Delineation of Management Zones in Precision Agriculture by Integration of Proximal Sensing with Multivariate Geostatistics. Examples of Sensor Data Fusion

Annamaria CASTRIGNANÒ [1] (✉)
Carla LANDRUM [2]
Daniela DE BENEDETTO [1]

Summary

Fundamental to the philosophy of Precision Agriculture (PA) is the concept of matching inputs to needs. Recent research in PA has focused on use of Management Zones (MZ) that are field areas characterised by homogeneous attributes in landscape and soil conditions.

Proximal sensing (such as Electromagnetic Induction (EMI), Ground Penetrating Radar (GPR) and X-ray fluorescence) can complement direct sampling and a multi-sensor platform can enable us to map soil features unambiguously. Several methods of multi-sensor data analysis have been developed to determine the location of sub-field areas. Modern geostatistical techniques, treating variables as continua in a joint attribute and geographic space, offer the potential to analyse such data effectively.

The objective of the paper is to show the potential of multivariate geostatistics to create MZ in the perspective of PA by integrating field data from different types of sensors, describing two study cases. In particular, in the first case study, cokriging and factorial cokriging were employed to produce thematic maps of soil trace elements and to delineate homogenous zones, respectively. In the second case, a multivariate geostatistical data-fusion technique (multi collocated cokriging) was applied to different geophysical sensor data (GPR and EMI), for stationary estimation of soil water content and for delineating within-field zone with different wetting degree.

The results have shown that linking sensors of different type improves the overall assessment of soil and sensor data fusion could be effectively applied to delineate MZs in Precision Agriculture. However, techniques of data integration are urgently required as a result of the proliferation of data from different sources.

Key words

Precision Agriculture, Management Zones, Proximal Sensing, Multivariate Geostatistics, Data Fusion

[1] Council for Agricultural Research and Economics (CREA),
Via Celso Ulpiani 5, Bari, 70125, Italy
✉ e-mail: annamaria.castrignano@entecra.it
[2] AMEC Environment & Infrastructure, 10670 White Rock Road, Suite 100 Rancho Cordova, CA 95670, USA

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Introduction

Soils commonly exhibit spatial variability in inherent soil properties, such as texture, depth of topsoil and organic C content. Edaphic properties may be affected by pedogenetic processes and/or anthropogenic activities, such as tillage, fertilization and irrigation, which cause spatial and temporal variation in soil. Further, soil properties influence many chemical and biological properties that may ultimately affect plant growth; therefore, a crop growing in spatially variable soil may differ in yield potential within the same field.

Optimum benefits on profitability and environment protection depend on how well land use and agricultural practices are fitted to local conditions. The goal of Precision Agriculture is to optimize the use of soil, water resources and chemical inputs on the basis of spatial patterns in soil properties. It then becomes very critical to assess soil variation quantitatively and locally (Castrignanò et al., 2000). Soil surveys have traditionally provided estimates of crop productivity, but the advent of precision farming requires more accurate estimates at a finer spatial resolution. Adequate techniques of data analysis are then necessary to put in evidence important spatial relationships and to identify the main factors that locally control the variability of soil properties.

To implement site-specific crop management and reduce detrimental environmental impact, a cost-effective approach has been proposed based on delineation of classified management zones (MZ), defined as homogeneous subfield regions with similar yield limiting factors or similar attributes affecting yield (e.g. topography, soil nutrient test levels), that can be uniformly managed (Khosla and Shaver, 2001; Fridgen et al., 2004). Determination of these sub-field areas is difficult due to the interactions among several biotic, abiotic and climate factors that affect crop yield and work on different spatial and temporal scales.

Spatially varied management can be performed by those systems that are able to work differentially in various areas of the field. However, Evans et al. (1996) acknowledged that the greatest obstacle to implement precision agriculture derives from the difficulty to determine accurate local applications of water and nutrients. A substantial aid to this can come from the use of proximal soil sensing, which uses instruments operating very near or in contact with the soil, in conjunction with a GPS receiver, offering the opportunity to automate the collection of soil and/or crop data at high spatial resolution (Adamchuk et al., 2004). At present many alternative methods are being considered to complement conventional survey for estimation of soil and plant properties, for example Electromagnetic Induction (EMI), Electrical Resistivity (ER) and Ground Penetrating Radar (GPR), gamma sensor and hyperspectral spectro-radiometer. The drawbacks of these sensors stem from the lack of uniqueness of the relation between sensor outcomes and, as an example, soil texture, moisture and nutrient concentrations. Their measurements, in fact, are typically the end result of a vast number of factors whose complex interactions are often unknown, which makes their interpretation quite problematic (De Benedetto et al., 2010). Due to the complex nature of agricultural systems, a sensing technique that provides information about soil/plant from only one sensor is considered of limited use and sometimes not reliable. Therefore, more sensors, based on different measurement principles, are needed to separate various effects, which could enhance the capability of quantifying soil within-field variability. Most recently, researchers have focused on the development of a new approach for soil and vegetation sensing, based on combining several sensing techniques to obtain a more comprehensive representation of the area under analysis (sensor fusion system). In particular, sensor datasets could be actually used as auxiliary information to supplement a sparsely sampled target variable and improve the accuracy of its estimation (Taylor et al., 2008; De Benedetto, 2014).

However, this is not without difficulties, because remote and proximal sensing data are often massive, taken on different spatial and temporal scales, and subject to measurement error biases. Moreover, differences between the instruments are always present, nevertheless a data fusion approach could take advantage of their complementary features by combining the sensor data sets in a manner that is statistically robust. Data fusion can be regarded as an inference problem: given two or more heterogeneous input datasets with different statistical characteristics, it searches to optimally estimate the quantity of interest and obtain uncertainty measures associated with this inference.

Actually geostatistics offers a set of optimal linear univariate (kriging) and multivariate (cokriging) estimators (unbiased and with minimum error variance) and requires a spatial statistical model of dependence. A spatial model does not differ from any other statistical model except that the variables pertain to specific locations rather than to the whole statistical data distribution. However, the derivation of (co)kriging estimate requires the inversion of a covariance matrix, describing the relationships between the observations. Because remote or proximal sensing datasets are often massive, inversion of the covariance matrix is difficult if not impossible. In many cases, practical implementation requires a reduction of the number of data but such approximations introduce the risk that the result deviates from what is expected. Multicollocated cokriging (Rivoirard, 2001) makes use of the auxiliary variable known at all points where the target variable is available and was shown to enable better estimation with reduced uncertainties, compared to estimation based on observations from a single instruments (Castrignanò et al., 2010; Chatterjee et al., 2010). This approach relies on the availability of auxiliary variables (such as on-the-go geophysical sensor data) at all locations where the variable of interest is to be estimated. It combines effectively the differences among the sensor data sets and reinforces the complementary value of remote or proximal sensing and ground-based observations of the variable of interest (Castrignanò et al., 2012). By fusing these measurements with ground-based observations using multivariate geostatistical techniques, it is then possible to obtain more reliable estimates of soil properties at different spatial scales, which can increase the efficacy of site-specific management.

The objective of this paper was to show the potential of multivariate geostatistics in combination of proximal sensing to create management zones in the perspective of Precision Agriculture. After a short description of the methodology, two case studies were described.

Materials and methods

Methodology: An overview of the Geostatistical Data Fusion Approach

The main geostatistical procedures applied to fuse the multiple data sets are briefly described below.

Linear Model of Coregionalization

The LMC, developed by Journel and Huijbregts (1978), considers all the *n* studied variables as the result of the same independent physical processes, acting over different spatial scales *u*. The *n(n+1)/2* simple and cross semivariograms of the variables are modelled by a linear combination of N_S standardized semivariograms of unit sill, $g^u(h)$. Using the matrix notation, the LMC can be written as:

$$\Gamma\left(\mathbf{h}\right) = \sum_{u=1}^{N_S} \mathbf{B}^u g^u(\mathbf{h}) \quad (1)$$

where $\Gamma(\boldsymbol{h})=[\boldsymbol{\gamma}_{ij}(\mathbf{h})]$ is a symmetric matrix of order $n \times n$, which diagonal and out-of-diagonal elements represent simple and cross semivariograms, respectively; $\mathbf{B}^u=[b^u_{ij}]$ is called coregionalization matrix and it is a symmetric positive semi-definite matrix of order $n \times n$ with real elements b^u_{ij} at a specific spatial scale *u*. The model is authorized if the functions $g^u(\mathbf{h})$ are authorized semivariograms models (Castrignanò et al., 2000).

Gaussian Anamorphosis Modelling

A difficulty in the practical application of a multivariate approach occurs when the variables are of widely differing sizes. A solution is to standardize the individual variables to give each an average of zero and a variance of unity. Variogram modelling is further complicated by the presence of outliers in highly skewed data distributions. In this case it is better to perform a normalization of data through Gaussian anamorphosis modelling. Gaussian anamorphosis is a mathematical function that transforms a variable Y with a Gaussian standardized distribution in a new variable Z with any distribution. This is made by fitting a Hermit polynomial expansion (Chiles and Delfiner, 1999) and, in order to transform the raw variable into a Gaussian one, the anamorphosis function has to be inverted (Wackernagel, 2003).

Adopting a Gaussian model, a LMC was fitted to all experimental variograms, both direct and cross-variograms, of the transformed data, and then ordinary cokriging (Goovaerts, 1997) was applied as conditional expectation estimator. Finally, the estimates were back-transformed to the raw values of the variables through the anamorphosis functions previously calculated.

Multi-collocated cokriging

The approach is quite similar to ordinary cokriging with the only difference in the neighbourhood search. Since using all secondary information contained within the neighbourhood may lead to an intractable solution, due to too much information, the secondary variable is used at the target location and also at all the locations where the primary variable is defined within the neighbourhood. This solution has generally produced reliable and stable results (Castrignanò et al., 2009; Rivoirard, 2001). In contrast to other kriging techniques, in this approach the influence of the secondary variable on the primary variable is explicitly taken into account through the estimation of the direct secondary variable variogram and the cross- variogram.

Principal Component Analysis

Regionalized principal component analysis consists in decomposing each coregionalization matrix into eigenvalues and eigenvector matrices (Wackernagel, 2003). The transformation coefficients correspond to the covariances between the original variables and the principal component, called regionalized factor, at a given spatial scale and express the influence of each variable on the factor. They are then quite determinant in assigning a meaning to the factor.

Factor cokriging

Mapping the regionalized factors $Y_v^u\left(x\right)$ provides an illustration of the behaviour and relationships among the variables at different spatial scales. The estimation of the factors is performed by a modified co-kriging system, as described by Wackernagel (2003).

It is important to acknowledge that the underlying assumptions of the approach described are linearity and independence of factors. Moreover, factorial co-kriging depends on variogram modelling, i.e. on a somewhat arbitrary choice of the number/type of nested structures and range of variogram models; hence, when modelling variograms, any physical knowledge of the phenomena, acting in the study area, should be taken into account.

Results

First Case Study

Soil trace element (TEs) composition can vary widely across landscapes and may have implications for land-use. Traditional spatial sampling is generally sparse due to the high costs of labor and laboratory analyses. Portable X-ray fluorescence spectrometry provides a multi-element analytical method which can be applied directly in the field or laboratory. The main advantage of the proposed PXRF approach (Weindorf et al., 2010) is to provide a viable, rapid and cost-effective method for soil characterization. This method, used in combination with multivariate geostatistical techniques, could reduce costs of mapping TEs. The objective of this study was to characterize the spatial variability of soil TEs across a central Kentucky field by using multivariate geostatistics.

Description of the study site and sampling scheme

The site investigated is at Spindletop Farm in Kentucky's bluegrass region, Fayette County, Lexington, KY (38.116030 N, -84.491093 W). The area is dominated by a karst landscape underlain by Orodovician phosphate limestone, calcareous shales, and interbedded limestone shales. The site encompasses a variety of soil series (USDA-NRCS, 2013), and soil depths range from 40–200 cm, according to landscape position. Preliminary soil core analysis indicates argillic and fragillic confining layers approximately 55-70 cm below the surface in some locations.

Site topography exhibits undulating swells (convex features) and swales (concave features). A meandering creek runs N/NW of the area. A drainageway, suspected to be a relic of subsidence from the underlying karst geology, is situated diagonally (SW/NE trajectory) across the area and exhibits considerable wetness after rainfall events. Several small (≤1m²) karst swallets reside within the drainageway.

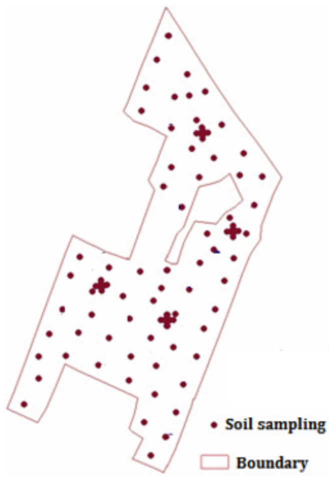

Figure 1. Soil sampling scheme

A total of 100 samples were collected over the study field (Fig. 1). Soil samples were dried at 105°C for 24 h, and gently ground with a mortar and pestle to <2 mm. The prepared samples were then scanned on the sample surface using an innovative battery operated Omega Xpress PXRF (Innov-X Systems, Inc., Woburn, MA, USA) with Ag anode X-ray tube operated at 40 keV. Fluorescence detection was accomplished via ultra-high resolution (<165 eV) silicon drift detector. Factory standardization was accomplished via a stainless steel '316' alloy clip containing 16.130% Cr, 1.780% Mn, 68.760% Fe, 10.420% Ni, 0.200% Cu, and 2.100% Mo, and was fitted tightly over the aperture. The instrument can detect and quantify 30 components including both pollutant metals and nutrients. The limit of detection (LOD) is defined as three times the standard error for each element. Logged data were exported to geostatistical software package for further analysis. Multivariate geostatistical techniques of cokriging and factorial cokriging were employed to 1) produce elemental concentration maps; 2) estimate synthetic scale-dependent regionalized factors to delineate homogeneous within-field zones.

Results

Out of the 30 measured elements 19 were within the detection limits (LOD). In total 14 variables, including 10 elements (As, Ca, K, Mn, Pb, Rb, S, Sr, Ti, Zr) and four soil properties (CEC, clay, sand, organic matter), previously determined (Landrum et al., 2015), were selected as the most relevant after applying various exploratory techniques (correlation matrix, PCA and stepwise regression). A LMC was fitted to the set of direct- and cross-variograms, resulting in three basic structures: nugget effect and a double spherical model with short (78 m) and long (331 m) ranges. Multivariate geostatistical analyses grouped the elements based on their spatial associations. Two main groups were detected: the one including the variables (OM, CEC, sand, clay, Mn, Ca, Pb and Rb) (Fig. 2), revealing some basic spatial structures in common, as an area at N/NW corner, close to the creek flow, and a median strip running in line with the drainageway, characterized by higher values; the other group (Sr, As, K, S, Zr and Ti) showing weak spatial association with the previous one

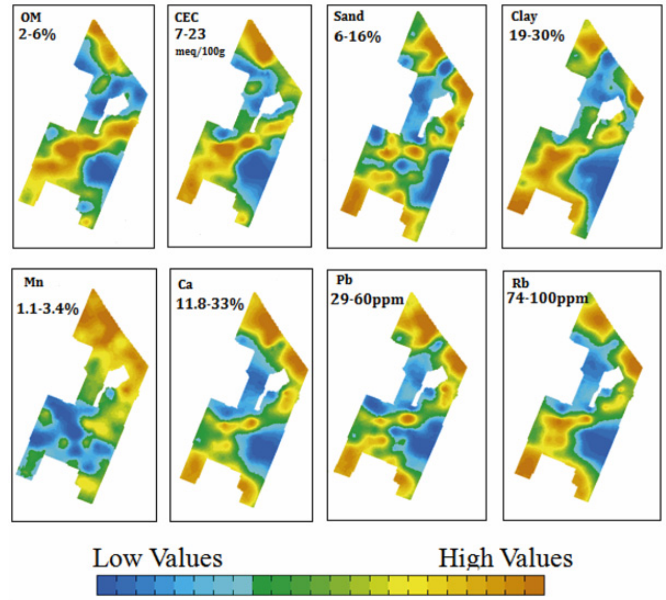

Figure 2. Maps of estimated variables (OM, CEC, sand, clay, Mn, Ca, Pb and Rb)

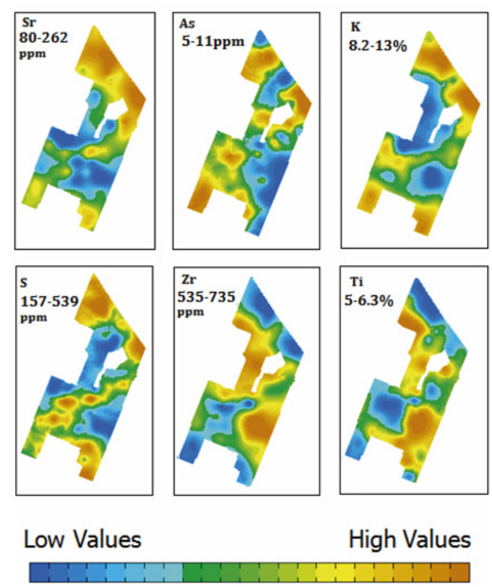

Figure 3. Maps of estimated variables (Sr, As, K, S, Zr and Ti)

and with Ti and Zr, in particular, displaying spatial patterns in some sense reversed compared with the resting elements (Fig. 3).

To synthesise the complex multivariate variation of the field, multi-collocated factor cokriging analysis was applied and only the eigenvectors producing eigenvalues greater than one were retained, because this indicated that their variation was significantly greater than the one of each individual variable. Eigenvectors associated with the nugget effect were omitted, because these were mostly affected by experimental errors.

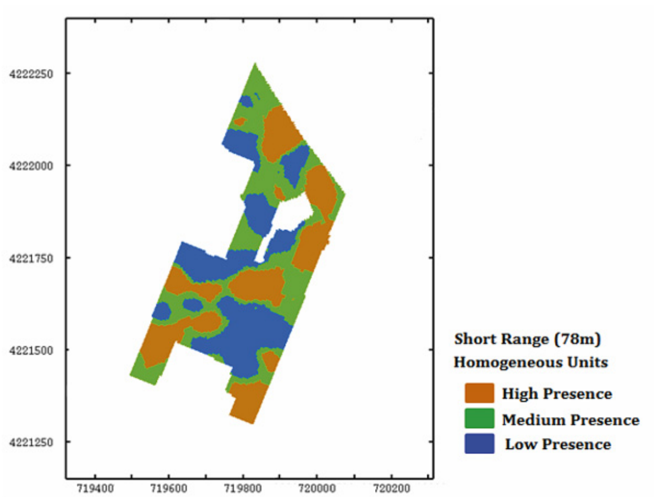

Figure 4. First regionalized factor at short range (78 m)

The first factors at shorter and longer scale, which accounted for approximately 57% and 81% of the variation at the corresponding spatial scales, were retained. The loading values for the first regionalised factor at 78-m range indicated CEC, Ca, Pb, Sr as the variables most influencing soil variation positively, whereas Zr negatively. This suggests that the geochemistry of Ca affects mainly the intrinsic variability of topsoil at short scale.

Conversely, clay and Rb weighed mainly and positively, whereas Zr negatively, on the first long-range factor and this result can be interpreted as, at longer range, the variation is mainly affected by local differences in texture. Rb sorption onto clay mineral can influence pedogenetic processes, whereas Zr is more related to soil weathering because its spatial distribution resembles aged (paleo) soils in this field. Therefore, using the first regionalised factor, it is possible to classify the soil into homogeneous zones with similar geochemical and textural properties (Fig. 4). As an example, the finer-textured zones are localised at NW and NE corners, in correspondence of drainageway and at south.

This study has proven that, when fully integrated with a GPS-GIS system and geostatistical analysis, the Innov-X Xplorer provides instant metal mapping, ideal for Precision Agriculture. However, more investigations of PXRF are needed to assess the impact of external factors (e.g., soil moisture, temperature, texture, etc.) on the outcomes of the sensor in the field.

Second Case Study

Knowledge of soil water content (SWC) variation in both spatial and temporal scales is fundamental in many studies and applications, such as land use planning, irrigation management, ecological and hydrological modelling.

Assessment of SWC variability is complicated due to soil heterogeneity and variability of several environmental factors, so that SWC often appears as an ephemeral, erratic and ambiguous variable. The necessity of accurate soil moisture prediction at very fine resolution, as required in Precision Agriculture, has boosted the development of alternative soil moisture sensing techniques to the gravimetric method, which is the only direct soil moisture measurement method. At present several emerging methods and technologies from geophysics are used as auxiliary variables to effectively supplement the sparsely sampled target variable of soil water content.

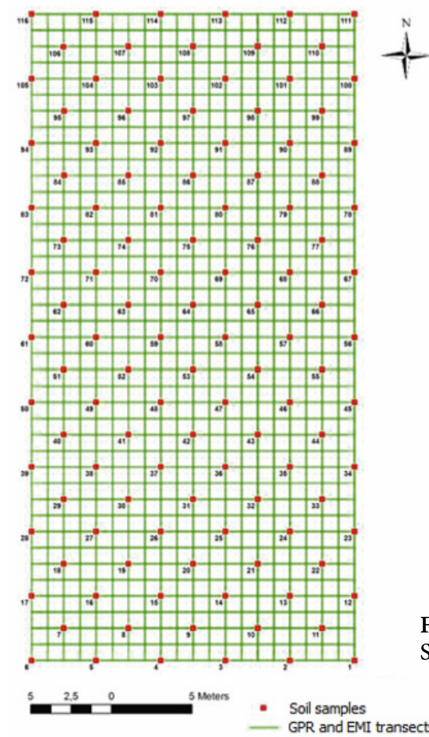

Figure 5.
Sampling scheme

The objective of the research was to explore the potential of geophysical sensors, in particular GPR and EMI sensors, to estimate soil water content at fine resolution, and delineate within-field zones with different wetting degree.

Description of the study site and sampling scheme

The surveys were carried out in a test site (40x20 m) at the agricultural experimental farm of CREA, located in south-eastern Italy (Rutigliano - Bari (40°59'48.25" N, 17°02'02.06" E). The pedon is classified as fine, mixed, superactive, thermic Typic Haploxeralfs according to the Soil Taxonomy (Soil Survey Staff, 2010) and as Cutanic Luvisol (Hypereutric, Profondic, Clayic, Chromic) according to the WRB (IUSS Working Group WRB, 2007). Soil texture is mainly clayey with a clay content ranging from 30 to 60% by weight and an increasing trend in depth (De Benedetto et al., 2010).

The field was monitored along parallel longitudinal and transversal transects, 1 m apart, with an EMI sensor that measures bulk electrical conductivity (EC_a) simultaneously in two, horizontal and vertical, orientations of polarization with different depth response profile (Fig. 5). Along approximately the same transects, a GPR system with two antennas of different (600 and 1600 MHz) frequencies was used, operating in mono-static mode. One hundred and sixteen samples were collected up to 0.30-m depth to measure SWC with gravimetric method (Fig. 5). The measurements were collected after an irrigation event (drip irrigation) for a week until the saturation, and the surveys were carried out after water leaching by gravitation.

To create a multivariate file, the geophysical variables were estimated at the sample locations (De Benedetto, 2014). Point SWC data, EMI and GPR estimates were then jointly processed using multi collocated cokriging. The spatial dependence among soil water data and geophysical data was explored by fitting a LMC. A MCCOK map of soil moisture was then produced. Finally, the univariate estimate of soil water content was produced with ordinary kriging and the two approaches were compared through cross validation test.

Results

Several exploratory techniques were used in order to select the geophysical covariates, most correlated with soil water content that were: EC_a in horizontal polarization, the slices at 0.06-m, 0.18-m and 0.30-m depth for the frequency of 600MHz and the slices at 0.03-m, 0.09-m and 0.165-m depth for 1600MHz antenna. Since the strongest correlation occurred between soil water content and EC_a in horizontal polarization, the latter was chosen as the collocated variable. An intrinsic stationarity was assumed for all variables and an isotropic LMC was fitted to model all the experimental variograms, including two basic structures: a nugget effect and a spherical model with a range of 21.35 m.

Comparing the maps of SWC obtained with OK (Fig. 6a), as a reference, with the one obtained with MCCOK (Fig. 6b), the two types of maps seemed to reproduce the same main structures of spatial dependence, even if the MCCOK map looked more variable. The map revealed a wide northern area of higher values, though the MCCOK map looked more locally changeable in the southern area. The increased variability, observed in the MCCOK map, can be explained from the fine-scale variation introduced by geophysical data.

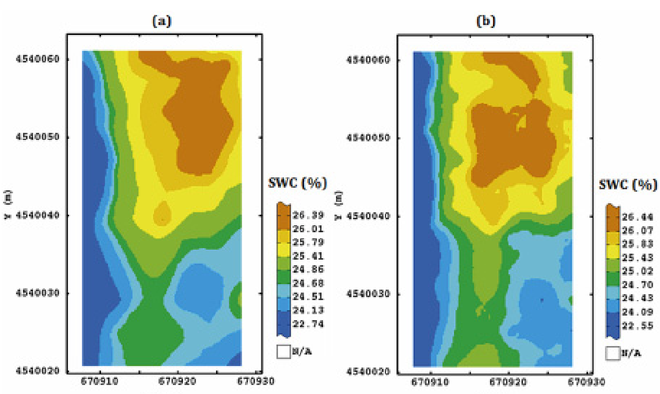

Figure 6. SWC maps obtained with kriging (a) and multicollocated cokriging (b)

The two maps were also quantitatively compared through cross-validation and three statistics (mean standardized error (bias), standard deviation of standardized error (accuracy), variance of error (precision)) (Carroll and Cressie, 1996) were calculated together with the correlation coefficient between estimates and observations. The results showed that MCCOK outperformed kriging in bias, precision and correlation with true values (Table 1), which proves the efficacy to use proximal sensor outcomes as auxiliary variables.

Table 1. Cross validation test of the estimation of SWC using OK and MCCOK. CV_1 represents the unbiasedness of the predictor, CV_2 the accuracy of mean squared prediction error, CV_3 the goodness of prediction and r the correlation coefficient

Estimation method	CV_1	CV_2	CV_3	r
OK	0.015	1.11	0.691	0.598
MCCOK	0.0065	1.207	0.643	0.66

This research, focused on the combined use of GPR, EMI and SWC data, has proved that a multivariate geostatistical approach is effective to fuse different sensors to improve soil water content estimation.

Conclusions

A method was described to fuse measurements of different sensors with sparse sample data using multivariate geostatistics in order to improve soil property prediction. The method proved to be viable, rapid, cost-effective for soil characterization and moisture prediction, and can be used to direct more effective and efficient soil sampling for rapid site reconnaissance and precision irrigation. It could be useful for remediation specialists, soil surveyors and farmers willing to apply Precision Agriculture. However, further investigation in sensor data fusion, also exploring different setting of sensors, is strongly recommended in the light of the current proliferation of data from different sources.

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