Geostatistics and its potential in Agriculture 4.0

Geoestatística e suas potencialidades na Agricultura 4.0

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ABSTRACT - In order to meet future food demands and ensure sustainability new technologies have been incorporated into agriculture. Some researchers believe that we are living in the fourth agricultural revolution or Agriculture 4.0. Among the many technologies involved in the Agriculture 4.0, it is necessary to highlight the importance of geostatistics in the implementation of those technologies. Geostatistics is a class of statistics used to analyze and predict the values associated with spatial or spatiotemporal phenomena, and it is very important to understand the spatial distribution of agricultural variables. Therefore, the objective of this review is to show the potential of geostatistics in Agriculture 4.0. The article presents an exhaustive literature review of geostatistics and its potential in agriculture, by showing a brief of geostatistical approaches, some practical use of geostatistics in agriculture, and a description of multivariate geostatistics for multi-source data fusion using some case studies. This review showed that geostatistics has been used for agricultural purposes and has been producing exciting results. In addition, more advanced analysis such as multivariate geostatistics in fuse heterogeneous data can be easily adapted to any experimental conditions and type of sensor data and/or sampling data to increase estimation accuracy.

Key words: Data fusion. Kriging. Multivariate geostatistics. Semivariogram.

RESUMO - Para atender as demandas futuras de alimentos e garantir sustentabilidade, novas tecnologias foram incorporadas à agricultura. Acredita-se que a quarta revolução agrícola ou Agricultura 4.0 esteja ocorrendo. Dentre as diversas tecnologias envolvidas na Agricultura 4.0, é necessário destacar a importância da geoestatística na implementação dessas tecnologias. A geoestatística é uma classe de estatística usada para analisar e predizer os valores associados à fenômenos espaciais ou espaço-temporais, e é muito importante para entender a distribuição espacial das variáveis agrícolas. Portanto, o objetivo desta revisão é mostrar o potencial da geoestatística na Agricultura 4.0. O artigo apresenta uma revisão exaustiva da literatura sobre geoestatística e seu potencial na agricultura, mostrando um resumo das abordagens geoestatísticas, alguns usos práticos da geoestatística na agricultura e uma descrição da geoestatística multivariada para fusão de dados de múltiplas fontes usando alguns estudos de caso. Esta revisão mostrou que a geoestatística tem sido usada para fins agrícolas e produzido resultados interessantes. Além disso, análises mais avançadas, como geoestatística multivariada na fusão de dados heterogêneos, podem ser facilmente adaptadas a quaisquer condições experimentais e tipo de dados de sensor e/ou dados de amostragem para aumentar a precisão da estimativa.

Palavras-chave: Fusão de dados. Krigagem. Geoestatística multivariada. Semivariograma.

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INTRODUCTION

The population of the world is expected to reach 9.2 billion people by 2050 (FAO, 2013) and food demand which will inevitably lead to increased plant production for food and feed, is expected to increase by 70%. Meeting this demand, while avoiding further deterioration of agricultural systems and natural resources, will require a radical change in the way farmers manage their farms. It is then necessary to abandon practices that do not sustain the environment and open up to new methods and technologies that are based on rational use of resources.

In trying to meet the recent expectation from the agricultural sector, some researchers have stated that we are living the 'fourth agricultural revolution', or 'Agriculture 4.0' (KLERKX; ROSE, 2020). According to Rose and Chilvers (2018) this "new agriculture" is closely related to high technologies such as the internet of things (NYÉKI *et al*., 2020), cloud computing (MEKALA; VISWANATHAN, 2017), robotics (MARINOUDI *et al*., 2019), artificial intelligence (PATRÍCIO; RIEDER, 2018), sensors (OJHA *et al*., 2015), satellites (MURUGAN *et al*., 2017), etc. Consequently, Precision agriculture (PA) attempts to respond to the necessity for innovative actions in the field of primary production.

The current definition of PA by International Society of Precision Agriculture (ISPA) states that precision agriculture is a management strategy that gathers, processes, and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production.

Geostatistics is one of the most important tools in PA. This statistical approach, which was initially created for mining, is now used in many fields of study including agriculture. Its main function in PA is to understand spatial distribution patterns and obtain more accurate maps.

Therefore, the objective of this review is to show the potential of geostatistics as an important tool in Agriculture 4.0. The study presented a brief history of geostatistics and an introduction to its analysis. In addition, an exhaustive review of the use of geostatistics in agriculture is presented. Finally, the use of geostatistics in data fusion with some case studies is described.

Brief history and concepts of geostatistics analysis

Environmental variables usually present spatial continuity (LI; HEAP, 2011) and classical statistics are not efficient in analyzing this kind of data, because classical statistics do not take spatial distribution

into account. In a classical approach, the samples are considered independent and the error is random. Although the existence of spatial variability was undeniable, even for developers of classical statistics, spatial variation was regarded as a little consequence (OLIVER, 2010). However, Daniel Krige, a South African Mining engineer, noticed that the absence of a spatial structure in predicting ore grades could be a huge problem. Therefore, in 1963 his empirical approach was mathematically formalized by Matheron (1963).

Matheron developed the regionalized variable theory. A regionalized variable is an actual function that, takes a definite value in each point of space (MATHERON, 1963). To assess whether data are spatially correlated and to what extent, the variogram or semivariogram was developed. The variogram or semivariogram is a curve representing the degree of continuity of some variables (MATHERON, 1963).

The equation of a semivariogram is defined as (Equation 1):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(x_i) - Z(x_i + h) \right]^2 \tag{1}$$

where $N(h)$ is the number of h-distant point pairs (x_i, $x_i + h$). The result of the point estimates is a set of semivariogram values for various distances h between points. However, to compile Kriging equation is necessary to know the semivariogram values for any distance h. Therefore, when quantifying spatial dependence, the obtained estimates are approximated with a theoretical curve. The most common semivariogram models used in agricultural variables are spherical, exponential, and Gaussian model (ZŮVALA *et al*., 2016).

From the fittings of the mathematical models to experimental semivariograms, parameters were defined as a spatial dependence range (a) which defines the distance, where the semivariogram value is constant. Sample locations separated by a distance shorter than the range are spatially autocorrelated; locations farther apart than the range are uncorrelated. Sill ($C_0 + C$) is the semivariogram value in the range. The nugget effect (C_0) is defined as the limit of the semivariogram for h decrease o zero. The nugget effect can be caused by measurement errors or by the fact that the process includes spatial variability at distances smaller than the sampling interval (ZŮVALA *et al*., 2016).

The semivariogram is an important tool to determining whether a variable presents spatial dependence and quantifies this dependence. However, it is necessary to introduce another geostatistical tool for mapping: the kriging interpolation method, which name was in honor of Daniel Krige. Kriging is a generic

term for a range of least-squares methods to provide the best linear unbiased predictions, best in the sense of minimum variance (OLIVER; WEBSTER, 2014). In the beginning, kriging was used to map ore in South African minings; however, it is now used for many kinds of data, including variables related to agriculture, such as soil properties, weed, crop yield, etc (CHAVES *et al*., 2018; METWALLY *et al*., 2019; SAN MARTÍN *et al*., 2018).

Kriging usually performs better than other interpolation methods. This is because kriging takes into account the manner in which a property varies in space through the variogram. In addition, kriging provides not only predictions but also kriging variances or errors (OLIVER, 2010).

The ordinary kriging system can be explained by: Letting $z(x_i), i = 1,2,\dots,N$, be the observed values of variable z at points $x_1, x_2, \dots, x_N$, in two dimensions $x_i \equiv \{x_{i1}, x_{i2}\}^T$. For any new point x_0 we predict Z by (Equation 2):

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i z(x_i) \qquad (2)$$

The λ_i, i = 1,2,…,N, are the weights chosen to minimize the prediction error variance by the following set of equations (Equations 3 and 4):

$$\sum_{i=1}^{N} \lambda_i \gamma(x_i - x_j) + \psi(x_0) = \gamma(x_j - x_0) \quad \text{for all } j \qquad (3)$$

$$\sum_{i=1}^{N} \lambda_i = 1 \qquad (4)$$

Here, $\gamma(x_i - x_j)$ is the semivariance between data points i and j, $\gamma(x_j - x_0)$ is the semivariance between data point j and the target point x_0, and $\psi(x_0)$ is a Lagrange multiplier introduced for the minimization of error variance.

A detailed description of semivariogram and kriging method was provided by Oliver (2010) and Oliver and Webster (2014).

Use of geostatistics in agriculture

Geostatistics have been shown to be very efficient defining the spatial variability of agricultural variables. It has been used for many different variables such as crop yield, soil properties, weed, etc. In this review, we focused on the soil and weed application. In addition, other applications using crop yield and sensor data were approached in the data fusion topic.

Geostatistics applied to soil sampling

The soil samples must accurately reproduce the condition of an agricultural field, using a minimum number to satisfactorily estimate the mean value of the soil attributes, thus the management of irrigation and soil fertility in crop fields will be refined (BUDAK, 2018). This is because has been estimated that 80-85% of the total error in the results used in the recommendation of fertilizers and correctives can be attributed to sampling in the field and 15-20% may be due to laboratory analyses (CARVALHO *et al*., 2002).

Based on classical statistics, the traditional study carried out by Catani *et al*. (1954) defines as representative sampling 20 individual soil samples to obtain a sample composed in areas of up to 10 hectares considered homogeneous by farmers (same soil type, crop, slope, etc) are commonly applied in Brazilian agricultural fields (SILVA *et al*., 2020). Random sampling, based on classical statistics, is also widely used in other countries, such as the United States (LAWRENCE *et al*., 2020). However, for classical statistics to be properly applied, one of its premises is that the randomness of errors is met, that is, the samples are spatially independent (BUDAK *et al*., 2018).

However, the presence of spatial dependence has been verified in most agricultural variables, such as soil attributes (ARMANTO, 2019; GAO *et al*., 2019; LI *et al*., 2017; MIRZAEE *et al*., 2016; ROSEMARY *et al*., 2017; USOWICZ; LIPIEC, 2017; YANG *et al*., 2020), thus limiting the use of classical statistics. According to Welsch *et al*. (2019), soil variability can affect sampling plan, and may result in inadequate sampling intensities and high levels of uncertainty in evaluated attributes and, consequently, inappropriate management if the spatial distribution is not taken into account.

Therefore, geostatistics has been shown to be a viable alternative for the optimization of a number of individual soil samples, considering the spatial dependence (MONTANARI *et al*., 2012), where semivariogram is the main tool used for the description of spatial autocorrelation (SEIDEL; OLIVEIRA, 2016). Based on the knowledge of semivariogram parameters, Carvalho *et al*. (2002) state that it is possible to define a sampling radius with the its range value because distances greater than its value guarantee the independence of the sampling points.

Scaled semivariogram, which is obtained from the division of the semivariance by the statistical variance of experimental semivariograms, can be used in definition samples, and it is useful because it allows several attributes to be inserted in the same graph, obtaining a single range value (PEREIRA *et al*., 2013).

Some studies on crops of agronomic importance such as sugar cane - *Saccharum officinarum* L. - (MONTANARI *et al*., 2012), beans - *Phaseolus vulgaris* L. - (CASTIONE *et al*., 2019), and mango - *Mangifera*

indica L. - (SILVA *et al*., 2020) have shown the efficiency of the use of geostatistics compare to classical statistics in determining the ideal number of individual soil samples.

Soil chemical attributes of two areas cultivated with sugar cane, located in Jaboticabal county, São Paulo state, Brazil, were assessed by Montanari *et al*. (2012) to optimize the procedure of soil sampling plan, and they found that the use of geostatistics, using the range of experimental semivariogram reduced the number of individual samples needed to represent the area. In addition, the number estimated by classical statistics would make collection unviable in practical terms.

In a study to define the minimum sampling density of soil physical attributes in a central pivot area cultivated with beans, in Cristalia county, Goiás state, Brazil, Castioni *et al*. (2019) identified that geostatistics, through scaled semivariogram, must be utilized as a strategy for characterizing spatial variability and determining the minimum scale of points in a sampling area.

Soil sampling approaches and point allocation sampling methods in irrigated mango orchards in the Brazilian semiarid region, Silva *et al*. (2020) observed the efficiency of geostatistics compare to classical statistics since the method of 20 individual soil samples proved to be inefficient. They noticed that the addition of spatial component, using the range of the scaled semivariogram was appropriate in obtaining the minimum soil sample density in each of the studied areas. In addition, the allocation of sample points demonstrated that, in the sampling method, the collection site is as important as the number of individual soil samples to be collected.

Based on the above considerations, it is evident that careful sampling, which accurately represents the sampled area, aims at cost reduction and resources optimization, guaranteeing agricultural viability. It is essential to study sampling projects for each area, depending on the intrinsic characteristics of each one, since variability could be affected by several factors such as topography, management, vegetation, and soil formation factors (WELSCH *et al*., 2019).

Hence, geostatistics is the most appropriate tool for defining sample density when compared to classical statistics, because geoestatistics takes into account the spatial dependence found in most crop fields. Therefore, the range parameter to define the number of individual soil samples may be a satisfactory method to define soil sampling.

Geostatistics applied to weed science

The presence of undesirable plants in agricultural fields, also known as weeds, can be defined as higher plants that interfere with the interests of humans and environment (PITELLI, 2015). The establishment of these plants to form plant clusters with different populations (weed community) causes environmental disturbances and various damages, especially when it comes to agricultural production systems.

In addition, to the factors inherent to the species and its biotype, climatic, physiographic factors, and biotic factors determine the occurrence and permanence of weeds in any given environment and period (FRIED *et al*., 2019), and interferes with the way populations are distributed: generalized or punctual.

The ability to describe and map the weed spatial distribution is the first step in the study of its spatial variability, guaranteeing efficient management the concepts of precision agriculture. In-plant health, the spatial pattern of unwanted populations can be studied through statistical indexes based on mean and variance, which gives the degree of aggregation of pests and diseases. This degree can vary between highly aggregate, aggregate and uniform, and many studies have already shown that the degree of weed distribution in agricultural fields, generally shows an aggregate population pattern (LOPES *et al*., 2020; MARTÍN *et al*., 2018; SILVA *et al*., 2017).

However, Schaffrath *et al*. (2007) affirm that the traditional measurements of tendency and dispersion are of little use and can induce overestimation since the position of individuals in space is not considered. Therefore, the use of geostatistics in studies of the spatial distribution of weed has technological and environmental potential (SCHAFFRATH *et al*., 2007), enabling more accurate mapping techniques, such as Kriging (KRAHMER *et al*., 2020).

Several studies have shown that the distribution of weeds in agricultural fields is not a random process but follows a spatial dependence. In the literature, there are reports of moderate to strong spatial dependence for weed variables (AVILA *et al*., 2019; CHIBA *et al*., 2010; IZQUIERDO *et al*., 2020; KALIVAS *et al*., 2012; LÓPEZ-GRANADOS *et al*., 2016; METCALFE *et al*., 2016, SIQUEIRA *et al*., 2016).

Among the weed species found in the agricultural fields of recent studies that showed spatial dependence, are: *Abutilon theophasti*, *Bidens pilosa, Bromus diandrus*, *Cenchrus equinatus, Commelina* spp., *Convolvulus arvensis*, *Conyza* spp., *Cynodon dactylon*, *Cyperus rotundus*, *Datura ferox*, *Euphorbia* spp., *Eleusine indica*, *Heliotropium indicum*, *Ipomoea triloba, Solanum nigrum*, *Sorghum halepense* and *Xanthium strumarium* (CHIBA *et al*., 2010; IZQUIERDO *et al*., 2020; KALIVAS *et al*.,

2012; KRAHMER *et al*., 2020; ROCHA *et al*., 2015; SCHAFFRATH *et al*., 2007).

Geoestatistical studies assists in the planning of sustainable control, carrying out site-specific management, that is, where it is strictly necessary, bringing benefits such as greater economic return and less environmental impact (MARTÍN *et al*., 2018; ROCHA *et al*., 2015). For example, there is the possibility of using a precision agriculture technique called variable rate application, that is, when an input, (in this case, the pesticides), is applied based on the spatial distribution of the target to be controlled. This technique can maximize the effectiveness of herbicides, and studies showed savings of approximately 25% (GUNDY *et al*., 2017; KEMPENAAR, 2017).

In addition, an important characteristic of this type of study is the possibility of correlational analysis with agro-environmental variables with the same coordinate as weed variable, in assisting the understanding of the occurrence of weeds. These variables include metrics or qualitative data on soil properties, types of management, and crop characteristics (AVILA *et al*., 2019; COMAS *et al*., 2016). According to Pätzold *et al*. (2020), weed population maps integrated with soil maps can potentially be used in weed planning and management to estimate herbicide requirements or meet application limitations.

In a study of weed community of a corn crop field in Arganda del Rey, Madrid, Spain, Martin *et al*. (2018) revealed that the variance for *S. halepense* and *A. theofhasti* along the direction of crop rows was larger at lags exceeding 5 m. This indicates the existence of large patches at this scale and that there might be an interaction between the effect of cultivation or harvester dragging seeds with variable soil properties. In correlating the weed seed bank in a soybean field with the soil properties, Avila *et al*. (2019) found a significant negative correlation between the grass seed seminal bank and the variation in the sand content. Regarding chemical management and reporting, the authors recommended the use of their result in field management, because that lower doses of pre-emergents could be applied in sandy areas, warning against the risk of fixed-rate applications.

Therefore, weed mapping, favors the understanding of how the weed community is distributed in the field and the reasons for its distribution, whether they are of ecological or anthropic origin, enabling, not only a more efficient plant health management but also a deep understanding of its ecophysiology (BOTTEGA *et al*., 2018; KRAHMER *et al*., 2020; MARTÍN *et al*., 2018). Krahmer *et al*. (2020) also pointed out that comparative tests for different locations, improvement of existing maps for more frequent species, standardization, expansion of herbicide resistance maps, and mapping of rare weeds as potentials and objectives for infestation mapping works.

Based on the information collected, it can be considered that geostatistical analyses, and mapping techniques are integrated with the so-called Agriculture 4.0 model, enabling digital and technological tools for local diagnosis and guiding modern agriculture for weed management and more sustainable, economical, and efficient crop production.

Multivariate geostatistics for multi-source data fusion

To achieve a sufficient degree of agronomic and financial effectiveness, it is necessary to improve the accuracy of estimation of relevant variables, which could be achieved by intensifying sampling. Given the costs associated with both sample collection and laboratory analyses, an advantage in terms of accuracy of estimation could come from the integration of sparse sample data with variables recorded using remote and/or proximal sensors on a variety of spatial and temporal scales.

In particular, there are different types of real-time on-the-go sensors, that are, already widely used and capable of recording both soil and plant attributes at a very fine spatial resolution (CASTRIGNANÒ *et al*., 2017; 2018; VISCARRA ROSSEL *et al*., 2011). However, the relationship between the property of interest and output of sensor is not direct because the latter depends on several factors (CASTRIGNANÒ *et al*., 2017; 2018; DE BENEDETTO *et al*., 2012). Therefore, more sensors are needed, based on different measurement principles, to separate the different effects and consequently improve the interpretation of the different causes of variability. A new technique, called sensor data fusion (CASTRIGNANÒ *et al*., 2017, 2018, 2019; MASARIK *et al*., 2016; WANG *et al*., 2013), has been developed, it combines several sensing techniques and is more informative about reality than the one based on a single sensor.

However, these multi-source data are collected for a variety of spatial scales more often than the one of interest and most environmental variables display spatial structures, such as gradients, patches, trends, and complex spatial autocorrelations, which may exist at many scales. Moreover, the assessment of spatial variations strongly depends on the size of the sampling unit or measurement unit of the sensor. Therefore, the size of the sampling/measurement unit is quite important in the process of investigation because it can critically influence our perception of environmental phenomena (BELLEHUMEUR *et al*., 1997).

Multivariate Geostatistics offers a set of linear unbiased estimators (cokriging) with minimum error

variance, and allows one to combine a virtually infinite number of variables with different characteristics and with different degrees of uncertainty. In particular block cokriging, in its more general formulation, considers both upscaling and downscaling (CASTRIGNANÒ; BUTTAFUOCO, 2020). However, the generation of cokriging estimates may require the inversion of very large matrices, due to the often massive character of proximal/remote sensing data. This operation with big data may take a lot of computer time or even be impossible to perform. Multicollocated cokriging (RIVOIRARD, 2001) is a simplified version of full cokriging, and makes use of secondary variable(s) only at the point being estimated and at all points where the primary variable is known (CASTRIGNANÒ *et al*., 2009). This approach requires the secondary variable(s) to be known at all points where estimation of the primary variable is desired, therefore, it is well suited for remote/proximal sensing data, usually in grid format. Moreover, it effectively combines the differences among sensors and enhances the integration between remote/proximal sensing observations and ground-based truth data (CASTRIGNANÒ *et al*., 2012).

Another geostatistical data fusion technique, widely used especially in PA, is factor cokriging, which allows to synthesis of a wide array of variables in spatial indices that are scale-dependent. These can be used to partition an agricultural field into more homogeneous units (Management Zones), with respect to a large variety of soil physical, chemical, and hydraulic properties and crop attributes, which can be used for differential management (CASA; CASTRIGNANÒ, 2008). Moreover, some factors affecting crop response are expected to act over a short-range action, however, others act over longer distances, and such field delineation is expected to be scale-dependent. Using this geostatistical technique, it is possible to perform within-field delineation at different spatial scales, differently compared to traditional clustering, thus increasing the efficacy of site-specific management.

The objective of this contribution is to describe a method of geostatistics-based data fusion that is widely applied, as evidenced by numerous bibliographic references, and sufficiently flexible to be able to jointly analyse a virtually infinite number of multi-source data with applications particularly in precision agriculture.

The various steps, which make up the proposed approach for the delineation of homogeneous areas in PA, are indicated below.

1. Exploratory data analysis

A dataset with selected variables for analysis generally requires some preliminary adjustment. If some variables are gridded, they have to be migrated to the nearest sample location to create the co-regionalised dataset. Exploratory data analysis is then performed by calculating basic statistics (mean, median, minimum and maximum values, standard deviation, skewness, and kurtosis).

2. Point Gaussian anamorphosis

Skewed or erratic data can often be made more suitable for geostatistical modeling by appropriate transformation. Therefore, normalization and standardization may be required before kriging (ARMSTRONG, 1998). One way is to perform all geostatistical procedures in the Gaussian domain and at the end to back-transform the estimates to the original units. Each variable is transformed into a normally distributed variable beforehand if it shows a large departure from Gaussian distribution. This is performed by fitting a mathematical function, called Gaussian Anamorphosis, expressed as an expansion of Hermit polynomials (CHILES; DELFINER, 2012; WACKERNAGEL, 2003). An advantage of the Gaussian distribution is that spatial variability is easier to model because it reduces the effects of extreme values providing more stable semivariograms (ARMSTRONG, 1998).

3. Block/support correction

If the estimates are produced on a block instead of a point support, a coefficients is needed to obtain an anamorphosis on a block support (CHILES; DELFINER, 2012), which will be later used to back-transform block Gaussian estimates into raw data. A support correction coefficient r is determined from the variance of blocks, and the punctual variance calculated as the sill of the variogram assumed stationary. The variogram based on a point support is calculated on the smallest support, whereas a variogram on a given block support requires a process of regularization, consisting of discretizing the blocks into equal cells after which a pseudo-experimental variogram is calculated in the fictitious cell centers, and then the point variograms are averaged over the block (MANZIONE; CASTRIGNANÒ, 2019).

4. Spatial modelling of multivariate dataset

Multivariate spatial correlations are modeled under the scope of the linear model of co-regionalization (LMC) (JOURNEL; HUIJBREGTS, 1978), which considers all the studied variables to be generated by the same independent physical processes acting at N_s different spatial scales (WACKERNAGEL, 2003). Therefore, all (both direct and cross) variograms are modeled as linear combinations of the same basic spatial structures

(authorized mathematical functions) corresponding to the N_s spatial scales.

5. Geostatistical solutions for support correction

Geostatistical techniques are used to model the effects of re-scaling data due to the change of support when treating heterogeneous spatial data. Block cokriging is the traditional geostatistical interpolation method used in solving a change of support problem (ARMSTRONG, 1998; CHILÈS; DELFINER, 2012; JOURNEL; HUIJBREGTS, 1978) when observations on-point support are used to predict the average values of a multivariate process on a larger scale. The main difference between block (co)kriging and point (co)kriging is in the calculation of the point-to-block covariance through the regularization process as described above.

The display of cokriging estimates after back-transformation allows the production of thematic maps of individual attributes and may be an effective support for decision making.

6. Multi-collocated block cokriging

Multivariate spatial prediction, or cokriging, is used to treat the multivariate data set. It is a quite popular geostatistical estimator because it enables the coestimation of poorly sampled variables from secondary more exhaustive information. Details of the cokriging system can be found in reports of Wackernagel (2003), and Chilès and Delfiner (2012). The equations are valid regardless of the support of data; however, taking into account the different supports in the calculation of autocovariance and cross-covariance functions is crucial to obtain valid inference (CASTRIGNANÒ *et al.*, 2018). Once a consistent model for the point covariance functions is estimated, using LMC, block cokriging is applied by replacing the point cross-covariances in point cokriging by their block-averaged counterparts through the above-mentioned variogram regularisation (MYERS, 1984).

The variant multi-collocated block cokriging is used when fusing sparse sample data with gridded variables as the ones from remote or proximal sensing. Here it is sufficient to point out that its use is indispensable in the treatment of big data, whereby the inversion of a huge matrix for the resolution of the cokriging system could be otherwise impossible. Indeed, bock cokriging, in its more general formulation, can also be used in downscaling, when the estimates are on a smaller support than the one of observations. In this case it is necessary a process of deregulation and deconvolution to transform variograms on areal support into variograms on point support. This is achieved through an iterative fitting process (CASTRIGNANÒ; BUTTAFUOCO, 2020), but unfortunately, at present, it is implemented only on very few commercial or free softwares.

7. Factor block cokriging

This geostatistical procedure is similar to the traditional Principal Component Analysis (PCA) instead of applying it to the whole variance-covariance matrix, it applied to its individual spatial components (co-regionalization matrices). This decomposition is accomplished through the determination of the linear model of co-regionalization. PCA decomposes each co-regionalization matrix into two additional matrices: the eigenvalues and egeinvector matrices (WACKERNAGEL, 2003). The transformation (loading) coefficients correspond to the covariances between the variables and principal component, which are called regionalized factors, relative to a given spatial scale. They express the influence of each variable on the factor at a given spatial scale and are then used to assign a physical meaning to the factor. Mapping the scale-dependent regionalized factors is a very powerful and synthetic way to display the spatial relationships among several variables at different spatial scales. Therefore, it is commonly used in PA to produce a partition of the field in homogeneous zones, according to the attributes represented by the variables chosen for the analysis. In addition, if exhaustive information is available, multi-collocated factor block cokriging is preferred to the full version. Figure 1 provides a complete overview of the proposed method.

Some applications

The approach previously described is now widely applied in various experimental contexts with space-time data of different nature, spatial support, temporal frequency, and different degrees of uncertainty for a variety of objectives. The most frequent application is the subdivision of study areas into relatively homogeneous zones, according to the attributes selected and measured using various sensors, submitting them to site-specific management in PA. The wide flexibility of the method, which is applicable to a practically infinite number of sensors of any type, is demonstrated by the numerous bibliographical references. Interested readers should refer to them for more details and clarifications (AGGELOPOOULOU *et al.*, 2013; BUTTAFUOCO *et al.*, 2015, 2017, 2019; CASTRIGNANÒ *et al.*, 2009, 2012, 2017, 2018; CASTRIGNANÒ; BUTTAFUOCO, 2020; DE BENEDETTO *et al.*, 2013, 2013a; LANDRUM *et al.*, 2015; MANZIONE *et al.*, 2019; SHADDAD *et al.*, 2019).

Three case studies are briefly presented here as examples to illustrate the potential of the approach. The first one (BUTTAFUOCO *et al.*, 2017) is located in Foggia,

Figure 1 - Flowchart of the proposed methodology based on geostatistical data fusion techniques

among the growing seasons, and the variation was mainly in rainfall: the 2005-2006 season had the highest rainfall, while the 2006-2007 season had the least rainfall. The polygon to the north showed the greatest variability over time, probably due to the coarse texture that negatively affected the soil water content during the dry periods.

Figure 2 - Polygon yield maps for the 2005-2006, 2006-2007 and 2007-2008 growing seasons
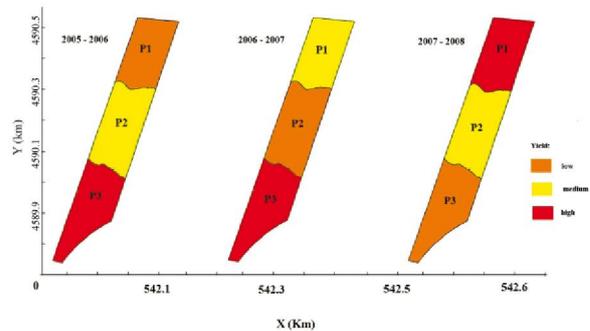
It is now known that the simple traditional sampling is not capable of assessing the variability of agricultural system at a space-time scale that is necessary for effectively PA management. Therefore, it is then necessary to integrate it with proximal and/or remote sensing of both soil and crop at finer scales.

The second case study shows an example of data fusion including both soil variables measured in the laboratory and the ones obtained from online visible spectroscopy (SHADDAD *et al*., 2016). The study was conducted in an 18-ha field located in Wilstead, Bedfordshire, UK. A total of 183 soil samples on a 30 m x 30 m cell grid were collected and submitted for different physical and chemical analyses in the laboratory. The field was also surveyed with a mobile fibre-type Vis-NIR spectrophotometer along parallel transects of 700-m length and 15 m apart for four variables: pH, P, K, and water content. The regionalized factor over a scale of approximately 181 m was used to delineate homogeneous zones. It was mainly and positively correlated with total carbon, pH, total N, and cation exchange capacity, therefore it could be interpreted as a soil fertility indicator. The field was then partitioned into three macro-zones of equal size with the central and northern parts characterised by lower fertility (Figure 3).

In order to evaluate the productive capacity of such delineation, the map as shown in Figure 3 was compared with a barley yield map of the same field (Figure 4) and the yield was calculated for each macro-area. As shown

southeastern Italy in a field of 12 ha cultivated with rainfed durum wheat (*Triticum durum* Desf.). One hundred soil samples, arranged according to a regular grid, were picked up at two depths (0.20 and 0.40 m) and analyzed in the laboratory for different physical, chemical, and hydraulic attributes. In addition, the grain yield was measured with a John Deere combine over three growing seasons (2005-2007). The regionalized factor with an effective range of approximately 285 m was used for partitioning the field. The organic matter content, total nitrogen, and field capacity weighed were mainly and positively correlated, whereas clay negatively correlated because the soil was heavy and moderately drained. Therefore, this factor could be interpreted as an indicator of soil chemical fertility. The field could be roughly divided into three macro-areas of equal extension with a central area, which was less fertile due to the reduced values of organic matter and N.

For each macro-area, the expected value and standard deviation of grain yield were also estimated over the three crop seasons (Figure 2) using polygon kriging (CASTRIGNANÒ; BUTTAFUOCO, 2020), a sort of block cokriging but on an irregular block (polygon). As can be seen in Figure 2, the spatial variation in yield differed

Figure 3 - Map of three management zones (MZ) according to the estimates of the factor (F1) with scale of 181 m
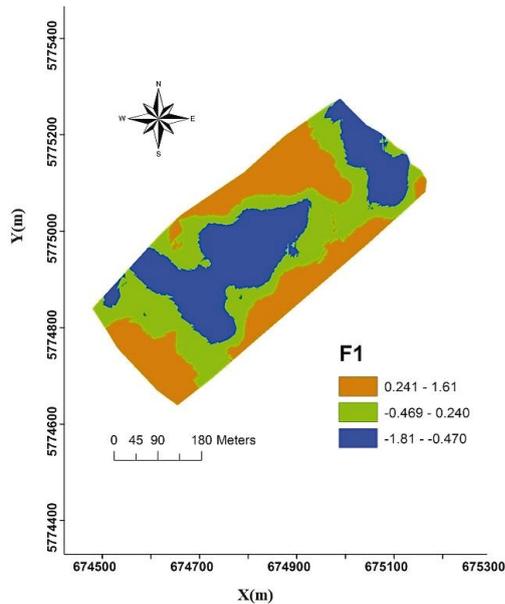
Figure 4 - Barley yield map
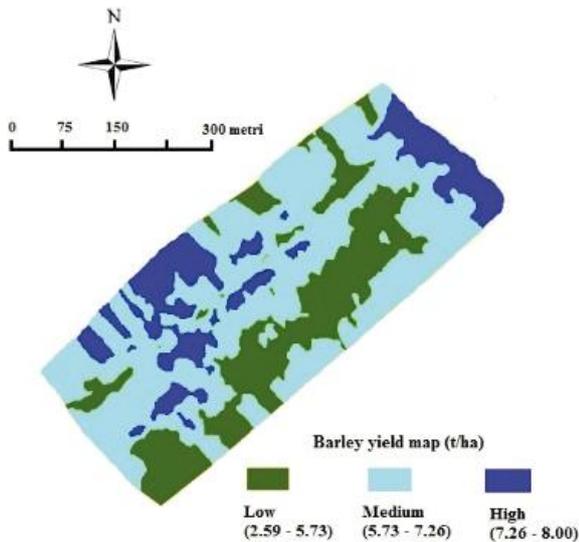
in Table 1, there is a direct relationship between soil fertility, as expressed by the regionalized factor, and yield. However, the degree of spatial association between the two maps was less than 40%. This means that even if soil variation affects yield variation, it does not fully explain yield variation, which seems more related to dynamic factors. For effective site-specific crop management, it

would then be necessary to integrate soil characterization with on-time monitoring of plant status.

Table 1 - Mean yield of each management zone delineated by F1

F1	Mean Yield (Mg ha^{-1})
Low	6.19
Medium	6.65
High	6.97

The third case study is taken from Precision Viticulture (ANASTASIOU *et al.*, 2019), which requires a very fine space-time monitoring scale to accurately assess the variation in a vineyard. The study was conducted at a commercial table grape vineyard located in Corinth, southern Greece, planted with *Vitis vinifera* L. cv. Thompson seedless. Two different types of proximal sensors were used to assess and map the spatial-temporal variation of the vineyard: the one on the plant was a crop circle canopy sensor (ACS-470, Holland Scientific Inc., Lincoln, NE, USA), used to scan the side vine canopy and collect georeferenced radiometric data at three bands: 670 nm (red), 730 nm (red-edge) and 760 nm (NIR) at three crop stages: start of veraison, mid of veraison and technological maturity/harvest. For soil monitoring, a single electromagnetic induction (EMI) soil survey was conducted using an EM38 sensor (Geonics Ltd, Ontario, Canada). The two sensors had different supports: the one of Crop Circle was a spot of 0.40-m diameter, whereas the one of EM38 was of approximately 1-m horizontal length. The application of the proposed approach then required a change of support. While EMI map showed some spatial dependence structures, due to differences in soil texture, the radiometric ones appeared noisier.

This was reflected in the map of the regionalized factor with 32-m scale (Figure 5), obtained from the joint analysis of 10 variables, 9 radiometric variables and one variable relative to the soil that was the most influential. Actually, the examination of Figure 5 shows that it is difficult to subdivide the vineyard into macro areas to be subjected to differential agronomic management. In fact, the field is characterized by high micro variability, due to the particular vine management, for which it would be better to apply variable rate technology at a very fine spatial scale.

From the analyses of the three case studies may be verified that the method is quite flexible and can easily adapt to any experimental conditions and type of sensor

data and/or sampling data. However, its application poses many statistical problems; therefore, that it is desirable that proper (geo)statistical analysis techniques are increasingly implemented in the wide used GIS systems.

Figure 5 - Map of the regionalised factor (F1) obtained by fusing the outputs of two sensors
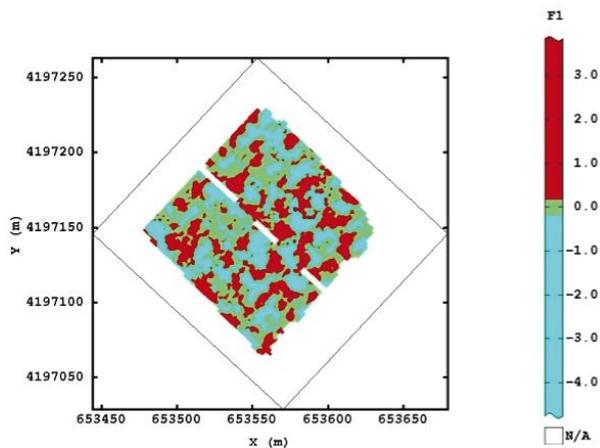
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