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Short Communication

The Contribution of Geostatistics to Precision Agriculture

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Agriculture is facing two challenges which are apparently contrasting: enhancing food production and promoting environmental sustainability. According to projections included in the 2016 World Population Data Sheet [1], the world population has been forecasted to reach 9.9 billion in 2050. Such increase in population would result in a decrease of land availability for agriculture and, in order to provide sufficient food to future generations, farmers should try to produce 'more from less land' [2]. Since soil is a non-renewable and limited resource, it is required that food production should follow an environmentally sustainable agriculture. In this perspective, the farm system could be considered as a decision making unit [3] within which soil properties vary both spatially and temporally [4]. This is mainly a result of the interaction of many biotic, abiotic and climate factors [5].

Precision Agriculture (PA) offers the potential for both increasing crop yields and ensuring food security. In contrast to the conventional farming that treats a field uniformly, PA allows to meet the actual crop site-specific needs, managing natural resources (such as soil, nutrients, yield, field topography) and crop [3,6,7], based upon spatial variation.

Geostatistics [8] provides the tools to quantify the spatial variability of environmental properties, taking into account data spatial autocorrelation. Moreover, it allows producing continuous maps, starting from sparse data. The variogram is a mathematical model of spatial dependence, describing the data variance between two locations and their separation distance [9]. By using the variogram and different interpolation techniques [10], generally known as kriging, the variable can be estimated at unsampled locations. Differing from classic statistical interpolators, geostatistics provides kriging variances or standard errors which can guide to the reliability of the estimate [2]. The application of geostatistical methods requires an assumption of data stationarity but such condition is not always verified. Multivariate geostatistics may allow to simultaneously quantify local changes in the spatial relations of several environmental properties (Cokriging) [11] or reveal the influence of ancillary data (e.g. landscape attributes) to model the primary variable in the regression kriging [15] or kriging with external drift techniques [12,13]. For instance, topographic attributes [14] or electromagnetic data have been used as auxiliary variable to improve the estimation of soil texture and other properties related to soil fertility, in the regression kriging [15] or kriging with external drift techniques [16].

Each geostatistical approach has advantages and drawbacks. The choice of the best method depends on the specific case under study, data availability and presence of a spatial trend.

Cokriging considers two or more variables contemporarily but needs that variables be related. Moreover it is computing demanding because of the modelling of simple, and cross variograms which describe the correlation of pairwise variables. Kriging with external drift describes the spatial changes in the relationship between variables, but such relationship must be linear and many software deal with only a single covariate.

Geostatistics may help to solve different aspects of PA. It might be profitably applied to guide and optimize the number and location of soil samples, based on the consideration that sampling distance should be at an interval within the correlation range of spatial variation [17-19]. Starting from a variogram model, it is possible to determine a sampling scheme with specified precision [20,21], by also using auxiliary information coming from satellites, geophysical sensors or topographic data as indicators of the likely scale of variation in the soil or crop [22].

Many types of data may be obtained through different sources such as field sampling, laboratory analyses and proximal and remote sensors (e.g. spectral, electrical, electromagnetic or radiometric measurements of soils or of plants) with different spatial and temporal scales [23]. Such big amount of available data can be treated through a multivariate geostatistics technique called "data fusion" [24], appropriate for integrating data coming from different input and for adjusting them to the same spatial resolution [13,25,26].

Research in precision agriculture is also focused on the use of management zones, representing subfield regions with homogeneous characteristics within which a single rate of a specific crop input is appropriate [27]. Generally, the identification of subfield areas is difficult because of the complex combination of factors which could influence the effectiveness of a specific input (i.e. fertilization, irrigation, pesticide) that affects variation in response variables such as requested quality and quantity of crop yield. One possibility to summarize the variation of attributes or limiting factors affecting agricultural production, is to use factorial kriging [4,11,28] which allow to quantify and reduce spatial variability of multivariate data to only a few factors, related to different spatial scales. Such factors, summarizing the variability of multivariate data, can be used to divide the field in areas of size manageable by farmers. Further, polygon kriging can be used to assess the effectiveness of field delineation based on soil attributes [3,29].

Different studies have highlighted the benefits of PA deriving from the increasing of yields and/or lowering of the quantity of inputs, even though the extra-investment needed for implementing PA technologies and practices could be high. Since collecting

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sufficient data to fully implement the system may take a long time, PA should be seen as a long-term investment. To account the principles of PA, in fact, farmers should invest for: (i) data collection and positioning system, (ii): data processing and (iii) inputs application such as computer-guided fertilizer spreader or seeder. Although the economic advantages of PA cannot be generalizable, the higher the variability of the field, the higher the benefit of PA.

The present short note highlighted the potential of geostatistical approaches in PA, with the aim to enhance its application and diffusion that is actually limited in reality, due to the few number of user-friendly software products. In addition, PA has not been uniformly applied to all croplands, since it has been mainly focused on arable lands [30]. Nowadays, one of the most limiting factors to the use geostatistics for PA is not only the required number of data on soil, plants and environmental properties but converting them into useful information for modelling spatial variability. The use of proximal and remote sensors may allow collecting data on large areas providing the required spatial resolution of information more rapidly than traditional laboratory analyses and at a relatively cheaper cost. To improve the application of geostatistics to PA, incentive-based technologies should be activated and robust decision support systems developed. The use of geostatistical methods could help framers and managers to understand the causes of the variability of crop yield and quality.

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