potassium (K_2O) in topsoil for apple orchards and vineyards, South Tyrol, Italy

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ABSTRACT
Accurate fertilization management is a present-day challenge and can conciliate profitability and sustainability in agriculture production. This study presents topsoil concentrations of P_2O_5 and K_2O in apple orchards and vineyards in South Tyrol, Italy. Sixteen thousand georeferenced soil samples were collected and spatialized using ordinary local kriging. Measured average and maximum concentrations of P_2O_5 were 260 and 1500 mg/kg, respectively, in apple orchards, and 280 and 880 mg/kg, respectively, in vineyards. Similarly, measured average and maximum concentrations of K_2O were 210 and 1040 mg/kg, respectively, in apple orchards, and 250 and 820 mg/kg, respectively, in vineyards. Overall, K_2O concentration was mostly within the recommended thresholds, while P_2O_5 concentration was frequently higher than the target level for optimal production. The resulting maps (1:25,000 scale) of P_2O_5 and K_2O showed modest accuracy with RMSE of 115.7 and 78.3 mg/kg, respectively. These maps can support evidence-based decision making by multiple stakeholders.

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Digital soil mapping; sustainable agriculture; permanent crops; phosphorus; potassium; fertilization

1. Introduction

Soil productivity and food production are directly linked to soil fertility and plant nutrition (Munson, 2018). Farmers commonly use fertilizers to sustain crop yield and profitability (Havlin, Beaton, Nelson, & Tisdale, 2005). On the one hand, fertilizer production costs are increasing, and therefore they may become less accessible to farmers (Cordell, Drangert, & White, 2009). On the other hand, excessive fertilization management can lead to detrimental environmental impacts and indirect costs to ecosystems (King et al., 2015). Therefore, a present-day challenge is to conciliate intensive agriculture production with profitability and environmental sustainability (Tilman, Cassman, Matson, Naylor, & Polasky, 2002). Integrated farming has become a widely adopted sustainable agriculture practice worldwide (Hendrickson, Hanson, Tanaka, & Sassenrath, 2008; Morris & Winter, 1999). It establishes guidelines aiming to promote optimal nutrient management through detailed knowledge of *in-situ* soil properties and nutrient availability. Integrated farming may eventually allow farmers to reduce application rates of synthetic chemicals, thus preserving the self-maintenance of soil functions (Vogel et al., 2019). Soil testing is the best management tool to ensure optimal fertilization recommendations, as it quantifies phytoavailable nutrients in soil samples.

The macro elements Potassium (K) and Phosphorus (P) are essential for plant health and growth, and are assimilated by plants to the largest extent after Nitrogen (N) (Hawkesford et al., 2012; Lawlor, 2004; Zörb, Senbayram, & Peiter, 2014). Therefore, knowledge of K and P phytoavailability support optimal fertilizer application that favours optimal yields and sustainability. Note that P and K are known to be very mobile; while optimal management of P would support the protection of nearby surface and groundwater resources from eutrophication due to P runoff and leaching (Carpenter, 2008; Conley et al., 2009), the efficient K fertilization would reduce use of K fertilizer without compromising soil fertility (Dhillon, Eickhoff, Mullen, & Raun, 2019). To support best management practices in agriculture, the Association of German Agricultural Analytical and Research Institutes (VDLUFA) has proposed five classes according to ranges of nutrient concentrations in soil. The classes range from A (lowest level) to E (highest level), with Class C being the target class for optimal production (VDLUFA, 1991). The continuous monitoring of phytoavailable soil nutrients at a plot-scale in South Tyrol has resulted in a large dataset of observations covering the whole region (Della Chiesa et al., 2019). The dataset can be used to generate information and trigger actions at larger spatial scales.

Digital soil mapping (DSM) of chemical–physical properties is an additional tool for sustainable farming,

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and it is becoming crucial for large-scale assessment of soil security, environmental health and soil ecosystem service assessment (Adhikari & Hartemink, 2016; Carré, McBratney, Mayr, & Montanarella, 2007; McBratney, Field, & Koch, 2014). DSM turns pointwise soil surveys into continuous maps through robust interpolation methods (McBratney, Mendonça Santos, & Minasny, 2003; Minasny & McBratney, 2016). Several interpolation methods have been extensively tested by various authors (Hengl, Heuvelink, & Stein, 2004; Scull, Franklin, Chadwick, & McArthur, 2003); kriging has been proven to have good predictive capability for continuous variables such as K and P (Bogunovic, Pereira, & Brevik, 2017, Bogunovic, Trevisani, Seput, Juzbasic, & Durdevic 2017). However, spatial interpolation models require robust input data for high prediction accuracy (Li & Heap, 2014). Data quality and consistency can be achieved by following standardized protocols to conduct soil sampling and testing (Jordan-Meille et al., 2012; Tóth, Hermann, Da Silva, & Montanarella, 2016). Della Chiesa et al. (2019) showed that demand for agricultural sustainability allows the development of sustainable farming programmes with standard protocols and guidelines for soil information data sourcing. The latter can provide comprehensive datasets ideal for DSM and can overcome the challenge of developing detailed spatial–temporal maps of soil physical–chemical properties in agriculturally managed ecosystems (McBratney et al., 2003). Thus, maps of spatial and temporal concentrations of P and K can provide a base of knowledge to manage P and K fertilization in permanent crop systems, including apple orchards and vineyards (Aggelopoulou, Pateras, Fountas, Gemtos, & Nanos, 2011; Blanchet et al., 2017; Bogunovic, Pereira, et al., 2017; Jordan-Meille et al., 2012). Moreover, knowledge of the P spatial distribution allows the assessment of the risk of diffuse P losses (Fischer, Pöthig, & Venohr, 2017).

By exploiting the promising framework in Della Chiesa et al. (2019), this study fills knowledge gaps of detailed spatially-distributed information of phytoavailable P and K in the form of P_2O_5 and K_2O, respectively, in apple orchards and vineyards in South Tyrol, Italy.

2. Materials and methods

2.1. Study area

This study covered agricultural soils cultivated with permanent crops (i.e. apple orchards and vineyards) on the floors of the Venosta/Vinschgau and Adige/Etsch valleys, in the Province of Bolzano/Bozen, South Tyrol, Italy, between 46°20′N and 46°70′N and 10°50′W and 11°45′W (Figure 1). South Tyrol is Europe's largest apple-growing area, covering nearly 19,000 ha, while vineyards cover about 5500 ha. South Tyrol lies on the southern side of the main Alpine ridge; the study area has a typical continental Alpine precipitation regime with mean annual precipitation of ca. 723 mm and mean annual temperatures of

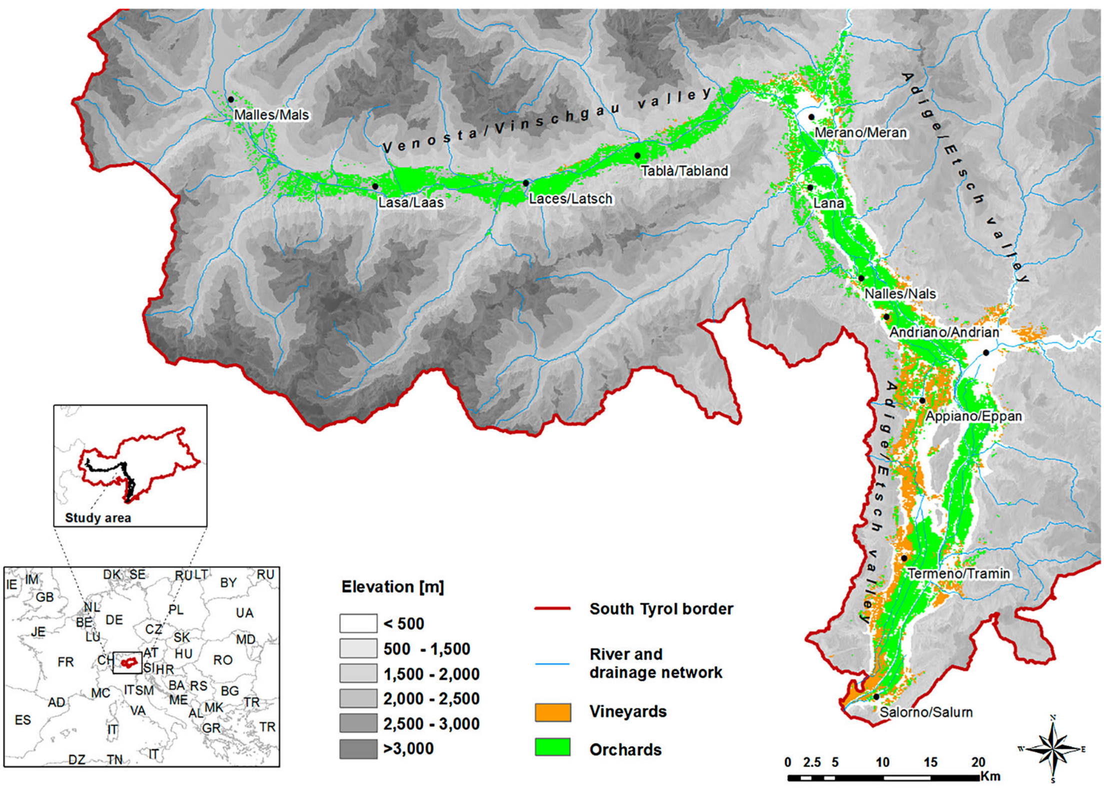

Figure 1. Study area in the Venosta/Vinschgau and Adige/Etsch valleys in South Tyrol, Italy.

12.9°C (1987–2017 mean data from the Meteorological Station of Bolzano/Bozen, Hydrographic Office, South Tyrol). The prevalent soil types on the valley floor are gleyic Cambisols (partially calcaric), Fluvisols, or Gleysols (Grashey-Jansen, 2010).

2.2. Soil sampling

In South Tyrol, most of the farmers and viticulturists practice integrated farming. They are required to regularly submit soil samples to a centralized public chemical laboratory of the Research Centre for Agriculture and Forestry, Laimburg (Dalla Via & Mantinger, 2012), which analyses the samples following common protocols and standards. The Centre stores digital soil data from across South Tyrol from 2006. The current study focuses on nearly 16,000 georeferenced soil samples collected from apple orchards and vineyards located in the Venosta/Vinschgau and Adige/Etsch valleys during the years 2006–2013. Each soil sample was analysed to determine phytoavailable P_2O_5 and K_2O soil concentrations (mg/kg). Further details on soil sampling design and georeferencing can be found in (Della Chiesa et al., 2019). Nutrient concentration was measured in an extract of calcium-acetate-lactate (CAL), according to ÖNORM L 1087:2012 (ÖNORM, 2012).

2.3. Spatial interpolation

Georeferenced soil concentrations of phytoavailable P_2O_5 and K_2O were spatialized using ordinary local kriging (OLK) in the R environment (Gräler, Pebesma, & Heuvelink, 2016; Pebesma, 2004). The data distribution of P_2O_5 and K_2O were investigated for normality; a log-transformation before spatial interpolation was necessary to reduce skewness and thus minimize the influence of spurious points (Mcgill, Tukey, & Larsen, 1978).

The OLK method computes the spatial continuity of the dataset by variogram analysis. The model training consists of fitting a suitable model variogram on an experimental variogram. The optimal parameters for the model variogram were estimated using auto-calibration in the training process; the geospatialisation algorithm was run 400 of times to fine-tune the model parameters extracted within user-defined thresholds. The optimal parameters were assessed using a 5-fold cross-validation approach (Hastie, Tibshirani, & Friedman, 2009). The parameter set that returned the best root mean square error (RMSE) was selected for final interpolation. HydroPSO (Zambrano-Bigiarini & Rojas, 2013) within the R software package was used for auto-calibration. The final validation of the maps was performed leaving out 20% of the samples as a validation set. A raster mask using the land use map of South Tyrol was adopted to constrain the interpolation to only agricultural fields on the valley bottom. Thus, urban areas, industrial sites, and forests were masked out to avoid inaccurate or invalid spatial predictions for these land uses.

3. Results and discussion

3.1. Exploratory statistics

Exploratory statistics of the measured P_2O_5 and K_2O concentrations are summarized in Table 1. The raw data highlighted that the P_2O_5 and K_2O distributions are slightly skewed. P_2O_5 ranged from 10 to 3200 mg/kg, with a mean of 270 mg/kg and standard deviation of ±168. P_2O_5 showed a slightly skewed distribution, with a moderate positive skewness of 2.9 and large kurtosis. K_2O ranged from 10 to 1400 mg/kg with a mean of 222 mg/kg and standard deviation of ±114. K_2O showed lower positive skewness of 2.1 and relatively lower kurtosis. The investigated parameters showed moderate variability, and P_2O_5 showed relatively higher variability with a coefficient of variation (CV) of 62.2% in comparison to K_2O's CV of 51.6% (Zhang, Sui, Zhang, Meng, & Herbert, 2007).

3.2. Mapping soil properties

The remarkably high number of about 16,000 soil samples with a mean sampling interval of about 143 m ensures adequate sampling design in terms of sample number and density (Brus, Kempen, & Heuvelink, 2011; Stahl, Moore, Floyer, Asplin, & McKendry, 2006), satisfying the requirements for the best possible performance of the interpolation models (Li & Heap, 2014). Figure 2 shows the model semivariograms and Table 2 presents the parameter for the OLK model and overall cross-validation. The exponential model performed better than other models. In agreement with similar studies (Liu, Zhang, Zhang, Ficklin, & Wang, 2009; Robinson & Metternicht, 2006), the nugget value is small for all the variables, which indicates adequate sample number and spatial variability. The

Table 1. The table shows the statistical summary of the raw data for P_2O_5 and K_2O.

	Min. (mg/kg)	Q1 (mg/kg)	Mean (mg/kg)	Q3 (mg/kg)	Max. (mg/kg)	Skew.	Log. Skew.	Kurt.	CV (%)	Std. (mg/kg)
P_2O_5	10	170	270	340	3200	2.9	−0.8	27	62.2	168
K_2O	10	150	222	270	1400	2.1	−0.3	12	51.6	114

Notes: Min: minimum value, Max: maximum value, Mean: mean value, Median: median value, Q1: first quartile value, Q3: third quartile value, Skew.: Skewness value, Log. Skew. Log Skewness value, Kurt. Kurtosis value, Std: Standard deviation, CV: Coefficient of variation.

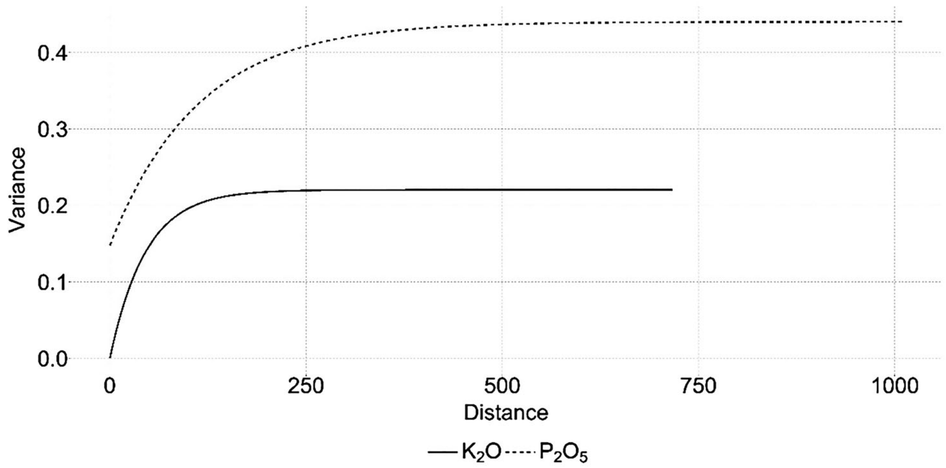

Figure 2. Model semivariograms for P_2O_5 and K_2O. Model fit parameters are in Table 2.

Table 2. Semivariogram parameters for the P_2O_5 and K_2O maps and overall goodness of fit.

	Model fit parameters					OLK parameters				Validation	
	Model	Psill (mg/kg)	Nugget (mg/kg)	Range (m)	Nugget/Sill	Radius (m)	nmax	nmin	omax	RMSE (mg/kg)	R^2
P_2O_5	Exp.	0.29	015	112.23	0.33	1009.65	97.59	1.00	15.03	115.7	0.30
K_2O	Exp.	0.22	0.00	45.91	0.01	717.13	46.74	1.00	14.55	78.3	0.32

Notes: Psill (partial sill): value of semivariance at which a stationary trend is reached. Nugget: value of semivariance at distance zero. Range: distance at which 95% of the psill is reached. Radius: maximum distance for which 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.

range is 112.30 m for P_2O_5 and 45.91 m for K_2O; both values are lower than the mean sampling distance, which may indicate the irregular spatial structure of the sample set (Marchant & Lark, 2006). Comparison between predicted and measured P_2O_5 and K_2O concentrations showed a relatively low R^2 of 30% with RMSE of 115.7 mg/kg and R^2 of 32% with RMSE of 78.3 mg/kg, respectively. When the data density is very high, as in this study, diverse interpolation methods generally do not improve the prediction accuracy (Bogunovic, Mesic, Zgorelec, Jurisic, & Bilandzija, 2014; Burrough, 1986). The low accuracy is likely linked to the nature of the parameters investigated in this agro-system, which are highly variable with large spatial heterogeneity due to different management practices (Blanchet et al., 2017; Roger et al., 2014). In addition, despite the data were produced following the same extraction methods and homogenous protocols for soil sampling, the data used in this study had been collected over 8 years, and may thus contain seasonal and annual differences.

Indeed, the maps of P_2O_5 and K_2O exhibit high spatial variability, which suggests large local differences in fertilization. Considering the nugget/sill ratio (Cambardella et al., 1994), P_2O_5 shows a moderate spatial dependence with a nugget/sill ratio of 0.33, as reported in other studies (Bogunovic et al., 2014), while K_2O has a very high spatial dependence, with a nugget/sill ratio of nearly zero. This analysis corroborates that the K_2O distribution is strongly controlled by extrinsic factors, such as intense agricultural practices (e.g. uneven fertilization). Finally, the fact that the range for both variables is lower than the mean sampling distance indicated that most of the variance represents differences from field to field. A deeper understanding of the driving forces behind this high spatial variability may be achieved by adopting more advanced geostatistical techniques. Regression kriging (Hengl, Heuvelink, & Rossiter, 2007; McBratney et al., 2003), combined with a set of sound predictors, such as detailed spatial distributed information of land management and farming practices, can improve prediction accuracy (Blanchet et al., 2017; Roger et al., 2014). However, such data are rarely publicly available.

Probability density distributions of P_2O_5 and K_2O concentrations for apple orchards and vineyards highlight similar distributions, which may support the speculation that intensive agriculture has homogenized nutrient availability over large areas. However, vineyards show overall higher mean and median values but lower variability; in contrast, apple orchards show lower mean and median values but larger variability (see Table 3). This is to be expected, as the two permanent crops have diverse nutrient needs.

Although no eutrophication has ever been reported along the main river in the Venosta/Vinschgau and Adige/Etsch valleys (Chiogna et al., 2015), available P and K in soils frequently exhibit higher values in comparison with other studies (Aggelopoulou et al., 2011; Fischer et al., 2017). In fact, optimal P concentrations in soil should range from 120 to 200 mg/kg while K should range from 60 to 350 mg/kg (see Figure 3 and 4). Figure 3 shows that P frequently exceeds the recommended maximum threshold, while Figure 4

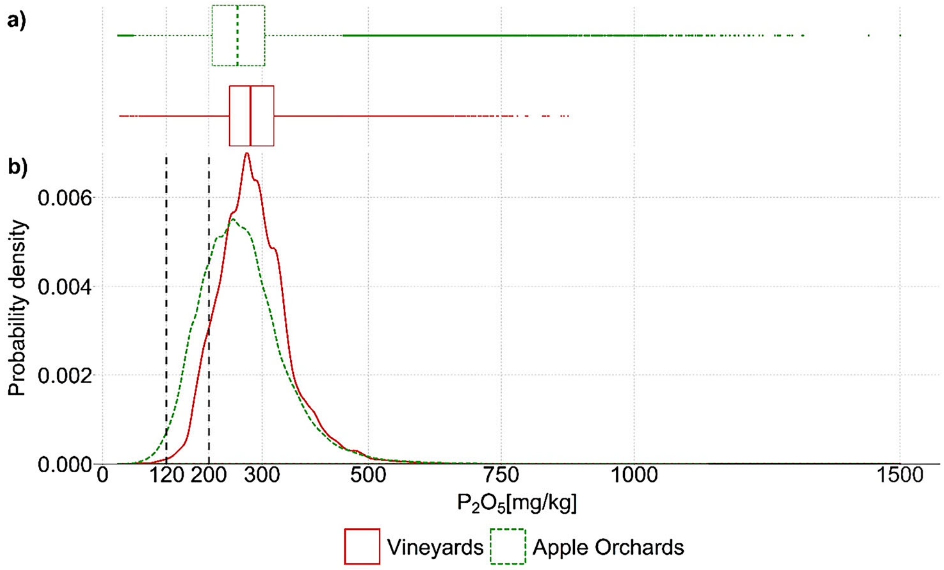

Figure 3. P_2O_5 map probability density distribution for the two land uses. The vertical dashed lines refer to the ranges of the Class C (120–200 mg/kg) defined as the target class for optimal production analysis (VDLUFA, 1991).

shows that K is mostly within the recommended thresholds. Finally, Table 4 summarizes the percentage of the map area below, within and above the suggested thresholds. This highlights that P exceeds the suggested concentration on more than 80% of the map surface. Thus, these results suggest the need for more efficient nutrient management and they identify source areas of potential diffuse P losses. Note that fertility maps of P_2O_5 and K_2O must consider the feedback mechanism in the soil solution of soil pH, SOM, and soil texture. Thus, future fertility maps will be produced by using recently available auxiliary data of pH, SOM, and soil texture (Della Chiesa et al., 2019) for large-scale spatial prediction of micro and macronutrients needs (Kerschberger, Hege, & Jungk, 1997; VDLUFA, 1991). This study provides regional scale information on macronutrient concentration in soils which can be exploited as a baseline for future studies

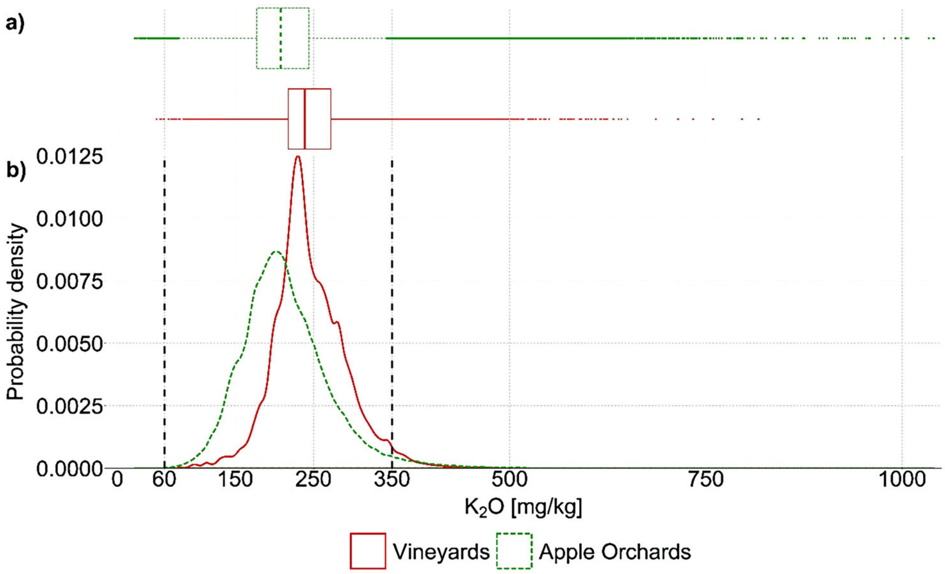

Figure 4. K_2O map probability density distribution for the two land uses. The vertical dashed lines refer to the ranges of the Class C (60–350 mg/kg) defined as the target class for optimal production analysis (VDLUFA, 1991).

Table 3. Statistical summary of the map density distribution for P and K of Figures 3 and 4.

	Landuse	Mean (mg/kg)	Min (mg/kg)	Q1 (mg/kg)	Median (mg/kg)	Q3 (mg/kg)	Max (mg/kg)
P_2O_5	Vineyards	284.3	33.4	238.6	278	322.1	875.6
	Apple Orchards	262	28.7	206	253.6	304.8	1500.6
K_20	Vineyards	245.7	50	217.6	239	271.9	817
	Apple Orchards	214.8	22	177.6	208.1	243.8	1040.7

Table 4. Map area in percent which is below, within and above the ranges of the Class C defined as the target class for optimal production analysis (VDLUFA, 1991).

	Below target class C	Within target class C	Above target class C
P_2O_5	1.20%	18.37%	80.42%
K_2O	0.02%	97.50%	2.48%

to compare fertilizer consumption and recommended doses (Tóth, Guicharnaud, Tóth, & Hermann, 2014).

The final representation of the spatial interpolation is digital topsoil maps of P (P_2O_5) (Main Map) and K (K_2O) (Main Map) in apple orchards and vineyards in the Adige/Etsch and Venosta/Vinschgau valleys, South Tyrol (Italy) at 20-m × 20-m pixel resolution.

4. Conclusions

Digital topsoil maps of P_2O_5 and K_2O in permanent crop fields in the Venosta/Vinschgau and Adige/Etsch valleys were developed using a large soil dataset and a geostatistical approach. Overall, available K is mostly within the recommended optimal range while P frequently exceeds recommended concentrations. No specific data distribution of available P and K is related to the different land uses, which could be a consequence of intensive farming. Because of these particular environmental settings, detailed land use and farming management as auxiliary variables are needed to improve the prediction accuracy for highly variable parameters such as P_2O_5 and K_2O. This research stems after the synergism between standard laboratory techniques and digital applications, through which plot-scale measurements are rendered to provide valuable large-scale information to identify potential areas suffering from nutrients mismanagement. The maps could eventually promote for long-term planning of sustainable use of fertilizers in South Tyrolean permanents crops. These maps provide great utility for large-scale environmental management plans affecting multiple stakeholders, including land managers, farming consulting companies, and policy makers.

Software

The geocoded soil database was produced using Esri ArcGIS 10.4®. Geostatistical interpolation, calibration, validation were performed in R (www.cran.r-project.org) using the following packages: caret, Gstat, hydroPSO, raster, sp, SpatialPosition. The map and layout were produced in Esri ArcGIS 10.4®.

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Disclosure statement

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