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,
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$_2$O$_5$ and K$_2$O, 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 gleic Cambisols (partially calcaric), Fluvisols, or Gley-sols (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$_2$O$_5$ and K$_2$O 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$_2$O$_5$ and K$_2$O were spatialized using ordinary local kriging (OLK) in the R environment (Gräler, Pebesma, & Heuvelink, 2016; Pebesma, 2004). The data distribution of P$_2$O$_5$ and K$_2$O 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$_2$O$_5$ and K$_2$O concentrations are summarized in Table 1. The raw data highlighted that the P$_2$O$_5$ and K$_2$O distributions are slightly skewed. P$_2$O$_5$ ranged from 10 to 3200 mg/kg, with a mean of 270 mg/kg and standard deviation of ±168. P$_2$O$_5$ showed a slightly skewed distribution, with a moderate positive skewness of 2.9 and large kurtosis. K$_2$O ranged from 10 to 1400 mg/kg with a mean of 222 mg/kg and standard deviation of ±114. K$_2$O showed lower positive skewness of 2.1 and relatively lower kurtosis. The investigated parameters showed moderate variability, and P$_2$O$_5$ showed relatively higher variability with a coefficient of variation (CV) of 62.2% in comparison to K$_2$O’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$_2$O$_5$ and K$_2$O. |
|---|---|---|---|---|---|---|---|---|
| Min. (mg/kg) | Q1 (mg/kg) | Mean (mg/kg) | Q3 (mg/kg) | Max. (mg/kg) | Skew. | Log. Skew. | Kurt. | CV (%) | Std. (mg/kg) |
| P$_2$O$_5$ | 10 | 170 | 270 | 340 | 3200 | 2.9 | −0.8 | 27 | 62.2 | 168 |
| K$_2$O | 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.
range is 112.30 m for P$_2$O$_5$ and 45.91 m for K$_2$O; 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$_2$O$_5$ and K$_2$O 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$_2$O$_5$ and K$_2$O exhibit high spatial variability, which suggests large local differences in fertilization. Considering the nugget/sill ratio (Cambardella et al., 1994), P$_2$O$_5$ shows a moderate spatial dependence with a nugget/sill ratio of 0.33, as reported in other studies (Bogunovic et al., 2014), while K$_2$O has a very high spatial dependence, with a nugget/sill ratio of nearly zero. This analysis corroborates that the K$_2$O 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$_2$O$_5$ and K$_2$O 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
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 P₂O₅ and K₂O 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.

| Landuse | Mean (mg/kg) | Min (mg/kg) | Q1 (mg/kg) | Median (mg/kg) | Q3 (mg/kg) | Max (mg/kg) |
|---------|--------------|-------------|------------|----------------|------------|-------------|
| P₂O₅    |              |             |            |                |            |             |
| Vineyards | 284.3        | 33.4        | 238.6      | 278            | 322.1      | 875.6       |
| Apple Orchards | 262        | 28.7        | 206        | 253.6          | 304.8      | 1500.6      |
| K₂O     |              |             |            |                |            |             |
| 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 (VDLUA, 1991).

|        | Below target class C | Within target class C | Above target class C |
|--------|----------------------|-----------------------|----------------------|
| P2O5   | 1.20%                | 18.37%                | 80.42%               |
| K2O    | 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 (P2O5) (Main Map) and K (K2O) (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 P2O5 and K2O 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 P2O5 and K2O. This research stems after the synergism between standard laboratory techniques and digital applications, through which plotscale measurements are rendered to provide valuable largescale 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 permanent crops. These maps provide great utility for large-scale environmental management plans affecting multiple stakeholders, including land managers, farming consulting companies, and policy makers.

Disclosure statement

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