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TABLE OF CONTENTS

ADOPTION OF PRECISION AGRICULTURE

APPLICATIONS FOR UAVS

CLIMATE SMART AGRICULTURE

DECISION SUPPORT SYSTEMS

ECONOMICS OF PRECISION AGRICULTURE

EDUCATION AND OUTREACH INNOVATIONS

MAPPING AND GEOSTATISTICS

ON-FARM EXPERIMENTATION

POLICY SUPPORT INNOVATIONS

PRECISION AGRICULTURE FOR FIELD AND PLANTATION CROPS

PRECISION AGRICULTURE FOR SMALLHOLDERS

PRECISION NUTRIENT MANAGEMENT

PRECISION WATER MANAGEMENT

PROXIMAL AND REMOTE SENSING

ROBOTICS, AUTOMATION, AND SMALL FARM MECHANIZATION

SATELLITE IMAGERY

SOFTWARE AND MOBILE APPLICATIONS

#7617 A GEOSTATISTICAL APPROACH TO DEFINE A SOIL FERTILITY INDEX BASED ON THE MAIN SOIL MACRONUTRIENTS

H.S. Aboelkier[1], A. Nasrallah[1], S. Shaddad[1], and G. Buttafuoco[2]
[1]Soil Science department, Faculty of Agriculture, Zagazig University, Egypt
shaddadsm@gmail.com +201016007959; [2]National Research Council of Italy - Institute for Agricultural and Forest Systems in the Mediterranean (ISAFOM), Rende (CS), Italy

ABSTRACT

Soil fertility is greatly affected by main soil macronutrients such as nitrogen (N), phosphorus (P), and potassium (K). These macronutrients can be used to define a synthetic fertility index to support soil fertilization. The study was aimed to propose a geostatistical approach to define a synthetic fertility index based on factorial cokriging. It consists in quantifying and reducing the spatial variability of multivariate data to only a few factors, related to different spatial scales. Such factors summarize the variability of multivariate data and can be used to divide the field in areas of similar levels of the three macronutrients. Hundred 100 soil samples were collected according to a quite regular grid (20 m x 20 m) from a field of 3.6 ha located in Bilbies district (Egypt). The joint variation of N, P, and K was modelled by a linear model of coregionalization including a nugget effect and two spherical models at short range (42.4 m) and long range (86 m). The joint multivariate variability of N, P, and K in the study area was synthetized by using the first two factor at short and long ranges. The first factor at long range allowed more effectively to delineate the field into different management zones than at short range.

INTRODUCTION

Nutrient supply to plants is one of the main soil factors constraining crop growth and consequently, the yield. The addition of fertilizers has become the main practice to overcome this constraint, often developing a meaning of soil fertility limited to the potential nutrient supply for crop growth (Stockdale et al., 2013). However, fertilization, together with irrigation, is essential to obtain profitable crop yields. In Egypt farmers add fertilizers to soil considering that fields are uniform without taking spatial variability into account. Although this is simpler in application, some areas may receive fertilizers that do not meet their needs, while others may be in excess with negative environmental consequences. Site-specific fertilization may result in maximize soil productivity and minimize the environmental impacts by adding fertilizer where and when they need, and with the precise quantity. Variable rate application of nutrients allows taking into account the field spatial variability of nutrients in soil and meeting the requirements of crops. Variable rate application may result in a more effective use of inputs enhancing crop yield to ensure food security promoting environmental sustainability. Variable rate application is based on the delineation of management zones which are defined as homogeneous subfield regions that have similar yield-limiting factors or similar attributes affecting yield (Doerge, 1999; Khosla and Shaver, 2001). Management zones being used to avoid over- or under application of agricultural inputs in some parts of the field and then wasting of natural and financial resources (Mzuku et al., 2005).

Geostatistics provides the tools to quantify the spatial variation of soil properties and to produce continuous maps using interpolation techniques, generally known as kriging (Chilès and Delfiner, 2012; Matheron, 1971). Differently from classic statistical interpolators, geostatistics provides a term of error (kriging variances) which can guide to the reliability of the estimate (Oliver, 2013). Cokriging is a multivariate generalization of kriging to deal with two or more soil properties which have been measured at the same sampling locations (Chilès and Delfiner, 2012). Geostatistics may help to solve different aspects of precision agriculture such as delineating management zones representing subfield regions with homogeneous characteristics within which a single rate of a specific crop input is appropriate (Buttafuoco et al., 2010). 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. Factorial cokriging (FK) allows to summarize the variation of attributes or limiting factors affecting agricultural production (Buttafuoco et al., 2010). FK allow to quantify and reduce spatial variability of multivariate data to only a few factors, related to different spatial scales. Such factors, can be used to divide the field in areas of size manageable by farmers.

The objective of this study is defining a synthetic fertility index to support soil fertilization. The index is based on three soil macronutrients such as nitrogen, phosphorus, and potassium.

MATERIALS AND METHODS

Study Area and Data

The study area (3.6 ha) is located in Bilbies district, Sharkia Governorate, Egypt. The coordinates of its centroid are: 31° 39′ 24.70″ E, 30° 25′ 47.45″ N. The study area was cultivated by two different crops: sesame in the southern half field and pepper in the remaining area. Its climate is characterized by hot dry summers and mild winters with very low annual precipitation (90-125 mm). Mean air temperature is 13.0 °C in January and 29.3 °C in August (El-Marsafawy et al., 2019).

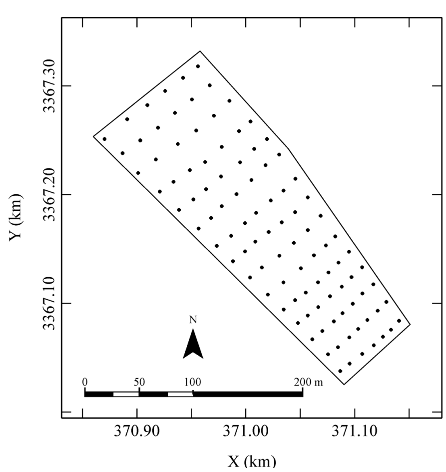

Figure 1. Study area and sampling locations

Topsoil samples were collected at 100 locations at the nodes of a quite regular grid (20 m x 20 m) and analyzed for available N, P, and K. Available nitrogen (NH_4-N and NO_3-N) was extracted by KCl 2 N and the extracted nitrogen was determined with steam - distillation procedure using MgO - Devarda alloy (it is an alloy of aluminum (44%–46%), copper (49%–51%) and zinc (4%–6%) according to Bremner and Keency methods as described by Black et al. (1965); available phosphorus content (P) (mg kg^{-1}) extracted by Olsen et al. (1954); the extracted phosphorus was measured calorimetrically using the ascorbic acid method (Watanabe and Olsen, 1965) with UV–vis-NIR spectrophotometer; available potassium (K) (mg kg^{-1}) extracted using 1.0 N ammonium acetate at pH 7.0 and determined using flame photometer method, (Jackson, 1973).

Geostatistical Methods

Each datum $z(\mathbf{x}_{□})$ at different location $\mathbf{x}_{□}$ (**x** is the location coordinates vector and □ the sampling points = 1, ..., *N*) of the three soil nutrients was interpreted as a particular realization of a random variable $Z(\mathbf{x}_{□})$ and analyzed by ordinary cokriging (Wackernagel, 2003) and Factorial kriging analysis (FKA) (Chilès and Delfiner, 2012; Matheron, 1982).Ordinary cokriging (OCK) is one of the most basic geostatistical interpolation methods under the assumption of intrinsic stationarity for all variables. OCK requires modelling the Linear Model of Coregionalization (LMC) (Journel and Huijbregts, 1978), which considers all the *n* study variables (the three nutrients in this case) as the result of the same independent physical processes, acting over different spatial scales *u*. The $n(n+1)/2$ simple and cross variograms of the three variables are modelled by a linear combination of N_S standardized variograms of unit sill, $g^u(h)$, each one corresponding to a spatial scale (*u*). The goodness of LMC fit was evaluated by the Mean Error (ME) and the Mean Squared Deviation Ratio (MSDR) (Webster and Oliver, 2007). Ordinary cokriging estimates the unknown soil properties values at the unsampled location as a linear combination of neighboring observations of all variables ordinary cokriging (Wackernagel, 2003). Factorial kriging analysis includes three basic steps: (1) modelling the coregionalization of the set of variables using the linear model of coregionalization, (2) analyzing the correlation structure between the variables, by applying PCA at each spatial scale, to obtain independent regionalized factors which synthesize the multivariate information and (3) estimating by cokriging the values of these specific factors at each characteristic scale and mapping them. In the geostatistical approach, even though it is not required the data to follow a normal distribution, variogram modelling is sensitive to strong departures from normality, because a few exceptionally large values may contribute to many very large squared differences. All data were transformed into Gaussian-shaped variables with zero mean and unit variance using a Gaussian anamorphosis (Wackernagel, 2003), which is a mathematical function that transforms a variable with a Gaussian distribution into a new variable with any distribution. All statistical and geostatistical analyses were performed by using the software package ISATIS®, release 2018.4 (www.geovariances.com).

RESULTS AND DISCUSSION

All the nutrient values were normalized before applying the multivariate geostatistical approach using the Gaussian anamorphosis and the variographic analysis allowed to compute the experimental simple and cross-variograms of all variables. No relevant anisotropy was observed in the variogram maps (not shown) and the experimental simple and cross variograms looked upper bounded. Then, the joint variation of the Gaussian values of N, P, and K was modelled by a LMC including a nugget effect and two spherical models at short range (42.4 m) and long range (86 m). Therefore, the LMC showed that the levels of N, P, and K occur to two different spatial scales. To synthesize the joint multivariate variability of N, P, and K in the study area in a restricted number of zones to be submitted to differential management, the first two regionalized factors at short and long ranges (Fig. 2) were retained and the ones corresponding to nugget effect were omitted, because mostly affected by measurement error and variation at a scale smaller than the sampling distance.

The most influencing soil variables on the first factor at short range were P and K, whereas K was the most influencing soil variable on the first factor at long range. The resultant maps, depicting the potential MZ are shown in Fig. 2. It is worth to mention that mapping the first factor at long range allowed more effectively to delineate the field into different management zones than at short range. In fact, the values of the first regionalized at long range would allow to split the field into larger and manageable zones than those for first regionalized at shorter range.

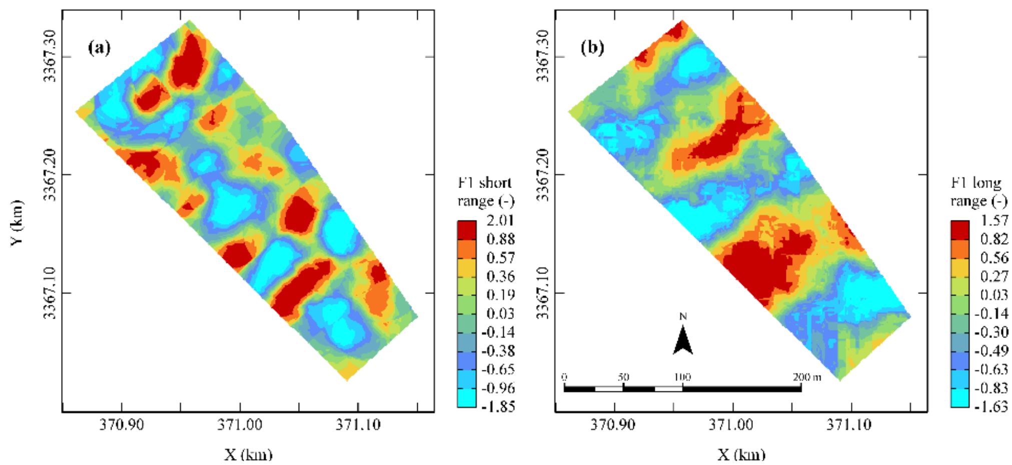

Figure 2. First two regionalized factors at short (a) and long (b) ranges

These results encourage the use of this approach for precise fertilization considering the type of cultivated crops.

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