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Mapping Soil and Leaf Micronutrients Distribution in an Olive (*Olea europaea L.*) Orchard

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Abstract

Plant nutrition plays an important role in increasing crop yields. Nevertheless, the need for more sustainable agricultural systems, reducing fertilization costs and concerns on environmental pollution have determined a shift towards precision agriculture. The study was aimed to quantify the spatial structure and map soil and leaf micronutrients in an olive (*Olea europaea L.*) orchard in a southern Italy area. The study was conducted in a 10,000 m^2 (100 m x 100 m) olive orchard located in southern Italy (Calabria) where at 100 locations both topsoil (0-0.20 m) and vegetation (leaves) samples were collected. Soil samples were air-dried and sieved at 2 mm. Then both soil and vegetation samples were analyzed in laboratory for the main micronutrients (B, Cu, Fe, Mn, Mo, and Zn) by Inductively Coupled Plasma Mass Spectrometry (ICP-MS).

A geostatistical approach was used

(I) to quantify the spatial structure of soil and leaf micronutrients, and

(II) to map their spatial distribution. Maps of each soil and leaf micronutrient were analyzed by visual comparison which confirmed a relation for almost all analyzed elements.

Keywords: Fertility; Micronutrients; Soil; Olive; Spatial variability

Introduction

Soil nutrient availability is one of the most important factors influencing olive growth. Both nutrient deficiency and toxicity negatively affect total biomass and fruit production [1]. The production of biomass and, of course, the economic benefit (crop yield) for the farmers can be maximized by controlling the optimum levels of nutrient availability in soil.

All nutrients play an important role in activating growth and fruiting through encouraging cell division and stimulating the biosynthesis of organic foods. Among them, although present in small quantities, the soil micronutrients have a key role in crop growth. The availability of micronutrients in agricultural soils is influenced mainly by parent material, pedogenic processes and soil management which may promote, in some cases, a reduction of cationic micronutrients content (Cu, Zn, Fe and Mn) [2-4]. Conversely, the deficiency of micronutrients in agricultural soils is due to soil with naturally low levels of micronutrients, reduction of the soil natural fertility caused by the crop yield increment or due to intensive cropping patterns, application of lime to soil reduces the availability of micronutrients.

Agricultural crops remove nutrients from soil through agricultural products and crop residues. Nutrient removal may result in a decline of fertility if replenishment with inorganic or organic nutrient inputs is inadequate [5]. Traditional fertilization systems are based on the assumption of homogeneity of agricultural fields and fixed doses of fertilizers are determined on the base of the nutrients concentration in soil samples. It is simpler to treat entire fields than to complicate the fertilization process with spot application [6].

In recent years, in North America and Western Europe there has been a trend to use less fertilizer by means of adopting extensive agricultural systems to grow crops in a more sustainable and less polluting manner [7]. Sustainable agriculture has the main goal to meet human requirements by making the most efficient use of non-renewable resources [8]. Since it is well known that agricultural practices based on non-conservative tillage and over-reliance of pesticides have a devastating effect on soil life and water quality, three pillars of sustainable agriculture should be taking into account [9]. They are relate to

(1) the factors that affect the economic sustainability of a company's business model such as using efficient inputs which generate a greater return on investment,

(2) the effect which farming and conservation practices have on social sustainability and public opinion, and

(3) how agricultural practices affect environmental sustainability [9].

In addition, given the increased costs of fertilizers and other agrochemicals and the increasing controls on agriculture in terms of leaching of nutrients and pesticides to water courses and groundwater, there has been a shift towards precision agriculture [10].

Precision Agriculture (PA) aims to manage the spatial variation in soil to supply the actual requirements of a specific soil and crop to parts of fields rather than average needs to whole fields [11].

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Table 1: Summary of main plant micronutrients roles.

Micronutrient	Role
Boron (B)	Formation of cell wall. Germination and elongation of pollen tube. Participates in the metabolism and transport of sugars
Copper (Cu)	Influences the metabolism of nitrogen and carbohydrates
Iron (Fe)	Chlorophyll synthesis
Manganese (Mn)	Necessary in the photosynthesis process
Molybdenum (Mo)	Component of nitrate-reductase and nitrogenase enzymes
Zinc (Zn)	Auxins synthesis; enzymes activation

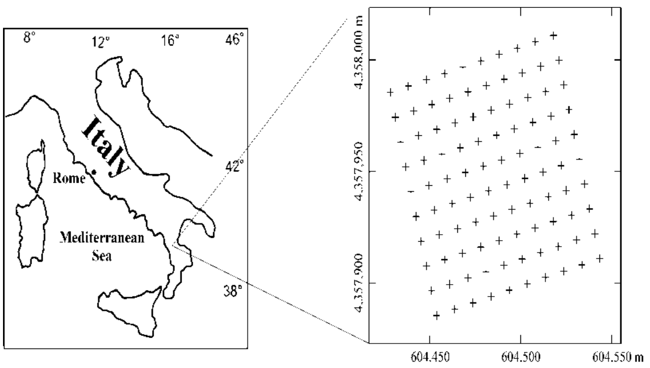

Figure 1: Study area and sampling point (black cross) locations.

PA requires characterization of the within-field soil spatial variation and delineation of Management Zones (MZs), which are defined as homogeneous sub-field regions that have similar yield-limiting factors or similar attributes affecting yield [12,13]. Soil variability is the result of both natural processes and management practices, acting over different spatial and temporal scales. Therefore, it is critical to characterize soil properties, both quantitatively and spatially [14,15].

Geostatistics [16] provides a valuable tool for the study of the spatial structure of micronutrients taking into account the spatial autocorrelation in data to create mathematical models of spatial correlation structures.

Olive (*Olea europaea L.*) has played an important role in the rural development of the Mediterranean's relatively poor rained areas over the centuries [17,18]. The olive is a medium-sized evergreen shrub/tree that grows and fruits well under a Mediterranean climate.In the whole Mediterranean area, Italy represent the central point of olive production because of its history and environmental conditions. As such, it can be considered as an open laboratory producing the latest and most advanced technologies able to support, for itself and for the world, the development of olive-production techniques and practices.

Olive trees are a typical case that does much better through balanced nutrient supply.

The olive tree requires small amounts of boron, zinc, manganese, copper and molybdenum. A deficiency in any of these elements can reduce growth and fruiting. Deficiencies of trace elements are commonly associated with alkaline, lime-rich (calcareous) soils, where they are retained in an oxide form. Table 1 reports a summary of main functions of micronutrients in olive plants [19].

In the study the concentrations of soil and leaf micronutrients are analysed and that doesn't mean equating soil fertility with the soil nutrients reserve because it is well known that nutrients uptake by plants involves several interconnected processes such as nutrients release from solid phase to solution, transport to roots for absorption, and plant translocation and utilization [20].

Mapping soil and leaf micronutrients is an essential step for operational decision making on precision fertilization.

The objective of the present study was to quantify the spatial structure and map soil and leaf micronutrients in an olive (*Olea europaea L.*) orchard in a southern Italy area.

Materials and Methods

Sampling and analytical methods

The study site was located in an olive orchard in Rende municipality (Calabria, southern Italy). Topsoil samples (0-0.20 m) and olive leaves were collected in 100 m x 100 m olive orchard (Figure 1) at 100 locations. The distribution of olive groves over the total study area is such that a homogeneous distribution can be considered as a good approximation. All samples were placed in plastic containers and transported to the laboratory for preparation.

Soil samples were oven dried at 50°C and then sieved through a pore size of 2 mm. The freshly collected olive leaves were washed using distilled water to remove all the adhered soil particles and after dried.

Soil samples and olive leaves weighed, digested in aqua regia and analysed for boron (B), copper (Cu), iron (Fe), manganese (Mn), molybdenum (Mo) and zinc (Zn) by means of the Inductively Coupled Plasma-Mass Spectrometry (ICP-MS) using an Agilent 7500 spectrometer. Analytical precision for the samples (20 replicates for soils and 20 for plants) and accuracy of the analysis, which was calculated using several referenced soils and olive leaves samples, were below 5%.

Geostatistical approach

For each micronutrient, each measured value, $z(\mathbf{x}_\alpha)$, at location $\mathbf{x}_\alpha$ (**x** is the location coordinates vector and the sampling points = 1, ..., N) is interpreted as a particular realization, or outcome, of a random variable $Z(\mathbf{x}_\alpha)$. The set of dependent random variables $\{Z(\mathbf{x}_\alpha)\ \alpha = 1,...,n\}$ constitutes a random function $Z(\mathbf{x})$. For a detailed presentation of the theory of random functions, interested readers should refer to textbooks such as [21-24,26], among others.

An important tool in geostatistics is the experimental variogram, which is a quantitative measure of spatial correlation of the regionalized variable $z(\mathbf{x}_\alpha)$. The experimental variogram $\gamma(\mathbf{h})$ is a function of the lag **h**, a vector in distance and direction, of data pairs values $[z(\mathbf{x}_\alpha)\ z(\mathbf{x}_\alpha+\mathbf{h})]$; it refers to the expected value of the squared differences; a way of calculating this is reported in Equation (1):

$$\gamma(\mathbf{h})=\frac{1}{2N(\mathbf{h})}\sum_{\alpha=1}^{N(\mathbf{h})}\left[z(\mathbf{x}_\alpha)-z(\mathbf{x}_\alpha+\mathbf{h})\right]^2 \qquad (1)$$

Where $N(\mathbf{h})$ is the number of data pairs for a given class of distance and direction. A theoretical function, known as the variogram model, is fitted to the experimental variogram to allow one to estimate the variogram analytically for any distance **h**. The function used to model the experimental variogram must be conditionally negative definite to ensure that the kriging variances are positive [24]. The aim is to build a model that describes the major spatial features of the attribute under study. The models used can represent bounded or unbounded variation. In the former models the variance has a maximum (known as the sill variance) at a finite lag distance (range) over which pairs of values is spatially correlated. The best fitting function can be chosen by cross-validation, which checks the compatibility between the data and the model. It takes each data point in turn, removing it temporarily from the data set and using its neighbouring information to predict the value of the variable at its location. The estimate is compared with the measured value by calculating the experimental error, i.e. the difference between estimate and measurement, which can also be standardized by estimating the standard deviation [24]. The goodness of fit was evaluated by the Mean Error (ME) and the Mean Squared Deviation Ratio (MSDR). The Mean Error (ME) proves the unbiasedness of estimate if its value is close to 0. The Mean Squared Deviation Ratio (MSDR) is the ratio between the squared errors and the kriging variance [24]. If the model for the variogram is accurate, the mean squared error should equal the kriging variance and the MSDR value should be 1. The variogram model will be used with the data to predict micronutrients values at unsampled locations using a kriging algorithm.

Variogram modelling is sensitive to marked departures from normality, because a few exceptionally large values may contribute to a high number of large squared differences [25]. In this scope and following suggestions from [25], when the micronutrients data had a skewness greater than 0.5 they were transformed into a Gaussian-shaped variable with zero mean and unit variance using a procedure is known as Gaussian anamorphosis [24, 26].

Finally, the variogram models of all soil and leaf micronutrients data were used with Ordinary Kriging (OK) [25] to estimate their values at the nodes of a 1 m by 1 m grid and map them.

The estimates of Gaussian micronutrients data were back transformed to the row data through the mathematical model calculated in the Gaussian Anamorphosis.

All geostatistical analyses were performed using the software Isatis®, release 2016.1 (http://www.geovariances.com).

Results and Discussions

Descriptive statistics of the soil and leaf micronutrients data are summarized in Tables 2 and Table 3. Among soil micronutrients data only B and Fe had a coefficient of skewness slightly less than 0.5, but for subsequent analysis it was chosen to transform into a Gaussian distribution all micronutrients data using the Gaussian Anamorphosis. Regarding leaf micronutrients data only Mn and Mo had a coefficient of skewness greater than 0.5, and for subsequent analysis Mn and Mo data were transformed into a Gaussian distribution using the Gaussian Anamorphosis.

Table 2: Basic statistics of soil micronutrients concentrations.

Element	B (mg kg^{-1})	Cu (mg kg^{-1})	Fe (g kg^{-1})	Mn (g kg^{-1})	Mo (mg kg^{-1})	Zn (mg kg^{-1})
Minimum	4.49	9.60	13.22	0.58	0.65	33.46
Maximum	24.24	33.37	39.98	2.65	2.38	172.36
Mean	12.99	19.31	23.37	1.36	1.21	83.30
Median	12.44	18.98	22.61	1.17	1.09	77.52
Lower quantile	9.28	16.41	21.05	0.93	0.91	68.67
Upper quantile	17.16	21.42	25.59	1.77	1.49	92.25
Standard Deviation	4.73	3.88	4.29	0.56	0.39	25.58
Skewness	0.44	0.87	0.49	0.58	1.00	1.42
Kurtosis	2.39	4.56	4.58	2.13	3.40	5.48

Table 3: Basic statistics of leaf micronutrients concentrations.

Element	B (mg kg^{-1})	Cu (mg kg^{-1})	Fe (mg kg^{-1})	Mn (mg kg^{-1})	Mo (mg kg^{-1})	Zn (mg kg^{-1})
Minimum	8.82	3.46	51.50	7.70	0.05	0.20
Maximum	22.47	22.96	221.55	36.88	1.13	31.14
Mean	14.62	11.81	127.19	19.69	0.37	14.72
Median	14.70	11.89	120.78	18.70	0.32	15.43
Lower quantile	13.00	8.79	100.90	14.75	0.21	11.58
Upper quantile	16.06	14.65	152.48	23.55	0.45	17.21
Standard Deviation	2.63	4.07	35.90	6.33	0.22	5.08
Skewness	0.30	0.34	0.40	0.56	1.27	0.00
Kurtosis	3.37	2.56	2.68	2.91	4.96	3.92

Table 4: Variogram model parameters for the soil micronutrients concentrations.

Variable	Model	Range (m)	Sill (-)
G B	Spherical	72.63	0.91
G Cu	Nugget	-	0.10
	Spherical	31.46	0.34
	Spherical	99.33	0.76
G Fe	Nugget	-	0.06
	Spherical	30.68	0.16
	Spherical	70.22	0.96
G Mn	Nugget	-	0.05
	Spherical	65.36	0.55
G Mo	Nugget	-	0.18
	Spherical	78.62	0.91
G Zn	Nugget	-	0.34
	Spherical	64.48	0.72

Maps of the 2-D variograms (not shown) were computed for each soil and leaf micronutrient and no anisotropy was evident. For all micronutrients data, semivariance values increased with the separation distance and they reached a maximum value showing that all experimental variograms were bounded.

With the exception of G B, the experimental variograms for each

Table 5: Variogram model parameters for the leaf micronutrients concentrations.

Variable	Model	Range (m)	Sill
B	Nugget	-	2.08(mg kg^{-1})^2
	Exponential	61.65*	4.96(mg kg^{-1})^2
Cu	Exponential	45.45*	16.59(mg kg^{-1})^2
Fe	Spherical	19.57	1216.56(mg kg^{-1})^2
G Mn	Nugget	-	0.53(-)
	Spherical	81.38	0.56(-)
G Mo	Nugget	-	0.08(-)
	Spherical	12.00	0.54(-)
	Spherical	42.11	0.22(-)
Zn	Nugget	-	5.45(mg kg^{-1})^2
	Spherical	37.11	6.96(mg kg^{-1})^2

G = variable transformed into a Gaussian distribution.
*Practical range.

soil micronutrient were modelled by a nested variogram (Table 4). For G Cu and G Fe it combines three basic structures including a nugget effect, a short range spherical model [25] with a range and a long range spherical model.

The nugget effect implies a discontinuity in $Z(\mathbf{x})$ and is a positive intercept of the variogram. It arises from errors of measurement and spatial variation within the shortest sampling interval [25]. The spherical model is:

$$\gamma(h) = \begin{cases} c\left[\frac{3}{2}\frac{h}{a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right] & \text{for } 0 < h \le a \\ c & \text{for } h > a \end{cases} \quad (2)$$

where a is the range and c the sill.

The nested model for G Mn, G Mo, and G Zn included two basic structures (Table 4): a nugget effect and spherical model.

Also for leaf micronutrients, with the exception for Cu and Fe, the experimental variograms for the other leaf micronutrients were modelled by a nested variogram (Table 5). For G Mn and Zn the nested model combines two basic structures including a nugget effect and spherical model (Table 5), whereas for G Mo three basic structures were combined including a nugget effect, a short range spherical model with a range and a long range spherical model (Table 5). The model for B combines two basic structures (Table 5): a nugget effect and an exponential model [25]:

$$\gamma(h) = c\left[1 - \exp\left(-\frac{h}{r}\right)\right] \quad (3)$$

where r is a distance parameter that defines the spatial extent of the model. The exponential model approaches its sill asymptotically and so has no finite range. For useful purposes, a practical range has been taken as the distance at which the variogram value equals 95% of the sill variance (approximately 3 r).

The goodness of fitting of all variogram models was verified by cross validation. The results were quite satisfactory because the

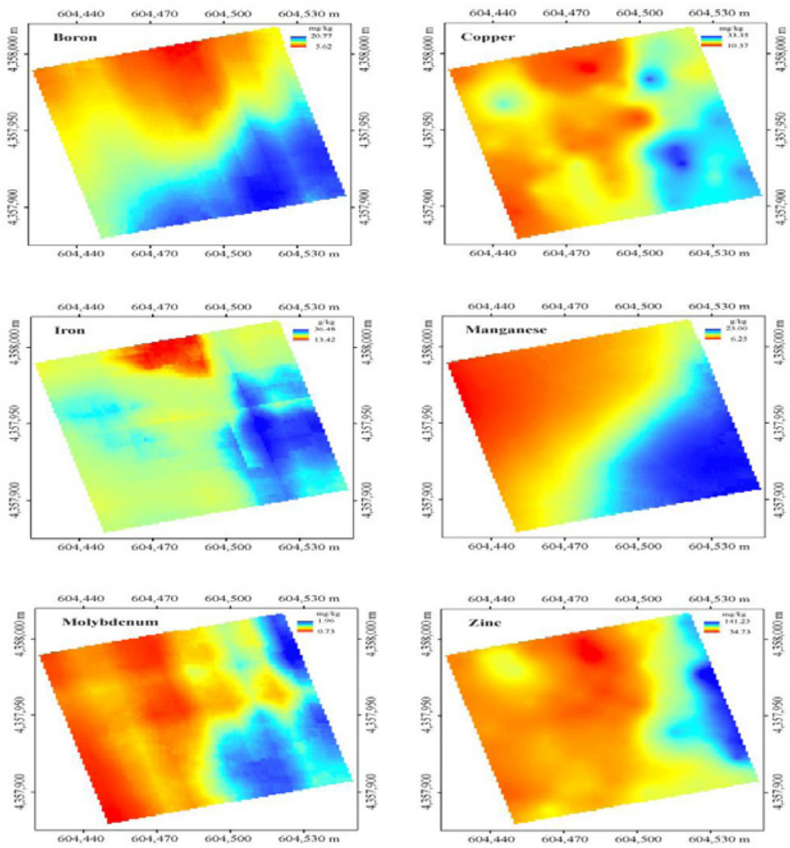

Figure 2: Maps of kriged estimates of soil micronutrients concentration.

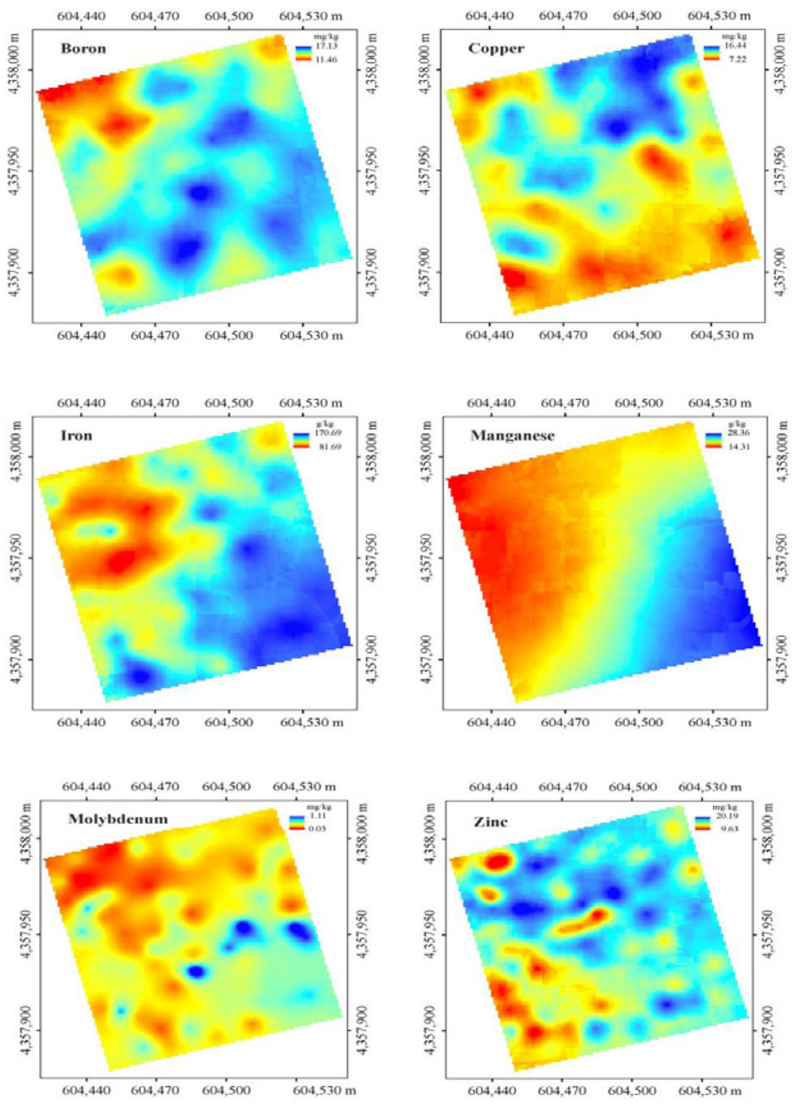

Figure 3: Maps of kriged estimates of leaf micronutrients concentration.

statistics used, i.e. mean of the estimation error and variance of the MSDR, were quite close to 0 and 1, respectively.

Finally, soil and leaf micronutrients data were interpolated and mapped (Figures 2 and Figure 3).

From a visual overview of micronutrients maps, some relations occur comparing soil and leaves contents. In particular, the clearest evidence concerns manganese map: both in soil and in leaves, it is similarly distributed confirming that its content in soil is basically bioavailable for plants.

Boron, iron, molybdenum and zinc exhibit related distribution in soil and leaves. The difference between the two distributions can be recognized in the presence of hot spots in leaves map than the most continuous distribution of soil map for each analyzed element. This evidence can be ascribed to single plants which influence individually the global distribution contributing to create an interpolated surface showing the density of occurrence. Copper doesn't show comparable soil and leaves maps distribution showing higher soil content in portions of map in which leaves have lower ones. As described above, copper plays a key role in many physiological processes of plants, and for this reason is commonly added in the soil as nutrient. The results of this study showed that the amount of soil copper is greater than that is required by the olive trees.

Conclusion

The bioavailability of micronutrients is one of the most crucial problems in agricultural concerns. In this study, some micronutrients, such as boron, copper, iron, manganese, molybdenum and zinc in soil and olive leaves were analysed in a southern Italy olive orchard.

The used geostatistical approach has allowed to quantify the spatial structure of soil and leaf micronutrients, and to map their spatial distribution.

A comparison between soil and leaves map distribution confirmed their relevance for almost all analysed elements exhibiting a good bioavailability of micronutrients for plants. As regards copper, the results suggest the opportunity to limit the addition of this nutrient in the soil. The proposed methodology has allowed knowing the real nutritional status of the plants and can represent a useful contribution to the farmers to define the fertilization plans that takes into account the needs of the crop. The demographic expansion in the world and the consequent increased need for food resources have highlighted many problems related to food production. Currently, the global food production is facing greater challenges than ever before. It is not easy to identify simple solutions to enhance crop productivity without compromising the quality and quantity of environmental resources, including soil nutrients. This study showed the suitability of geostatistics as a useful tool for improving crop yield and optimizing soil-plant system management. A more efficiency use of resource is the necessary premise for the protection of environmental quality.

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