A review of methodological contributions of geostatistics to precision agriculture

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Abstract

Stronger competitiveness and better productivity of Moroccan agriculture could only be achieved through the improvement of current cultivation techniques by the adoption of more efficient and rational techniques. In this way, precision agriculture (PA), a site-specific crop management, is a promising way. It seeks to apply the right amount, when and where it is needed using variable rate technology. This approach adjusts each input based on the specific condition of each part of the study area. To achieve this goal, the spatial variability of the soil must be known everywhere using both soil samples and ancillary data or environmental covariates like proximal and remote sensing imagery, digital elevation model, land use types, yield monitor data, etc. Geostatistics, the use of statistical methods for studying spatial data, offers excellent tools for describing and modelling spatial variability using variogram, interpolating at unsampled locations using kriging, mapping, simulating different scenarios by incorporating uncertainty, optimizing experimental designs and sampling schemes, etc. These different contributions of geostatistics to precision agriculture will be illustrated from examples taken from worldwide published research works regarding different crop production factors at various spatial scales.

Keywords: Digital mapping, Kriging, Site-specific crop management, Spatial variability, Stochastic simulation, Variogram.

Une revue des contributions méthodologiques de la géostatistique à l'agriculture de précision

Résumé

Une compétitivité plus forte et une meilleure productivité de l'agriculture marocaine ne peuvent être atteintes que par l'amélioration des techniques culturales actuelles grâce à l'adoption de techniques plus efficaces et plus rationnelles. De cette manière, l'agriculture de précision (AP), une gestion des cultures spécifique au site, est une voie prometteuse. Elle cherche à appliquer la bonne quantité, quand et où elle est nécessaire en utilisant la technologie à débit variable. Cette approche ajuste chaque entrée en fonction de la condition spécifique de chaque partie de la zone d'étude. Pour atteindre cet objectif, la variabilité spatiale du sol doit être connue partout en utilisant à la fois des échantillons de sol et des données auxiliaires ou des co-variables environnementales comme l'imagerie de détection proximale et de télédétection, le modèle numérique d'élévation, les types d'utilisation des terres, les données du moniteur du rendement, etc. La géostatistique, l'utilisation des méthodes statistiques pour l'étude des données spatiales, offre d'excellents outils pour décrire et modéliser la variabilité spatiale en utilisant le variogramme, interpoler à des endroits non échantillonnés en utilisant le krigeage, cartographier, simulater différents scénarios en incorporant l'incertitude, optimiser des plans expérimentaux et des plans d'échantillonnage, etc. Les différentes contributions de la géostatistique à l'agriculture de précision seront illustrées à partir d'exemples tirés de travaux de recherche publiés dans le monde entier concernant différents facteurs de production végétale à diverses échelles spatiales.

Mots clés: Cartographie numérique, Krigeage, Gestion des cultures spécifiques au site, Variabilité spatiale, Simulation stochastique, Variogramme.

مراجعة للمساهمات المنهجية للجيوإحصاء في الزراعة الدقيقة

أحمد الدويك

ملخص

لا يمكن تحقيق قدرة تنافسية أقوى وإنتاجية أفضل للزراعة المغربية إلا من خلال تحسين تقنيات الزراعة الحالية من خلال اعتماد تقنيات أكثر كفاءة وعقلانية. بهذه الطريقة، تعتبر الزراعة الدقيقة إدارة محاصيل خاصة بالموقع، طريقة واعدة. إنها تسعى إلى تطبيق الكمية المناسبة، متى وأين تكون هناك حاجة إليها باستخدام تقنية معدل متغير. يقوم هذا الأسلوب بضبط كل إدخال بناءً على الحالة المحددة لكل جزء من منطقة الدراسة. لتحقيق هذا الهدف، يجب أن يكون التباين المكاني للتربة معروفًا في كل مكان باستخدام عينات التربة والبيانات المساعدة أو المتغيرات البيئية مثل صور الاستشعار عن بعد والداني، ونموذج الارتفاع الرقمي، وأنواع استخدام الأراضي، وبيانات غلة المحاصيل، وما إلى ذلك. الجيوإحصاء ، استخدام الأساليب الإحصائية لدراسة البيانات المكانية ، يوفر أدوات ممتازة لوصف ونمذجة التباين المكاني باستخدام الفا ريوغرام ، و الاستنباط في المواقع غير المعينة باستخدام الكريجاج ورسم الخرائط ، ومحاكاة السيناريوهات المختلفة من خلال دمج عدم اليقين ، وتحسين التصاميم التجريبية وخطط أخذ العينات ، إلخ. سيتم توضيح المساهمات المختلفة لالجيوإحصاء في الزراعة الدقيقة من الأمثلة المأخوذة من الأعمال البحثية المنشورة في جميع أنحاء العالم بشأن عوامل إنتاج المحاصيل المختلفة على مقاييس مكانية مختلفة.

الكلمات المفتاحية: رسم الخرائط الرقمية ، الكريجاج ، إدارة المحاصيل الخاصة بالموقع ، التباين المكاني ،المحاكاة العشوائية، الفا ريوغرام.

Introduction

Since the appearance of the modern human being, people were nomadic and lived by collecting wild plants, fishing, and hunting. It is circa 12.000 BC that people became sedentary and experienced farming by domesticating plants and animals (Herrera and Garcia-Bertrand, 2018). This constitutes the first, also called Neolithic, Agricultural Revolution. The Industrial Revolution contributed to the second, or British, Agricultural Revolution that occurred between the mid-17th and late 19th centuries (Thompson, 1968) and was characterized by a huge increase in agricultural production due to its mechanization. The third, or Green, Agricultural Revolution took place in 1960-1970 (Pingali, 2012). It allowed combating hunger by using agrochemicals, biotechnologies, expansion of irrigation infrastructure, hybridized seeds, etc. At present, we are living the fourth, or Digital, Agricultural Revolution that is based on data and information technologies (Klerkx et al, 2019; Saiz-Rubio and Rovira-Mas, 2020).

Although there are subtle differences between them, digital agriculture is interchangeably called smart farming or precision agriculture (Klerkx et al, 2019). Smart farming is **“***the application of information and data technologies for optimizing complex farming systems, the focus is on access to data and the application of these data (how the collected information can be used in a smart way)*” (AgroCares website). In fact, “*Digital agriculture means to go beyond the mere presence and availability of data and create actionable intelligence and meaningful added value from such data; it integrates both precision agriculture and smart farming*” (AgroCares website).

Precision agriculture (PA) was defined as a site-specific management that recognizes the variability within a field and involves doing the right thing, in the right way, at the right place, and at the right time (Berry, 1998); this is known as the four Rs approach. Very recently, the International Society of Precision Agriculture (ISPA) defined PA, in 2019, in two formats. The short definition is "*PA is a management strategy that takes account of temporal and spatial variability to improve sustainability of agricultural production*". PA appeared in the early 1990s (McBratney et al, 2005; Mulla and Khosla, 2016).

PA is a very important issue in modern agriculture with the aim of improving crop and land productivity at reasonable cost and protecting the environment (Auernhammer, 2001) and this is confirmed by the devoted structure like the International Society of PA (ISPA) with its continental representations and a series of conferences as well as a specifically dedicated journal (Precision Agriculture published by Springer).

All precedent definitions of PA highlight the great importance of spatial and temporal variability or heterogeneity for PA. The temporal component is very important and spatio-temporal data can be evaluated for limited temporal measurement situations using statistical methods for temporal stability or persistence like Spearman rank correlation and relative differences (Vachaud et al, 1985; Douaik, 2005; Douaik et al, 2006, 2007, 2011; Iraqui et al, 2021: this issue) and for large temporal measurement scenarios using space-time statistical methods like geostatistics and Bayesian maximum entropy (Kyriakidis and Journel, 1999; Douaik, 2005; Douaik et al, 2004, 2005, 2008, 2011). However, in the present review, the discussion will be limited only to the spatial component.

There exists a large number of spatial interpolation methods (Robinson and Metternicht, 2006; Li and Heap, 2014); however, the most frequently used methods are inverse distance weighted, spline, and kriging. Although, all spatial interpolation methods predict a value at any unsampled location as a linear combination of weighted values of neighboring locations, they differ in the way the weights are computed. However, kriging, the geostatistical method of spatial interpolation, offers much more possibilities than the remaining methods since it is based on a specific tool, the variogram. These two geostatistical tools allow to consider spatial variability including configuration geometry and redundancy, take into account eventually the differences in spatial variability for different directions (anisotropy) (Gotway and Hergert, 1997), fuse data with different information supports by using block kriging and area-to-point and area-to-area methods (Sciarretta and Trematerra, 2014), compute a measure of the reliability of interpolated values (Mueller et al, 2004), and include auxiliary information (Gotway and Hartford, 1996). For all the above arguments, the focus in this research work will be exclusively on geostatistics.

Geostatistics was applied, in general, to different scientific areas like remote sensing (Van Der Meer, 2012), earth sciences (Sarma, 2009), GIS (Burrough, 2001), etc. For the particular case of agricultural sciences, geostatistics was applied to soil science in the beginning of the 1980s in a series of papers (Burgess and Webster, 1980abc, 1981). Other applications in agricultural sciences were in nematology (Webster and Boag, 1992; Avendano et al, 2003), entomology (Liebhold et al, 1993; Wang et al, 2016), weed science (Donald, 1994; Roham et al, 2014; Jurado-Exposito et al, 2019), plant disease (Nelson et al, 1999; Fabi and Varvaro, 2009), weeds and worms (Valckx et al, 2009; Webster, 2010), etc.

Oliver (1987) and Oliver and Webster (1991) were among the first review papers about the use of geostatistics in agricultural sciences in general and in soil science in particular. Later, Goovaerts (1998; 1999) focused on the study of the spatial variability of soil properties and discussed, very deeply, the state of the art and perspectives of the use of geostatistics in soil science while Meshalkina (2007) presented a short review for the same area. A book was dedicated to the different applications of geostatistics to PA (Oliver, 2010). Also, Oliver (2013) discussed how to manage agriculture more exactly using geostatistics. More recently, Buttafuoco and Luca (2016) and Rodrigues et al (2020) addressed this topic. The book handled in-depth the subject whereas the former paper was too short and the contributions were highly summarized. All the sources did not consider some other contributions of geostatistics to PA. This is the main reason behind developing this present research work. There are also other data processing methods for mapping such as machine learning (Cianfrani et al, 2018) but I will discuss only methods that are based on geostatistics (purely and hybrid methods).

The paper is organized as follows. In the second section, technology and data sources required for the use of geostatistics in PA are presented. Then, the different contributions are developed in the following sections and are illustrated using some examples. However, to keep the paper at a manageable size, sampling and design of experiments will not be presented. Finally, some concluding statements are discussed. Although geostatistics is plenty of equations and formulas, I deliberately avoided their use and limited myself to the description in plain English. Interested readers can find all required equations in many of the references cited in this paper.

Technology and data sources

The “raison d’être” of PA is the spatial and temporal variability; otherwise, PA is meaningless (Mulla and Schepers, 1997). PA is not limited only to large farms but can be used also for small fields (Van Meirvenne, 2003). Once there is spatial variability, the potential for PA is higher and its potential value is greater for higher spatial dependence (Pierce and Nowak, 1999); the latter can be quantified using the variogram, the cornerstone of any geostatistical analysis. PA is fully based on Information and Communication Technologies (ICT) (Zhang et al, 1999; Cisternas et al, 2020) with 5 categories: GPS, sensors, GIS, computers, and application control (Pierce and Nowak, 1999). GPS and sensors are used for collecting data, GIS and computers are used for processing data, and application control allows fine tuning the supply of crop production inputs.

There are essentially two types of data used in PA: primary data and secondary data, called also ancillary data, auxiliary data or environmental covariates (Grunwald, 2009). Primary data are directly related to the measured feature like soil nutrients, salinity, crop yield, water content, etc. They are called hard data since they are assumed to be accurate or error-free Secondary data are indirectly related to the observed properties like apparent electrical conductivity measured using electromagnetic induction or digital numbers and indices derived from remote sensing images. They are called soft data as they are estimated by calibration models using primary data; so they are inaccurate and present error (Kyriakidis et al, 1999; Douaik, 2005; Douaik et al, 2004, 2005, 2008, 2011; Van Meirvenne et al, 2005).

Primary data are measured using international standard methods like soil properties in laboratory and crop yield using yield monitor (Ping and Dobermann, 2005). Secondary data are mainly measured using sensors. There are different sensor systems used in PA that produce different secondary data like terrain attributes produced using digital elevation model (DEM) (Kravchenko et al, 2002; Jurado-Exposito et al, 2009; Shen et al, 2019), apparent electrical conductivity (ECa) (Johnson et al, 2003; Corwin and Lesch, 2005; Moral et al, 2010), aerial photographs (Stafford and Miller, 1993; Kerry and Oliver, 2008), proximal sensing including spectroscopy (Thomasson et al, 2001; Viscarra Rossel et al, 2011), and remote sensing using satellites (Moran et al, 1997; Mulla, 2013; Huang et al, 2018; De Queiroz et al, 20200) or unmanned aerial vehicle (UAV) like drones (Maes and Steppe, 2019 ; Radoglou-Grammatikis et al, 2020 ; Sishodia et al, 2020; Del Cerro et al, 2021).

Primary data as well as secondary data will be processed using geostatistical methods for evaluating their spatial variability, the first step towards PA. These methods are presented successively in the following sections.

Computing and modelling spatial variability

Geostatistics distinguish itself from all the remaining spatial interpolation methods by offering a tool that allows calculating and fitting a mathematical function to the spatial structure, i.e. semivariogram, or simply variogram to keep it short. Geostatistics is based on the theory of regionalized variables (Matheron, 1971). In this theory, each measured value at a given spatial location is considered as a random variable and the whole set of observed values is considered as a random function or a set of spatially

correlated random variables (Matheron, 1989; Goovaerts, 1997a). Consequently, geostatistics is a probabilistic model that allows to taking into account any uncertainty in data and evaluates that of predicted values.

In practice, any random function is characterized by its first two statistical moments. i.e. the mean or trend and the covariance function or variogram. The trend assesses the global spatial variability whereas the variogram quantifies the local spatial variability. There are four types of variograms: direct or simple variogram, cross-variogram, pseudo cross-variogram, and indicator variogram.

Direct variogram

The Tobler's first law of geography stipulates that ''*everything is related to everything else, but near things are more related than distant things*'' (Tobler, 1970). The direct variogram formalizes this intuition. It measures the average dissimilarity between data separated by a given vector defined by its distance and its direction (Goovaerts, 1997a). The experimental variogram is calculated, based on the sample data, for a limited number of spatial separation distances and directions whereas, for spatial interpolation, values are needed for any spatial separation distance and direction; this is why a theoretical model is fitted to the experimental variogram using permissible mathematical functions (Goovaerts, 1997a). Structural analysis seeks to define and determine the main characteristics of the variogram: the model, its behavior at the origin (nugget effect) and at infinity (range and partial sill), and its anisotropy ratio for differ spatial variability patterns with directions. The relative nugget effect, defined as the ratio between nugget effect and total sill, allows qualifying the level of spatial dependence (Cambardella et al, 1994).

Direct variograms are the most used spatial functions and are mainly computed for the features of interest from primary data (soil properties, crop characteristics like yield, etc.); however, sometimes they are also computed for complementary information from secondary data, mostly when they are required to improve the accuracy of the features of interest.

Examples of the use of direct variogram in PA are very abundant encompassing different soil and crop features and at different spatial scales. Moreover, direct variogram is used with all kriging algorithms except the indicator transform. Examples of direct variogram are given at the end of the presentation of the corresponding kriging algorithms.

Cross-variogram and pseudo cross-variogram

Variogram was defined for a univariate case (only one attribute of interest at time), considering one random function. In case that data are available for two or more attributes (multivariate case), and in a similar way to the correlation in statistics, it is possible to use two or more random functions (multivariate random function); each one of them is characterized separately by its variogram and each pair of random functions can be characterized by the cross-variogram that allows to evaluate simultaneous spatial variability of two attributes (Goovaerts, 1997a; Lark, 2003). Cross-variogram can be defined only if the spatial positions of the two attributes are exactly the same, when they are co-located. If it is not possible to have collocated attributes or there are

only few co-located samples, it is still possible to study the joint spatial variability using the pseudo cross-variogram (Papritz et al, 1993; Lark, 2002).

Compared to direct variograms, cross-variograms and, especially, pseudo cross-variograms are much less used in general and in particular in PA. They are used exclusively with cokriging and factorial kriging analysis. Some illustrating examples will be presented at these two subsections.

Indicator variogram, cross-variogram and pseudo cross-variogram

In some situations, the feature of interest is not continuous but rather categorical like soil types or the aim is not predicting the unknown value of an attribute at a unsampled location but, instead, estimating the uncertainty about this unknown value. For example, we would be rather interested in estimating the risk that the soil electrical conductivity at an unsampled location is below or above a given threshold (for example 4 dS/m) instead of predicting the value of soil electrical conductivity at this location. In such situations, an indicator transform is used with two possible values (for example 0 and 1 if the soil did not belong and belong to the given soil type or values are below and above 4 dS/m, respectively) and the original continuous values are replaced by these two values. Similarly to the direct variogram, an indicator variogram can be computed using the binary variable (Goovaerts, 1997a). This procedure can be repeated for any number of threshold values (for example 2, 4, 8, 16, and 32 dS/m).

As for cross-variogram, an indicator cross-variogram can be used to study the joint behaviour of two or more different thresholds for the same attribute or different attributes at their corresponding thresholds or an attribute at its corresponding threshold and one or more continuous attributes (Goovaerts, 1994). Indicator pseudo cross-variogram can be built in the same manner as was done for pseudo cross-variogram when there are few or no co-located samples for two binary attributes.

Indicator variogram is frequently used. However, indicator cross-variogram is much less used whereas, to the best of my knowledge, indicator pseudo cross-variogram was never used. Examples will be presented at the corresponding kriging algorithms.

Spatial interpolating and mapping

Kriging, the geostatistical procedure of spatial interpolation, allows prediction at unsampled locations. It is preferred over the other spatial interpolation methods for the reasons cited at the end of the introduction section. Kriging is the best unbiased linear predictor. A kriged estimate is a linear combination of data with different weighting of the neighboring data depending on their position, both relative to the unsampled location and relative to their locations themselves. The weights are obtained from the spatial structure via, for example, the variogram.

There are different types of kriging depending on the number of attributes used for prediction (univariate using only primary data or multivariate using both primary and secondary data), the nature of the attributes (continuous or categorical), what to predict (unknown values or uncertainty/risk), and how the mean value is considered (Nawar et al, 2017).

Univariate kriging

Simple kriging (SK) is the most basic algorithm. It considers the mean to be known and constant across the entire study area (Goovaerts, 1997a). However, since the mean is rarely known, this algorithm is not frequently used.

Webster and McBratney (1987) is one of the first and rare published works on application of SK to PA. They mapped soil fertility (pH, phosphorus, and potassium). Most of the time, SK is used as a reference for comparing more elaborate algorithms. For example, in a recent work, soil texture was mapped using multiple linear regression (MLR), SK, ordinary kriging (OK), and universal kriging (UK) (Mondejar and Tongco, 2019) and soil quality index was mapped using SK, OK, and UK (Senol et al, 2020). Abbreviations are defined in the following sections.

The most frequently used algorithm is that of OK (Goovaerts, 1997a). It is similar to SK; however, it considers the mean unknown and constant for each local neighborhood but not for the whole study area. Both SK and OK use only direct variogram of the primary attribute since there is no secondary data.

Examples are numerous but I quote only few of them like mapping of soil nematode (Wallace and Hawkins, 1994), weeds (Johnson et al, 1996), soil earthworms (Cannavacciuolo et al, 1998), soil cationic exchange capacity (CEC) (Bishop and McBratney, 2001), delineation of management units based on soil properties, yield data, and Quickbird images (Song et al, 2009), soil salinity (Dakak et al, 2011), different soil properties (Awal et al, 2019), etc.

Multivariate kriging using spatial coordinates as secondary information

A special multivariate algorithm is universal kriging (UK), also called kriging with an internal drift, where the secondary information is represented by the spatial x and y coordinates (Goovaerts, 1997a). It extends OK by considering the local mean as a smooth function of the two coordinates. As for SK and OK, UK uses only direct variogram of the attribute of interest.

As for illustration, Burgess and Webster (1980c) were the first to apply UK to soil, in particular to soil electrical resistivity. Bourennane and King (2003) mapped soil depth by comparing UK and kriging with external drift (KED) while Siqueira et al (2014) compared OK, UK, and cokriging (CK) for mapping soil properties, soil hydraulic conductivity and matric potential (Gumiere et al, 2014), etc.

Multivariate kriging with non-exhaustive secondary information

Cokriging (CK) considers both the attribute of interest and one or more ancillary variables for which the secondary information is not available for the whole locations to be predicted. It is the only kriging algorithm that uses cross-variogram, in addition to direct variogram of both variables (Goovaerts, 1997a).

There are many published research works that applied CK using either cross-variogram or pseudo cross-variogram, the former is assumed; otherwise, the latter will be indicated. Among them, I cite weed (Colbach et al, 2000), phosphorus and potassium using DEM as covariate (Kozar et al 2002), clay using pseudo cross-variogram and aerial photograph as covariate (Kerry and Oliver, 2003), soil properties using IKONOS images as covariate (Sullivan et al 2005), soil texture using ECa as auxiliary data (Vitharana et al, 2006), clay using pesudo cross-variogram and ECa as covariate (Reyes et al, 2018), soil thermal properties using soil properties as covariates (Gamage et al, 2019), *Xylella fastidiosa* in olive tree grove (Castrignano et al, 2021a), etc.

Multivariate kriging with exhaustive secondary information

When the secondary information is present everywhere in the area to predict, it is possible to use either simple kriging with varying local means (SKlm) or kriging with an external drift (KED). Both algorithms use only direct variogram of the attribute of interest.

SKlm extends SK by considering the global mean as local varying means that depend on secondary information (Goovaerts, 1997a). The secondary information can be either continuous or categorical. KED is similar to UK but the spatial coordinates are replaced by secondary information (Goovaerts, 1997a).

Examples of the use of SKlm are mapping soil texture using DEM as covariate with comparison to OK, UK, and CK (Meul and Van Meirvenne, 2003), mapping soil organic carbon (SOC) using, again, DEM as covariate with comparison to OK and CK (Luca et al, 2007), mapping magnetic susceptibility, clay, and base saturation using geology, geomorphology, and pedology as categorical secondary information (Teixeira et al, 2017). Regarding KED, as illustration I quote soil depth using slope gradient from DEM as a covariate (Bourennane et al, 1996), sunflower weeds using DEM as secondary data (Jurado-Exposito et al, 2009), soil water content using geophysical sensors like electromagnetic induction (EMI), ground penetrating radar (GPR), and time domain reflectometer (TDR) (Cafarelli et al, 2015), etc.

Uncertainty and risk

When the aim is to predict the uncertainty or the risk, rather than the values, at unknown spatial locations, three algorithms can be used: indicator kriging (IK), disjunctive kriging (DK), and probability kriging (PK). IK uses the indicator transform and indicator variogram to estimate the probability that the value of an attribute is below or above a given threshold (Goovaerts, 1997a). Simple, ordinary, and external drift algorithms can be used for the indicator transform and the multivariate form can be applied using indicator cross-variogram leading to indicator cokriging (ICK). DK is used for non-normally distributed data, even after using data transformations like square root or logarithm. The attribute of interest is transformed using Hermite polynomials that are kriged separately and the final predicted value is the sum of the formers (Yates et al, 1986a; Oliver, 1990; Webster, 1991; Oliver et al, 1996). PK, in contrast to IK, represents the information from all the available attribute values, including secondary information, by using the order relation of observed values (Carr and Mao, 1993), denoted by the uniform value or the standardized rank. The latter is assigned as the

only auxiliary variable in PK to improve estimation of the probability that the attribute value is below or above a cut-off. PK uses direct variogram and cross-variogram.

Among the three algorithms, IK is the most used whereas PK is the least used while DK is in-between. Examples are soil salinity using DK (Yates et al, 1986b), IK (Dakak et al, 2013) or IK and PK (Shaddad et al, 2020), soil heavy metal pollution using DK (Hani et al, 2010), soil texture classes using IK (Oberthur et al, 1999), drainage classes using IK and ICoK based on topographical data and ECa (Kravchenko, 2002), soil phosphorus using IK and DK (Lark and Ferguson, 2004), soil pH using IK and DK (Emery, 2006), nitrogen and phosphorus using PK (Lu et al, 2007), soil salinity using ICoK and FKA (Castrignano et al, 2008), nematode using IK, ICoK, FK, and FKA based on soil properties, ECa and DEM (Ortiz et al, 2010), the insect *Bactrocera minax* using PK (Wang et al, 2016), *Xylella fastidiosa* in olive tree using PK based on visual diagnostic, PCR molecular tests, UAV images, and GPR data (Castrignano et al, 2021b), etc.

Different spatial scales

The value of any soil property at any spatial location and/or any temporal period is the result of the interaction of a large number of physical, chemical, and biological processes as well as their interactions (Jenny, 1941; McBratney et al, 2003). These processes act at various spatial and temporal scales. For the spatial component, it is interesting to distinguish between micro-, local, regional, and global scales and also to filter any noisy variability. In geostatistics, for the univariate case, the scales are present in the linear model of regionalization (LMR) since the final variogram model is represented as a sum of different basic variogram models; each one corresponding to a given spatial scale while for the multivariate case, the scales are present in the linear model of co-regionalization (LMC) since the final variogram and cross-variogram models are represented as a sum of different basic variogram models (Goovaerts, 1992; Wackernagel, 2003). For the univariate case, factorial kriging (FK) allows detecting the different spatial scales using the variograms then their corresponding spatial components are estimated and mapped separately; the same procedure can be followed in the multivariate case using multivariate factorial kriging, also called factorial kriging analysis (FKA) (Goovaerts, 1992; Wackernagel, 2003). In fact, FKA combines the multivariate statistical method of principal component analysis (PCA) with FK.

Some illustrating examples of FK and FKA are sources of variation using FKA based on soil properties (Dobermann et al, 1997), soil heavy metal pollution comparing CK, RK, and FKA (Juang and Lee, 1998), soil physical, hydraulic and chemical properties using FKA (Bocchi et al, 2000), soil properties using FKA (Castrignano et al, 2000), relationships between topsoil and subsoil chemical properties using FKA (Bourennane et al, 2003), relationships between soil properties, plant development and biomass, LAI and NDVI, and yield components using FKA (Casa and Castrignano, 2008), delineation of management units using FKA based on primary data (physico-chemical soil properties) and secondary data (EMI and electrical resistivity tomography) (Morari et al, 2009), delineation of management units using FKA based on soil properties and soil water content (Buttafuoco et al, 2010), etc.

Geostatistical hybrid methods

All the above kriging algorithms are purely geostatistical except FKA. A hybrid geostatistical method combines a statistical and/or machine learning method for assessing the deterministic component (general trend) with one of the many forms of kriging for evaluating the stochastic component (local spatial variability) (McBratney et al, 2003).

Regression kriging (RK), also called residual kriging, is one among the first hybrid geostatistical methods (Odeh et al, 1994, 1995). In RK, a multiple linear regression (MLR) model between an attribute of interest and secondary variables is established, residuals are calculated and SK is applied to them, and predicted values by MLR are added to kriged residual values (Hengl et al, 2004; Keskin and Grunwald, 2018).

Examples of RK are soil salinity using OK, CK, and RK based on laboratory and ECa (Triantafilis et al, 2001), soil physical variables and ECa (Moral et al, 2010), soil properties as primary data and Landsat ETM images as secondary data) (Ge et al, 2011).

MLR, in RK, is a global model applied to the whole study area. To take into account the non-stationarity nature of the attribute of interest (local variability), MLR is advantageously replaced by Geographically Weighted Regression (GWR) (Brunsdon et al, 1996; Fotheringham et al, 2002), leading to Geographically Weighted Regression Kriging (GWRK).

For illustrations, I cite comparing MLR, IDW, RBF, OK, CK, RK, GWR, and GWRK for predicting soil phosphorus using DEM and RS as auxiliary covariates (Shen et al, 2019), SOC using PLSRK with ASTER images and laboratory spectroscopy as covariates (Aichi et al, 2021), etc.

Both RK and GWRK consider a linear relationship between the attribute of interest and secondary variables. However, more complex relationships can be used like generalized linear (Gotway and Stroup, 1996; Odeh et al, 1997; Kempen et al, 2012), generalized additive (Bishop and McBratney, 2001), and even non-linear models (McBratney et al, 2003; Hengl et al, 2007). This allows also combining geostatistcs and machine learning methods like artificial neural network (ANN), tree decisions like classification and regression tree (CART) and gradient boosted tree (Bishop and McBratney, 2001), extreme machine learning, etc.

Examples of methods combining geostatistics and machine learning are saturated hydraulic conductivity using MLR, ANN, OK, SKlm, CK, RK, and ANNK with DEM as covariates (Motaghian and Mohammadi, 2011), soil heavy metal pollution using RK and ANNRK (Sergeev et al, 2019), soil pH using MLR, RF, ANN, gradient boost, RFK, RK, ANNK, and gradient boost K and DEM as covariates (Tziachris et al, 2020), SOC using ANN, ANNOK, and ANNCK with remote sensing and DEM as covariates (Mallik et al, 2021), etc.

Stochastic simulation

Geostatistics offers different kriging algorithms that allow spatial interpolation by predicting either the unknown value or its probability to be below or above a given threshold at unsampled locations. The diversity of algorithms offers the opportunity to use different data sources (primary and secondary), with different natures (continuous or categorical), and with partial or full spatial coverage (non-exhaustive or exhaustive). However, since kriging has the objective of minimizing a local error variance, one of its major drawbacks or limitations is the smoothing effect which means that observed low values are overestimated and observed high values are underestimated (Deutsch and Journel, 1998). As a consequence of this smoothing effect, the spatial variability of kriged values decreases compared to that of observed values (Goovaerts, 2000). This is especially detrimental if one is interested, in particular, in extreme (very low or very high) values and their spatial distribution (Deutsch and Journel, 1998). Geostatistical simulation, called also conditional or sequential simulation / imaging, allows circumventing this drawback and has three major advantages: it honours the observed values (simulated and observed values are equal at sampled locations), it reproduces their histogram and it reflects their spatial variability (variogram) (Goovaerts, 1997b; Deutsch and Journel, 1998; Chilès and Allard, 2006).

At section 4.5, we discussed three kriging algorithms that allow evaluating the uncertainty about an unknown attribute value at any unsampled location. However, this uncertainty was calculated for each unsampled location separately (local uncertainty) whereas it may be more interesting to compute a joint uncertainty by considering simultaneously all the unsampled locations, called spatial uncertainty (Goovaerts, 1999; Mowrer, 2002). In addition, kriging algorithms give only one value for each unsampled location (one map); in contrast, stochastic simulation offers the possibility of getting many different values (many maps), called realizations. These are two additional advantages of stochastic simulation compared to kriging.

As for kriging, there are two main methods of geostatistical simulation: sequential Gaussian simulation (SGS) for normally distributed continuous attributes and sequential indicator simulation (SIS) for categorical attributes or continuous attributes that have been modified using the indicator transform (Deutsch and Journel, 1998; Goovaerts, 2001; Zhang et al, 2009; Chilès and Delfiner, 2012). Secondary information can be used extending the two simulation methods to sequential Gaussian co-simulation (SGCoS) and sequential indicator co-simulation (SICoS) (Verly, 1992).

As examples of case studies, I cite soil heavy metal pollution using either SICoS (Zhao et al, 2008), or SGS and SGCoS with pH and pXRF as covariates (Qu et al, 2018), soil nutrients using SGCoS with aerial hyperspectral images as secondary data (Yao et al, 2005), soil micronutrient (zinc) using SGS (Eze et Kumahor, 2019), SOM using SGS and SGCoS with DEM as covariate (Chai et al, 2007), soil salinity using SGS and SGCoS with ECa as covariate (Yao et al, 2013), soil quality (IQI) using SGS (Sun et al, 2012), soil texture using IK and SIS (He et al, 2009), soil types using SIS (Da Silva et al, 2014), SWC using SGS and SGCoS with resistivity as covariate (Bourennane et al, 2007), etc.

Conclusions

Farmers managed their fields by applying a uniform rate of agricultural inputs for the whole field even if they knew that there are zones with high yields and others with low yields. PA recognises this within-field variability, in space and time, and allows variable rate application or, at least, delineation of homogeneous management zones or units where crop production factors are assumed to be uniform. PA has three main aims: improve crop productivity, reduce economic costs, and sustain the environment by applying the right amount, at the right place, and at the right time.

Knowledge of variability is a prerequisite for the implementation of PA. In this research work, some of the contributions of geostatistics to the evaluation of spatial variability were reviewed. So, tools like variogram, kriging, and stochastic simulation were presented and illustrated at different spatial scales, for different crops, and from different crop production domains like soil, pests, diseases, etc.

Two other important contributions, sampling and design of experiments, were not discussed to keep the paper at an acceptable length. Also, the temporal component was not considered even if it is crucial for PA as it permits to assess the temporal stability of the spatial variability, thus understanding if management units can be defined once or should be defined each year. Finally, the focus of this paper was on the use of geostatistics for the evaluation of spatial variability, a first step in implementing PA; however, the next step would be managing spatial variability by delineating management units. This step needs the use of other data processing methods using multivariate statistics, machine learning, and also geostatistics.

The success of PA, a data-driven crop management based on big data and leading to digital agriculture, can be achieved only with the integration of new information and communication technologies and the multidisciplinary nature of the research teams that should involve the different scientific areas of agricultural research. The ultimate goal of PA would be to continue to feed an ever growing population with reduced agricultural area in the context of climate change.

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