Analysis of spatial relationships between soil and crop variables in a durum wheat field using a multivariate geostatistical approach

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Abstract

For important crop and soil properties, temporal variability is generally higher than spatial variability and the definition of stable low and high yield potential zones, for site-specific management, is very difficult.

In this study the application of a multivariate geostatistical methodology, factorial kriging analysis (FKA), is proposed for this purpose, allowing simultaneous processing of several layers of information on spatially and temporally variable crop and soil properties.

The methodology was applied to measurements carried out in a durum wheat field in Viterbo (Central Italy). Soil properties, plant development and biomass, LAI and Normalized Difference Vegetation Index (NDVI) were measured following a grid sampling scheme. Yield components were assessed at the same points at harvest. Coregionalisation analysis was carried out and FKA was applied in order to clarify the spatial relationships between the different variables acting at the different scales. The application of FKA to soil, plant and

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yield properties allowed to discriminate between variables with a different rate of variation, pointing out at those more stable which could be used as a basis to site-specific management.

Keywords: geostatistics, durum wheat, yield components, factor kriging analysis

1. Introduction

Achievement of high yields and good quality of durum wheat in Mediterranenan environments is only possible by precise management of the complex interactions between environmental factors and husbandry decisions. Due to large soil variability existing even at a small scale within a field, uniform crop management does not always allow to tackle appropriately these tasks. Nowadays variable rate technologies for sowing and fertiliser spreading (see e.g. Elhert et al., 2004; Lawrence et al., 2005; Griepentrog et al., 2005), combined with large amounts of geo-referenced information that can be gathered from different sources ranging from satellites (e.g. Coquil and Bordes, 2005) to yield monitors (e.g. Reyns et al., 2002; Blackmore et al., 2003), allow unprecedented fine tuning of site specific management.

This requires that reliable monitoring and proper analysis methodologies are developed in order to allow the efficient integration of different information layers concerning the soil and the crop. The easiest and most rapid way of obtaining information on the spatial variability of a field is through yield mapping, a technology increasingly available to farmers (see e.g. Reyns et al., 2002 for a review), who still require, however, robust methodologies for putting this vast amount of information into practical use (Blackmore et al., 2003; Doberman et al., 2003).

The final spatial variation in grain yield is the result of integration of the action of limiting and reducing factors acting on each point in the field. Spatial analysis of phenology, canopy development and final yield components offers valuable information for the clarification of the factors responsible for yield decreases during different yield formation stages (Hay and Walker, 1989). The combined analysis of spatial variability of soil and crop parameters offers additional insight on the relationships between the factors acting at different scales, hence offering guidance for the development of site-specific crop management strategies (Stewart et al., 2002; Bourennane et al., 2004).

There are many reports on the use of geostatistics to describe and analyse spatial variability of soil and yield properties (e.g. Stewart et al., 2002; Pringle et al., 2004), however very few authors employ multivariate geostatistical approaches to investigate soil or yield variability (e.g. Bourneanne et al., 2004; Bocchi et al., 2000; Castrignanò et al., 2000a). Moreover in the few applications to agronomic studies reported, multivariate techniques are only applied to soil data and the results are seldom correlated to crop canopy and yield variables. In one of the few of such applications, Bourneanne et al. (2004) applied factorial kriging analysis (FKA) to soil properties and then compared regionalised factor scores to yield mapping data, though yield variables were not included in the FKA.

There are no works, we are aware of, in which a joint analysis of soil and crop parameters is carried out including all these variables in a FKA. Therefore, the novelty of the present work is not in the FKA methodology itself, which was mainly developed by Matheron in 1982, but in its application in a joint multivariate statistical analysis of soil, canopy and yield properties, in order to analyse spatial correlations and determine the scale of spatial dependence among soil and crop properties. The approach assumes that crop growth is determined by complex phenomena varying over both time and space, suggesting that spatial data collected at different times during the growing season should be jointly processed.

Previous studies (Bocchi et al., 2000; Bourennane et al., 2004; Castrignano et al., 2000b; Dobermann et al., 1997; Goovaerts and Webster, 1994; Webster et al., 1994) have clearly shown that an analysis of co-regionalization could be more revealing than a univariate geostatistical analysis. To determine the scales of spatial dependence, FKA developed by

Matheron (1982) and previously used in soil science (Goovaerts, 1992) was performed in the present study. This multivariate geostatistical technique describes the spatial scale-dependant relationships among the variables and allows the separation of the sources of variation according to the spatial scale at which they operate.

The combination of Principal Component Analysis (PCA) with geostatistics is particularly suited to the study of complex processes which have a high degree of spatial and temporal variability, such as water and nitrogen cycling in the soil-crop system, and which can be appropriately monitored and described only by using a large number of variables.

Nitrogen is the most important limiting factor that can be managed in non-irrigated small grain cereals. However implementation and assessment of the benefits of variable rate nitrogen fertilisation strategies have proved to be difficult (e.g. Long et al. 2000; Delin et al., 2005; Berntsen et al., 2006). It has been found that the reliance on historic data of yield variability and the definition of potentially high and low yielding areas in a field, does not offer, alone, a robust basis for providing fertilisation prescriptions (Welsh et al., 2003; Blackmore et al., 2003). Similarly, the use of real-time monitoring techniques of actual crop conditions does not always provide an accurate assessment of real N site specific demand (Bernsten et al., 2006). These techniques, some of which are commercially available such as the Yara N Sensor (Link et al., 2002) or the Green Seeker system (NTech Industries Inc., 2006), give good results when N is the only limiting factor to canopy growth and grain yield. However, especially in (non-irrigated) small grain cereals grown in Mediterranean climates, there are important environmental stresses, such as drought and high temperatures that very often occur and typically in the late growing season. In such situations both N deficits and excesses can be detrimental to final yield. It has been shown that in dry conditions high rates of nitrogen fertiliser, stimulating excessive pre-anthesis biomass growth, can even decrease the yield of rainfed cereals (Cantero Martinez, 1995; Van Heerwaarden et al., 1998).

The above considerations suggest that a multivariate coregionalisation analysis of crop and soil variables may help to disclose the main causes of spatial variation in crop yield and quality. The objectives of this study were 1) to identify the multi-scale sources of yield spatial variation for durum wheat grown in a Mediterranenan environment and 2) to show how FKA can be used for joint co-regionalisation analysis of for soil and crop data. Such methodology can be used as an aid for the definition of management zones by taking into account both similarity and proximity criteria between the variables, differently from what is commonly done (Lark and Stafford, 1996; Fraisse et al., 1999; King et al., 2005).

2. Materials and methods

2.1. Field data acqusition

A durum wheat (cv Duilio) crop was sown in a 45 x 84 m field at the experimental farm of the University of Tuscia in Viterbo, Central Italy (latitude 42°43’N, longitude 12°07’E, altitude 310 m) on November 11th 2003. The soil, classified as an Ando Eutric Cambisol (FAO-ISRIC-ISSS, 1998), had an average (0-30 cm depth) composition of 37.4% (±6.3 standard deviation) clay, 28.4% (±2.9) silt and 33.6% (±5.5) sand (ISSS method). No fertilisation or other agrochemical application was carried out in order to maximise the effect of intrinsic soil variability and reduce the impact of management on the ongoing crop. Thus, the probable spatially variable management factors were only those related to the field history and tillage and sowing operations.

A grid with 5 x 6 m unit cell was overlaid on the field, for a total of 112 sampling points. During the whole growing season repeated measurements of different types were carried out at each grid point. Canopy reflectance in the red and NIR bands was measured using the Dycam ADC digital camera (Dycam Inc., Chatsthereworth, CA, USA). ADC measurements were carried out in the field from a height of about 2.4 m above the soil, corresponding to an area viewed on the ground of about 1 m^2. The images were obtained on three dates: 91, 126 and 162 days after sowing (DAS). Data, recorded in clear days within 2 hours of solar noon, uncorrected for sun angle or athmospheric effects, were used to compute the Normalized Difference Vegetation Index (NDVI) (Baret and Guyot, 1991).

A linear quantum sensor was used on 127 and 163 DAS to measure direct and diffuse photosynthetically active radiation above and below the canopy. These measurements were used to estimate leaf area index (LAI) by inversion of the Norman and Jarvis model (Norman and Jarvis, 1975) assuming a leaf transmittance of 0.85 (Jacquemoud and Baret, 1990) and a spherical leaf angle distribution.

Plants were harvested, from areas of 0.1 m^2, on two dates (94 and 128 DAS) to assess: phenology using Zadoks Growth Stage (ZGS) codes (Tottman, 1987), total above ground dry weight and total plant nitrogen using the Kjeldahl method (only on 94 DAS). Soil samples from the 0-0.3 m layer were collected during the growth season on 120 DAS in order to assess total N. At each grid point 3 cores (5 cm diameter each) spaced 15 cm from each other were collected and mixed. An additional set of soil samples was collected at the end of the growing season. They were used for soil texture analysis using the pipette method and for assessing field capacity (CC) and wilting point (PA) in the laboratory, using Richard's pressure plate apparatus, at 0.03 and 1.5 MPa, respectively (Richards and Weaver, 1943; Colman, 1947).

At harvest (29/6/2004, i.e. 231 DAS), the following yield components were measured for each grid point by harvesting plants within 0.9 m^2 quadrats: grain yield (Mg ha^{-1}) (YIELD), total above ground biomass (g m^{-2}) (TDW), number of plants per unit area (SD), number of ears per unit area (ED), number of kernels per unit area (KD), number of kernels (KE) per ear and thousand seed weight (g) (TSW).

2.2. Preliminary univariate geostatistical analysis

For each variable, exploratory data analysis and univariate geostatistical analysis had been previously performed and reported (Casa et al., 2005). Each variable had its own distinct spatial pattern and it was difficult to discern common processes at the origin of their spatial variation.

Therefore it was assumed that a multivariate geostatistical analysis, such as Factor Kriging Analysis (FKA), could be more explicative than univariate approaches.

2.3. Multivariate geostatistical analysis

The multivariate spatial data set was analysed through FKA, a methodology developed by Matheron (1982). The theory underlying FKA has been described in several publications (Goovaerts and Webster, 1994; Castrignanò et al., 2000b; Wackernagel, 2003); here we will describe only the most salient points. The approach consists of decomposing the set of n original second-order random stationary variables $\{Z_i(\mathbf{x});\ i=1,...,n\}$ into a set of reciprocally orthogonal regionalised factors $\{Y_v^u(\mathbf{x});\ v=1,...,n;\ u=1,\dots,N_S\}$ where N_S is the number of spatial scales, through transformation coefficients a_{iv}^u, combining the spatial with the multivariate decomposition:

$$Z_i(\mathbf{x}) = \sum_{u=1}^{N_S}\sum_{v=1}^{n} a_{iv}^u Y_v^u(\mathbf{x}) \qquad \text{(Eq. 1)}$$

The three basic steps of FKA are the following:

1) analysis of the coregionalization of a set of variables leading to the definition of a linear model of coregionalization (LMC);
2) analysis of the structural correlation coefficients;
3) principal component analysis on the coregionalization matrices and cokriging of specific factors at different spatial scales.

2.3.1. Linear Model of Coregionalization

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

$$\boldsymbol{\Gamma}(\mathbf{h}) = \sum_{u=1}^{N_S} \mathbf{B}^u g^u(\mathbf{h}) \qquad \text{(Eq. 2)}$$

where $\boldsymbol{\Gamma}(\boldsymbol{h}) = [\gamma_{ij}(\boldsymbol{h})]$ is a symmetric matrix of order n x n, whose diagonal and non diagonal elements represent simple and cross semivariograms, respectively for lag $\boldsymbol{h}$; $\boldsymbol{B}^u = [b^u_{ij}]$ is called coregionalization matrix and it is a symmetric positive semi-definite matrix of order n x n with real elements b^u_{ij} at a specific spatial scale u. The model is authorized if the mathematical functions $g^u(\boldsymbol{h})$ are authorized semivariogram models.

In the linear model of coregionalization, it is supposed that independent processes working at different spatial scales may affect the behaviour of experimental semivariograms, which can then be modelled by a set of functions $g^u(\boldsymbol{h})$. Fitting of LMC is performed by weighed least-squares approximation under the constraint of positive semi-definiteness of the $\boldsymbol{B}^u$, using the iterative procedures developed by Goulard and Voltz (1992). The best model was chosen by comparing the goodness of fit for several combinations of functions of $g^u(\boldsymbol{h})$ with different ranges in terms of different types of cross-validation results.It important to underline that the choice of the number and characteristics (model, sill, range) of the functions $g^u(\boldsymbol{h})$ is quite delicate and essentially subjective, but can be supported by a good previous knowledge and experience of the studied phenomena (Chiles and Guillen, 1984).

2.3.2. Analysis of the structural correlation coefficients

Each coregionalisation matrix $\boldsymbol{B}^u$ gives information on the relations between the variables at the particular spatial scale u. From these matrices the structural correlation coefficients $r_{ij}{}^u$ can be defined as:

$$r_{ij}^u = b_{ij}^u \Big/ \sqrt{b_{ii}^u \cdot b_{jj}^u} \qquad \text{(Eq. 3)}$$

These coefficients are more informative than the traditional correlation coefficients because the relationships between the variables are generally scale-dependent. However, $r_{ij}{}^u$ depends on the coefficients estimated in the coregionalisation model and on the somewhat arbitrary decomposition of the covariance function matrix at lag zero into the coregionalization matrices. Therefore, the decision of including a particular spatial component in the linear model of coregionalisation, as noted before, should be based on any physical knowledge about the considered phenomena and about the study area (Goovaerts, 1992; Bourennane et al., 2004)

2.3.3. Gaussian anamorphosis modelling

A difficulty in the practical application of the above approach occurs when the variables are of widely differing scales. A solution is to standardize the individual variables to give each an average of zero and a variance of unity. Variogram modelling may be further complicated by the presence of outliers when data distributions are highly skewed. In this case it is better to perform a normalization of data through Gaussian anamorphosis modelling. The Gaussian anamorphosis is a mathematical function which transforms a variable Y with a Gaussian distribution in a new variable Z with any distribution: Z = Φ(Y). As this function needs to be known for any Gaussian value, a model is required. This is made by fitting a polynomial expansion (Chiles and Delfiner, 1999):

$$\Phi(Y) = \sum \Psi_i H_i (Y) \quad \text{(Eq. 4)}$$

where H_i (Y) are called the Hermite Polynomials. In practice the polynomial expansion is restricted to a generally high order (30-100) and is monotonically increasing within a given interval of interest. Model fitting then consists of calculating the Ψ_i coefficients of the expansion and of transforming the raw variable into a Gaussian one. The anamorphosis function has to be inverted: $Y = \Phi^{-1}(Z)$. This inversion, outside the interval where the function is not strictly increasing for all the values of Y, is performed using a linear interpolation. Adopting a Gaussian model, a LMC was fitted to all experimental variograms, both direct and cross-variograms, of the transform data and then ordinary cokriging was applied as conditional expectation estimator. Finally, the estimates were back-transformed to the raw values of variables through the anamorphosis functions previously calculated.

2.3.4. Principal component analysis on the coregionalization matrices and cokriging of specific factors at different spatial scales

Regionalized Principal Component Analysis consists of decomposing each coregionalization matrix $\boldsymbol{B}^u$ into two other diagonal matrices: the matrix of eigenvectors and the diagonal matrix of eigenvalues for each spatial scale u through the matrix $\boldsymbol{A}^u$ of order n x n of the transformation coefficients a_{iv}^u (Wackernagel, 2003). The transformation coefficients a_{iv}^u in the matrix $\boldsymbol{A}^u$ correspond to the covariances between the original variables $Z_i(x)$ and the regionalized factors $Y_v^u(\mathbf{x})$. As a consequence of the application of PCA to coregionalisation matrices, which are the variance-covariance matrices describing the correlation structures of the variables at characteristic spatial scales, the correlated variables are transformed in a set of orthogonal factors which are spatially uncorrelated (Wackernagel, 2003).The behaviour and relationships among variables at different spatial scales can then be displayed by interpolating the regionalized factors $Y_v^u(\mathbf{x})$ using cokriging and mapping them (Castrignanò et al., 2000a). The cokriging system in FKA has been widely described by Wackernagel (2003).

3. Results

The timing of the measurements during the growth season is shown in Fig. 1 along with rainfall and maximum crop evapotranspiration patterns, the latter calculated using Cropwat 4 (Clarke et al., 1992). The basic statistics of the measured variables are reported in Table 1. Despite the small area of the experimental plot, considerable variability was found for most variables. Variability in total above-ground dry biomass was very high, decreasing from early samplings, such as TDW1 at 94 days after sowing (DAS), to harvest (TDW3). Also the variability in LAI was higher in the earlier sampling (LAI2 at 127 DAS) as compared to the later one (LAI3 at 163 DAS), which reflects a greater variability among the plants in the early season.

The Pearson's correlation coefficient matrix of all the measured variables is reported in Table 2. Sample size for different pairs of variables ranged between 28 and 112 as reported in Table 1. Only in very few cases significant correlations (reported in bold for $P<0.01$) were found between soil and plant variables (Table 2). For instance CLAY showed a positive correlation with YIELD, HI, KD and KE, but the values of the correlation coefficient (r) did not exceed 0.3. The remaining relationships between soil properties and crop variables were those of SAND, which showed a small negative correlation (-0.3) with HI, and CC that showed a weak (0.3) positive correlation with TSW.

The high correlation existing between NDVI measurements and either LAI or TDW confirms the usefulness of these remote sensing measurements for the assessment of canopy size, as illustrated by the well known non-linear relationship between LAI and NDVI (Fig. 2 top). This figure clearly shows the high variability in LAI found in the field at a given date, probably mostly due to non-homogeneous sowing operations and seedling emergence conditions. The relationship of NDVI with biomass and LAI explains the well known potential of NDVI as predictive indicator of final grain yield (e.g. Reyniers et al., 2006; Raun et al., 2001): in our case the correlation coefficient r between NDVI and yield was low (0.3) at tillering (91 DAS), but increased up to r = 0.71 at the stem elongation stage (162 DAS). There was no correlation between NDVI and total plant nitrogen concentration (PLANTN) (Fig. 2 bottom), as any existing relationship between reflectance and N (or chlorophyll content) at the leaf scale was masked by the large variability in stand density.

These results concern relationships among bulked data and disregard any effect of spatial scale dependence, which can be taken into account using multivariate geostatistical techniques such as FKA.

For this aim, an analysis of coregionalisation was carried out in the first instance separately for groups of homogeneous variables related to soil, plant and yield.

The coregionalisation modelling for the soil variables was carried out on PA, CC, SAND and CLAY, since SOILN showed no spatial structure (pure nugget effect). Among the soil variables, some such as CC and PA were sampled at only 28 locations, while others such as CLAY had a sample size of 101 data. However the use of a multivariate approach such as FKA allowed to use auxiliary variables to supplement the sparse information of the primary variables for the cases were few data were available. The LMC was fitted using three spatial structures: nugget effect, a spherical model with a range of 20 m and a spherical model with a range of 50 m. These two scales are very likely related to intrinsic properties of soil particle and aggregate distributions (shorter range) and field size (longer range).

Fig. 3 shows the matrix of the experimental variograms with the fitted model. All the variograms look upper bounded and generally well structured. To evaluate the strength of the spatial relationship between the variables we used the distance of the cross-variogram to the hull of perfect correlation (dashed line). The latter is defined by replacing the sills of the cross-variograms by the square root of the product of the sills of the corresponding direct variograms (Wackernagel, 2003). Quite strong correlations appear such as the positive correlation between PA and CC and the expected negative correlation between SAND and CLAY.

From the sums of the eigenvalues corresponding to the different scales (Tab. 3), 0.77 nugget effect, 0.54 short range and 4.19 long range, it resulted that the total spatial variation was mostly dominated by variation within a 50 m distance. Due to the small contribution of the other spatial scales, the correlations found among soil variables at the long range scale had the same sign as those obtained from bulked data (Tab. 4). However, filtering out the effect of the short range and of the nugget components, the positive correlation between CC and PA was much stronger (0.89) than that observed in the bulked data (0.61) as well as the negative correlation between PA and CLAY (from –0.22 to –0.60). These results show that the physical and hydraulic properties are generally well spatially structured within a range of 50 m.

Focusing only on the longer-range scale, the first factor (accounting for about 70% of the variability at this scale) was positively correlated with CLAY (Tab. 3). This factor could then be interpreted as assigning more positive scores to the soils with finer texture.

A coregionalisation analysis was then carried out by combining selected yield and plant variables, deemed the most relevant for production processes, i.e. TSW, YIELD, ED, TDW3, PLANTN, NDV1, KD, LAI3 which, from a variography analysis (not reported here), showed stronger spatial dependence.

Also in this case the linear model of coregionalisation included three distinct spatial structures: nugget effect, spherical model with range 15 m and spherical model with range 45 m. From the sums of the eigenvalues corresponding to the different scales (Tab. 5), 3.4 nugget effect, 4.3 short range and 0.8 long range, it turned out that the total spatial variability was mostly dominated by variation within a short range (15 m) and to a lesser extent by random variation.

From the decomposition into regionalised factors (Tab. 5), it resulted that the first factor at the short range scale accounted for about 82% of the variance, and it was mainly negatively correlated with ED, TDW3, NDV1 and LAI3. At this scale these variables were correlated positively with YIELD and negatively with TSW, a variable influenced by soil water availability during grain filling (Tab. 6). The filtering out of the nugget and long range component, allowed to disclose higher correlations between these variables (Tab. 6), than those appearing for the bulked data (Tab. 2). For example the correlation between NDV1 and YIELD was increased from 0.3 to 0.6, thereby indicating a better predictive ability of this index (at tillering) when only short-scale specific processes are taken into account.

At the short range scale, PLANTN was negatively correlated with ED and TDW3, the latter correlation being positive in the bulked data (Tab. 2), indicating that competitive phenomena between the plants at micro-scale can be partly counterbalanced at the field scale.

Finally the eight variables of the three groups, selected among those showing stronger spatial correlations, were retained to carry out a further co-regionalization analysis. These included: clay content (CLAY), soil moisture at 0.03 MPa (CC), NDVI measured on February 10th (NDV1), total plant N measured on February 13th (PLANTN), total above-ground dry weight measured at harvest (TDW3), stand density (SD), grain yield (YIELD) and thousand seed weight (TSW).

The three basic structures estimated by the analysis of co-regionalisation were again nugget effect, cubic model with a range of about 15 m and a spherical model with longer range of about 45 m, which confirms the strong relationships among the processes occurring in the soil and in the crop.

Looking at the spatial variances of the regionalised variables (not shown), it appeared that the short range variation was dominated by SD, NDV1, TDW3 and YIELD, whereas the long range variation was dominated by CLAY, CC and PLANTN and, to a less extent, by TSW.

From the decomposition of the factors at the different spatial scales, it was also possible to identify the variables most affecting spatial variation.

The sums of the eigenvalues corresponding to the different scales (Tab. 7), 2.4 nugget effect, 3.1 short range and 3.6 long range, showed that the total spatial variation was almost equally decomposed into variation at short (15 m) and long (45 m) range, whereas a smaller component was attributed to erratic variation.

From the decomposition into the regionalised factors (Tab. 7) it resulted that the first factor of the 15 m structure with an eigenvalue of 2.5 accounted for 81% of the variance at this scale. This factor was mainly related to plant and yield measurements. In particular it was negatively correlated with NDV1, SD, TDW3 and to a less extent with YIELD. This factor then attributes negative scores to areas estimated with more dense leaf canopy and overall more productive.

Table 8 shows that most of the correlations change their sign when moving from one spatial scale to the other. A probable explanation is that processes controlling growth and development of plants are scale-dependent. It is then critical to define the spatial and temporal scale of a simulation model when a sampling scheme is planned to validate it.

Fig. 4 shows the cokriged map of the first factor at the short range scale. To better understand the meaning of the patterns of this factor, it can be compared to grain yield patterns (Fig. 5). A pattern is defined as the spatial arrangement of high and low values, therefore two maps will display a similar pattern if the representations of high and low values occur at the same positions; on the contrary, inverse pattern if the locations of high and low values are exchanged. Of course, partly similar, partly inverse and non similar map patterns may occur as well. There are many ways to compare map patterns (Stein et al., 1997). In any case the maps have to be standardised to ensure that patterns do not depend on the particular scale of measurement and also to allow that maps of properties using different measurement units can be compared. As a map comparison method, we chose to use the cross-correlogram $\rho(h)$

between the two variables, first factor and yield, because it measures the correlation as a function of the distance between observation points separated by the vector **h** and produces the above referred standardisation (Stein et al., 1997). In Fig. 6 the cross-correlogram is shown, where the values with sign of h are related to the vectorial nature of distance. The correlogram at h=0 is equal to -0.46, which means that the patterns are each other's partly opposite. A sharp decreasing of the cross-correlogram value, in absolute terms, for increasing values of h, denotes a decreasing correlation between plant measurements (first factor) and yield, within the distance of 10 m. For distances larger than 10 m, it shows a peak at 15 m, then from this distance onwards it gradually decreases towards zero. However, the positive correlation remains very low, i.e. about 0.1. A possible interpretation of these results may be that, at this short scale, spatial variability is mostly affected by plant parameters, whereas yield seems to be affected by factors acting over longer distances.

The first two cumulative factors of the longer range structure (45 m) accounted cumulatively for 89% of the total variance (Tab. 7). The first factor, which explained more than 50% of the variance, was positively correlated to the soil parameters, CLAY and CC, and to PLANTN, this last variable presumably related to mineral soil nitrogen availability before the sampling date and therefore acting similarly to other soil variables. The previous variables are also positively correlated with TSW and YIELD, therefore this factor explains the joint variation of the soil and production variables at longer range. The second factor (about 39% of total variance explained) was dominated by CLAY and explains the residual variation of this variable independently of the others.

The interpretation of these two factors is that the first factor attributes positive scores to the areas characterised by higher contents of clay and water available for the plants and N, whereas the second factor reproduces mostly intrinsic variation of soil units.

The cokriged map of the first factor of the long range structure (Fig. 7) seems therefore useful for delineating areas characterised by higher soil water availability and yields, probably due to the positive post-anthesis conditions determining better grain filling and larger sized grains, as also shown by the positive correlation with TSW.

4. Discussion

Direct relationships between soil properties and crop variables, such as yield components, can be masked by the spatial variability of the processes influencing their interactions. Univariate data analyses, comparisons of the individual kriging results and examination of Pearson correlation matrices might not provide sufficient insight into the causes of canopy and yield spatial variability and their link with soil properties (Casa et al., 2005). Multivariate geostatistical analysis, such as the one applied in the present study, allowed the disclosure of spatial scale dependent correlations between soil and yield variables.

It should be noted that in this procedure the calculation of structural correlation coefficients is based on the sill of the variograms and is independent from the number of factors chosen. The main difference between bivariate Pearson correlation coefficients and structural coefficients is that the latter depend on the structural model, as any geostatistical analysis. Cross-validation can be a way to test the goodness of the adopted model, but any analysis remains essentially subjective.

In the present application, coregionalisation analysis was useful in identifying which groups of variables were affected by processes acting at different spatial scales.

It was apparent that variables related directly or indirectly to soil properties showed a pattern of spatial variability modelled by a spherical structure with a range of about 50 m. The most weighing soil variable was CLAY due to the particular soil type under study.

For what concerns canopy and yield properties, their spatial variability was dominated by short range variation with the exception of plant nitrogen concentration and grain weight (TSW). PLANTN (the total plant N content, measured during the tillering stage, i.e. average ZGS 1.3-2.3) had a pattern of variability similar to that of soil variables rather than canopy variables, probably because it is largely determined by soil mineral N content in the period precedent to the sampling.

The negative correlations between variables related to canopy size (LAI3, NDV1, TDW3, ED) and TSW, appearing at the short range scale (Tab. 6), seem to suggest that areas of high biomass development could have caused smaller grain size yield because of the increased soil water depletion.

A first result then was that biological processes, affecting directly plant development and growth, act at very short range (about 15 m). On the other hand, the soil processes, indirectly affecting plant growth and yield, have a longer range of influence (about 50 m).

Grain yield can be obtained from the combination of yield component factors such as ear density, ear size and kernel weight (Hay and Walker, 1989). Ear density is generally related to stand density and tiller fertility. However, whereas at a small spatial scale stand and ear density were positively correlated with yield, this correlation became negative at the larger spatial scale, probably because of the greater influence of soil properties. A similar behaviour appeared for the structural correlations between YIELD and canopy size, i.e. NDVI. A possible explanation might be that small scale variability is strongly influenced by the effects of non uniform sowing operations and emergence conditions. Where stand density is very low or very high, for example as a result of sowing skips or overlaps, there is a positive correlation between yield and stand density. Otherwise, excessive canopy growth in areas of low resources availability (notably N, but also water), as determined by the variability of soil properties, might cause yield decreases.

Kernel weight (TSW), which is constrained by assimilate availability during the grain filling stage and is negatively affected by water stress (Hay and Walker, 1989), was positively correlated with soil field capacity CC, as expected from its sensitivity to drought. This relationship was mostly determined by processes acting at the long range scale, as shown by the much higher correlation at this scale (0.93) than the one for bulked data (0.31), lowered by the negative correlation between CC and TSW at the short spatial scale. The correlation between TSW and YIELD was negative at the small spatial scale but positive at the longer range spatial scale. Also in this case, it is likely that at short spatial scale the large variability in stand density, due, for example, to sowing conditions, might have masked the positive contribution of TSW to the yield.

At the longer spatial scale, the effect of soil properties influencing soil water availability becomes more evident.

The first short-range factor of the model including jointly soil and crop variables, was mainly related to plant and yield variables (Tab. 7) and it is then expected to be subject to fairly large temporal variability. On the contrary, the first long-range factor was related to more temporally stable intrinsic soil properties besides yield parameters, even if it explains less proportion of the variance at this scale.

It seems therefore evident that many processes affected soil and crop properties acting with scale-dependent rates.

Actually, another important advantage of FKA is the possibility of extracting a restricted number of regionalised factors which, mapped, could be used as support to decision making in precision agriculture. They, indeed, attribute scores to the different portions of a field on the basis of a multivariate set of properties and can be used to partition the field into management zones. Because the main sources of variation change with spatial scale, using the traditional Principal Components Analysis, which merges all the scales together, to define uniform management zones may be unsatisfactory (Goovaerts, 1992). On the other hand, the application of FKA to soil, plant and yield properties allowed to discriminate between variables with a different rate of variation, pointing out at those more stable which could be used as a basis to site-specific management (Fig. 4).

Of course, these results should be verified over time by using historical series of yield maps, or as an alternative, confirmed by the predictions of a validated dynamic crop model using a multi-year series of meteorological data (Basso et al., 2007).

5. Conclusions

Several authors have shown the inconsistency over time of spatial variability patterns of important crop and soil properties such as yield, protein content and plant available N (e.g. Blackmore et al. 2003; Delin et al., 2005). A common finding is that temporal variability is generally much higher than spatial variability and the definition of stable low and high yield potential zones is very uncertain (Blackmore et al., 2003). It seems likely that the inclusion of within-season measurements, even remotely-sensed, in the definition of uniform management zones could add more robustness to the approach as compared to other methods (Lark and Stafford, 1996; Fraisse et al., 1999; King et al., 2005). A multivariate geostatistical methodology, such as that applied in this study, would allow an efficent analysis of several spatially and temporally variable crop and soil properties. Some of these variables could be obtained relatively easily and inexpensively, for example from yield mapping or remote sensing. Finally, FKA allows to attribute weights to the properties affecting yield variation as a function of spatial and temporal scales, so that appropriate management strategies can be fine-tuned over space and time in order to devise the most efficient agronomic practices.

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Table 1. Summary statistics of the measured variables

Variable	Abbreviation	Meas. date (dd/mm/yy)	Mean	Standard deviation	CV (%)	N
NDVI	NDV1	10/02/2004	0.4	0.1	26.2	112
Total above-ground dry weight (g m^{-2})	TDW1	13/02/2004	93.1	42.0	45.2	112
Total above-ground plant nitrogen (%)	PLANTN	13/02/2004	3.4	0.6	17.8	111
Total soil nitrogen (g kg^{-1})	SOILN	10/03/2004	1.1	0.2	17.7	63
NDVI	NDV2	16/03/2004	0.5	0.1	18.3	112
Leaf Area Index	LAI2	17/03/2004	1.2	0.5	44.8	112
Total above-ground dry weight (g m^{-2})	TDW2	18/03/2004	202.3	88.5	43.7	111
NDVI	NDV3	21/04/2004	0.5	0.1	20.4	112
Leaf Area Index	LAI3	22/04/2004	2.7	0.9	31.5	112
Clay (%)	CLAY	26/07/2004	37.4	6.3	16.7	101
Silt (%)	SILT	26/07/2004	28.4	2.9	10.3	62
Sand (%)	SAND	26/07/2004	33.6	5.5	16.2	62
Gravimetric soil moisture at 0.03 MPa	CC	26/07/2004	26.3	2.0	7.5	28
Gravimetric soil moisture at 1.5 MPa	PA	26/07/2004	19.8	1.6	8.0	28
Total above-ground dry weight (g m^{-2})	TDW3	29/06/2004	1275.9	408.8	32.0	111
Grain yield at 13% moisture (Mg ha^{-1})	YIELD	29/06/2004	2.9	0.9	29.3	112
Harvest Index	HI	29/06/2004	20.8	5.0	24.2	112
Stem density (n m^{-2})	SD	29/06/2004	133.0	61.0	45.8	112
Kernel density (n m^{-2})	KD	29/06/2004	6919.0	2046.6	29.6	112
Kernels per ear (n)	KE	29/06/2004	18.2	6.0	32.7	112
Ear density (n m^{-2})	ED	29/06/2004	400.6	113.6	28.3	111
Thousand seed weight (g)	TSW	29/06/2004	37.6	2.3	6.1	112

Table 2. Pearson's correlation matrix between all measured variables. Bold values are significant at P<0.01

	NDV1	TDW1	PLANTN	NDV2	LAI2	TDW2	NDVI3	LAI3	CLAY	SILT	SAND	CC	PA	TDW3	YIELD	HI	SD	KD	KE	ED
TDW1	**0.65**																			
PLANTN	-0.11	-0.09																		
NDV2	**0.87**	**0.51**	0.11																	
LAI2	**0.65**	**0.38**	0.14	**0.82**																
TDW2	**0.44**	**0.59**	-0.12	**0.33**	0.08															
NDVI3	**0.63**	**0.45**	**0.27**	**0.87**	**0.78**	**0.27**														
LAI3	**0.73**	**0.55**	0.18	**0.86**	**0.82**	**0.26**	**0.87**													
CLAY	-0.07	-0.13	0.21	-0.02	0.02	-0.11	0.12	0.01												
SILT	0.23	0.03	**-0.33**	0.04	-0.04	0.08	-0.11	-0.03	**-0.37**											
SAND	-0.03	0.06	-0.19	0.00	0.05	0.06	-0.06	0.06	**-0.87**	-0.14										
CC	-0.04	-0.10	0.37	0.06	0.17	-0.21	0.04	0.08	-0.19	-0.16	0.18									
PA	0.18	-0.04	0.24	0.23	0.25	-0.14	0.09	0.22	-0.22	0.02	0.14	**0.61**								
TDW3	**0.59**	**0.50**	**0.23**	**0.80**	**0.81**	**0.32**	**0.83**	**0.79**	0.06	-0.15	0.02	0.11	0.14							
YIELD	**0.28**	0.15	**0.31**	**0.55**	**0.58**	0.14	**0.71**	**0.53**	**0.25**	-0.14	-0.16	0.06	0.11	**0.77**						
HI	**-0.47**	**-0.53**	0.12	**-0.37**	**-0.32**	**-0.37**	-0.20	**-0.37**	**0.25**	0.06	**-0.30**	-0.08	-0.02	**-0.40**	0.22					
SD	**0.64**	**0.98**	-0.09	**0.47**	**0.34**	**0.57**	**0.41**	**0.53**	-0.13	0.09	0.06	-0.11	-0.05	**0.46**	0.10	**-0.55**				
KD	**0.35**	**0.23**	**0.29**	**0.59**	**0.59**	0.22	**0.74**	**0.56**	**0.25**	-0.12	-0.16	0.00	0.09	**0.78**	**0.98**	0.15	0.17			
KE	**-0.54**	**-0.55**	**0.37**	-0.24	-0.10	**-0.31**	0.08	-0.20	**0.30**	-0.18	-0.20	0.09	-0.03	-0.02	**0.47**	**0.67**	**-0.59**	**0.41**		
ED	**0.74**	**0.82**	-0.05	**0.68**	**0.60**	**0.46**	**0.56**	**0.68**	-0.15	-0.01	0.11	-0.10	0.09	**0.70**	**0.34**	**-0.57**	**0.81**	**0.41**	**-0.61**	
TSW	**-0.34**	**-0.42**	0.18	-0.16	-0.05	**-0.36**	-0.07	-0.12	0.01	-0.18	-0.05	**0.31**	0.14	-0.07	0.15	**0.40**	**-0.44**	-0.05	**0.33**	**-0.38**

Table 3. Decomposition into factors from the soil variables. Only factors for which eigenvalues are higher than zero are reported.

	CLAY	SAND	CC	PA	Eigenvalue	Variance percentage (%)
(a) Nugget effect component						
Factor 1	0.20	-0.14	0.21	0.95	0.63	82.09
Factor 2	-0.08	-0.95	-0.29	-0.06	0.14	17.91
(b) Short-range component (spherical model-range: 20 m)						
Factor 1	0.53	-0.56	0.63	-0.15	0.54	100.00
(c) Long-range component (spherical model-range: 50 m)						
Factor 1	0.68	-0.57	-0.35	-0.31	2.92	69.82
Factor 2	-0.20	0.47	-0.69	-0.51	1.07	25.45
Factor 3	0.54	0.55	0.51	-0.39	0.20	4.72

Table 4. Structural correlation coefficients of the soil variables at longer range (50 m). Figures in bold are significant for P<0.01.

	CLAY	SAND	CC	PA
CLAY	1			
SAND	**-0.87**	1		
CC	-0.43	0.27	1	
PA	**-0.60**	0.25	**0.89**	1

Table 5. Decomposition into factors from the crop variables. Only factors for which eigenvalues are higher than zero are reported.

	TSW	YIELD	ED	TDW3	PLANTN	NDV1	KD	LAI3	Eigenvalue	Variance percentage (%)
(a) Nugget effect component										
Factor 1	0.29	0.52	0.12	0.38	0.39	0.19	0.48	0.27	1.90	56.35
Factor 2	0.69	-0.14	0.00	0.11	-0.47	0.29	-0.28	0.33	0.59	17.64
Factor 3	-0.45	0.15	0.13	0.29	-0.68	-0.16	0.27	0.33	0.43	12.89
Factor 4	-0.41	-0.31	0.08	-0.03	0.32	0.46	-0.21	0.61	0.23	6.70
Factor 5	-0.09	0.13	-0.92	-0.08	-0.11	0.27	0.17	0.04	0.15	4.43
Factor 6	0.14	0.20	0.05	-0.78	-0.01	-0.30	0.18	0.45	0.05	1.47
Factor 7	-0.13	0.33	0.32	-0.36	-0.25	0.68	0.06	-0.35	0.02	0.50
(b) Short-range component (spherical model-range: 15 m)										
Factor 1	0.27	-0.25	-0.47	-0.41	0.03	-0.47	-0.29	-0.41	3.48	81.66
Factor 2	-0.42	-0.58	0.17	-0.30	0.11	0.33	-0.48	0.16	0.49	11.48
Factor 3	-0.26	0.19	-0.54	-0.11	0.69	0.08	0.16	0.28	0.21	4.97
Factor 4	0.54	-0.10	0.11	0.22	0.22	-0.25	-0.37	0.62	0.08	1.90
(c) Long-range component (spherical model-range: 45 m)										
Factor 1	0.03	0.13	-0.05	-0.46	-0.84	0.13	0.09	-0.18	0.38	47.44
Factor 2	0.18	0.50	-0.49	-0.10	0.13	-0.39	0.52	0.14	0.31	38.59
Factor 3	0.67	-0.12	0.07	-0.51	0.20	0.19	-0.17	0.41	0.11	13.68

Table 6. Structural correlation coefficients for crop variables at short range (15 m). Figures in bold are significant for P<0.01.

	TSW	YIELD	ED	TDW3	PLANTN	NDV1	KD	LAI3
TSW	1							
YIELD	**-0.35**	1						
ED	**-0.78**	**0.59**	1					
TDW3	**-0.63**	**0.88**	**0.90**	1				
PLANTN	-0.12	-0.13	**-0.36**	**-0.25**	1			
NDV1	**-0.94**	**0.57**	**0.94**	**0.85**	-0.07	1		
KD	**-0.51**	**0.98**	**0.69**	**0.92**	-0.16	**0.69**	1	
LAI3	**-0.82**	**0.64**	**0.89**	**0.89**	0.08	**0.94**	**0.71**	1

Table 7. Decomposition into factors from the selected soil, yield and plant variables. Only factors for which eigenvalues are higher than zero are reported.

	TSW	YIELD	SD	TDW3	PLANTN	NDV1	CC	CLAY	Eigenvalue	Variance percentage (%)
(a) nugget effect component										
Factor 1	0.48	0.60	-0.12	0.41	0.42	0.13	-0.20	-0.02	1.16	49.02
Factor 2	0.70	-0.22	0.08	0.09	-0.62	0.24	0.00	0.00	0.46	19.33
Factor 3	-0.45	0.29	0.15	0.48	-0.32	0.50	0.32	0.09	0.43	18.14
Factor 4	-0.06	0.38	0.34	0.20	-0.41	-0.71	-0.15	-0.11	0.26	10.99
Factor 5	0.01	0.61	-0.15	-0.71	-0.24	0.18	0.10	-0.06	0.04	1.84
Factor 6	-0.12	-0.02	-0.90	0.22	-0.28	-0.18	-0.04	-0.11	0.02	0.68
(b) Short-range component (spherical model-range: 15 m)										
Factor 1	0.23	-0.34	-0.53	-0.49	-0.08	-0.54	-0.10	-0.02	2.49	81.43
Factor 2	-0.28	-0.43	0.15	-0.39	0.69	0.22	0.11	0.16	0.32	10.58
Factor 3	0.44	-0.40	0.68	-0.20	-0.28	0.03	-0.22	-0.09	0.23	7.67
Factor 4	-0.16	0.66	0.30	-0.64	-0.01	-0.18	-0.01	-0.07	0.01	0.33
(c) Long-range component (spherical model-range: 45 m)										
Factor 1	0.35	0.24	-0.27	0.03	0.42	-0.16	0.56	0.49	1.83	50.35
Factor 2	-0.21	0.06	0.10	0.01	-0.09	-0.03	-0.50	0.82	1.40	38.68
Factor 3	0.27	0.45	-0.30	-0.46	-0.65	-0.02	-0.01	0.01	0.30	8.16
Factor 4	-0.40	0.33	-0.41	0.59	-0.15	-0.43	-0.01	-0.13	0.10	2.81

Table 8. Structural correlation coefficients of the soil, yield and plant variables at short and long ranges. Figures in bold are significant for P<0.01.

	TSW	YIELD	SD	TDW3	PLANTN	NDV1	CC	CLAY
(a) Short-range component (spherical model-range: 15 m)								
TSW	1							
YIELD	**-0.70**	1						
SD	**-0.61**	**0.65**	1					
TDW3	**-0.73**	**0.95**	**0.81**	1				
PLANTN	**-0.71**	0.00	0.25	0.08	1			
NDV1	**-0.84**	**0.78**	**0.94**	**0.90**	**0.43**	1		
CC	**-1.00**	**0.72**	**0.56**	**0.73**	**0.69**	**0.81**	1	
CLAY	**-0.77**	0.10	**0.26**	0.17	**0.99**	**0.47**	**0.76**	1
(b) Long-range component (spherical model-range: 45 m)								
TSW	1							
YIELD	**0.65**	1						
SD	**-0.84**	**-0.89**	1					
TDW3	**-0.25**	-0.22	0.03	1				
PLANTN	**0.65**	**0.28**	**-0.52**	**0.47**	1			
NDV1	**-0.53**	**-0.80**	**0.84**	**-0.40**	**-0.62**	1		
CC	**0.93**	**0.50**	**-0.82**	0.06	**0.75**	**-0.57**	1	
CLAY	0.11	**0.55**	-0.24	0.09	**0.34**	**-0.55**	-0.07	1

Figure captions

Fig. 1. Ten-days long-term average rainfall (RAINFALLclim), maximum evapotranspiration (ETm) and rainfall of the 2003-04 growing season (RAINFALL 2003-04), plus timing of the measurements carried out (arrows). The extended description of the measured variables is reported in Table 1.

Fig. 2. Scattergram plots between Normalised Difference Vegetation Index (NDVI) and LAI (top) and between NDVI and total plant nitrogen (bottom).

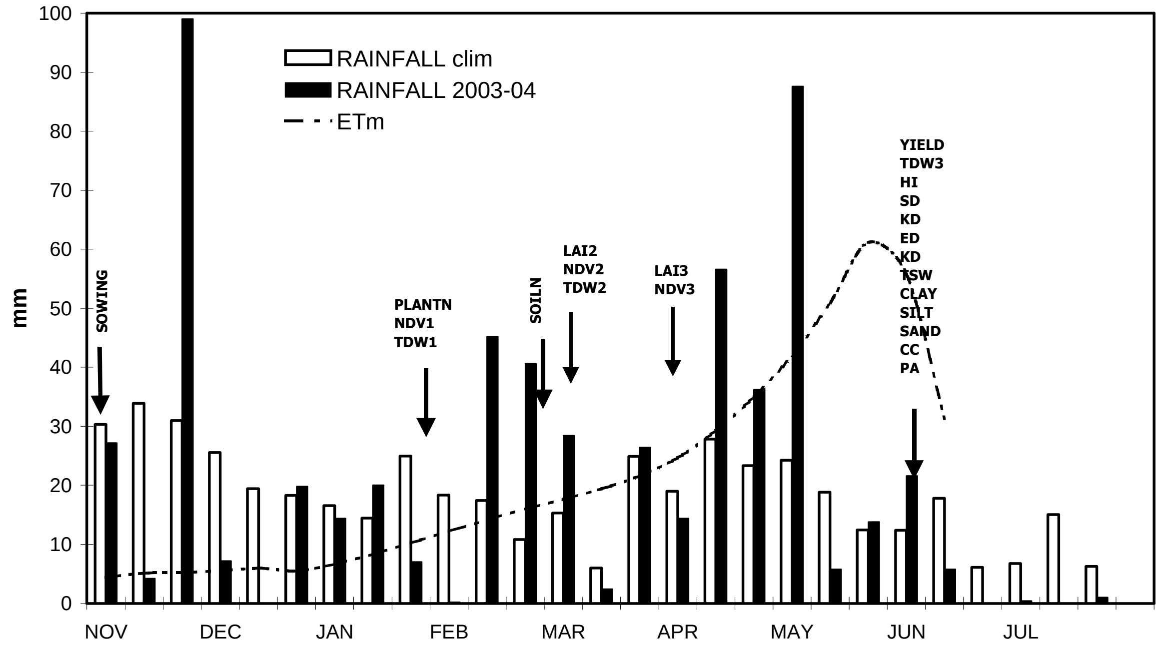
Figure 3. Variograms and cross-variograms of the soil variables. Thin solid line: experimental variogram; thick solid line: fitted model; dashed line: hull of perfect correlation. For the definition of the variables see Table 1.

Figure 4. Cokriged map of the first factor at short range (15 m). Values on the grey scale are factor scores.

Figure 5. Cokriged map of grain yield (Mg ha^{-1}).

Figure 6. Cross-correlogram between the first factor at short range (Fig. 4) and grain yield (Fig. 5).

Figure 7. Cokriged map of the first factor at long range (45 m). Values on the grey scale are factor scores.



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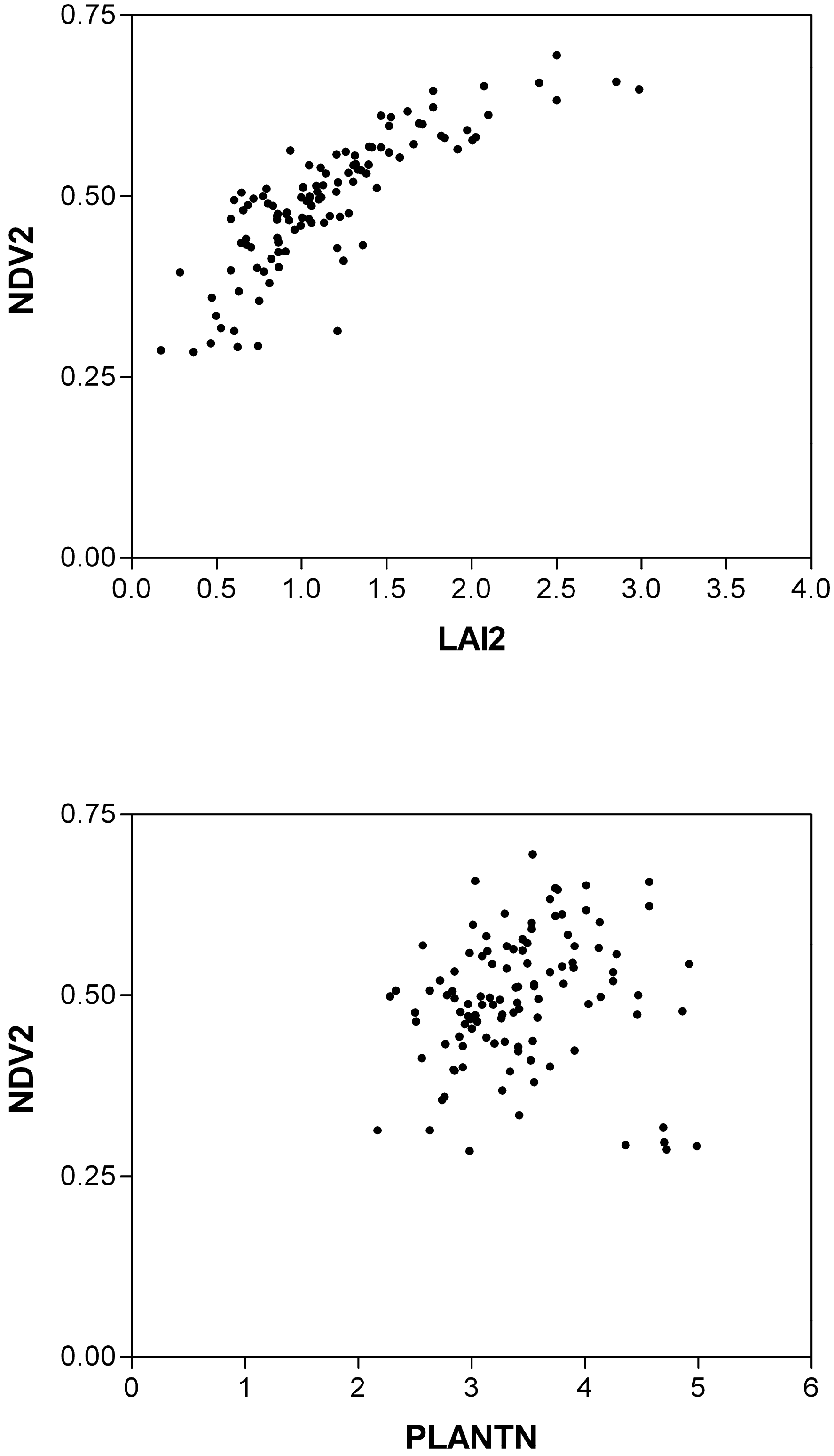
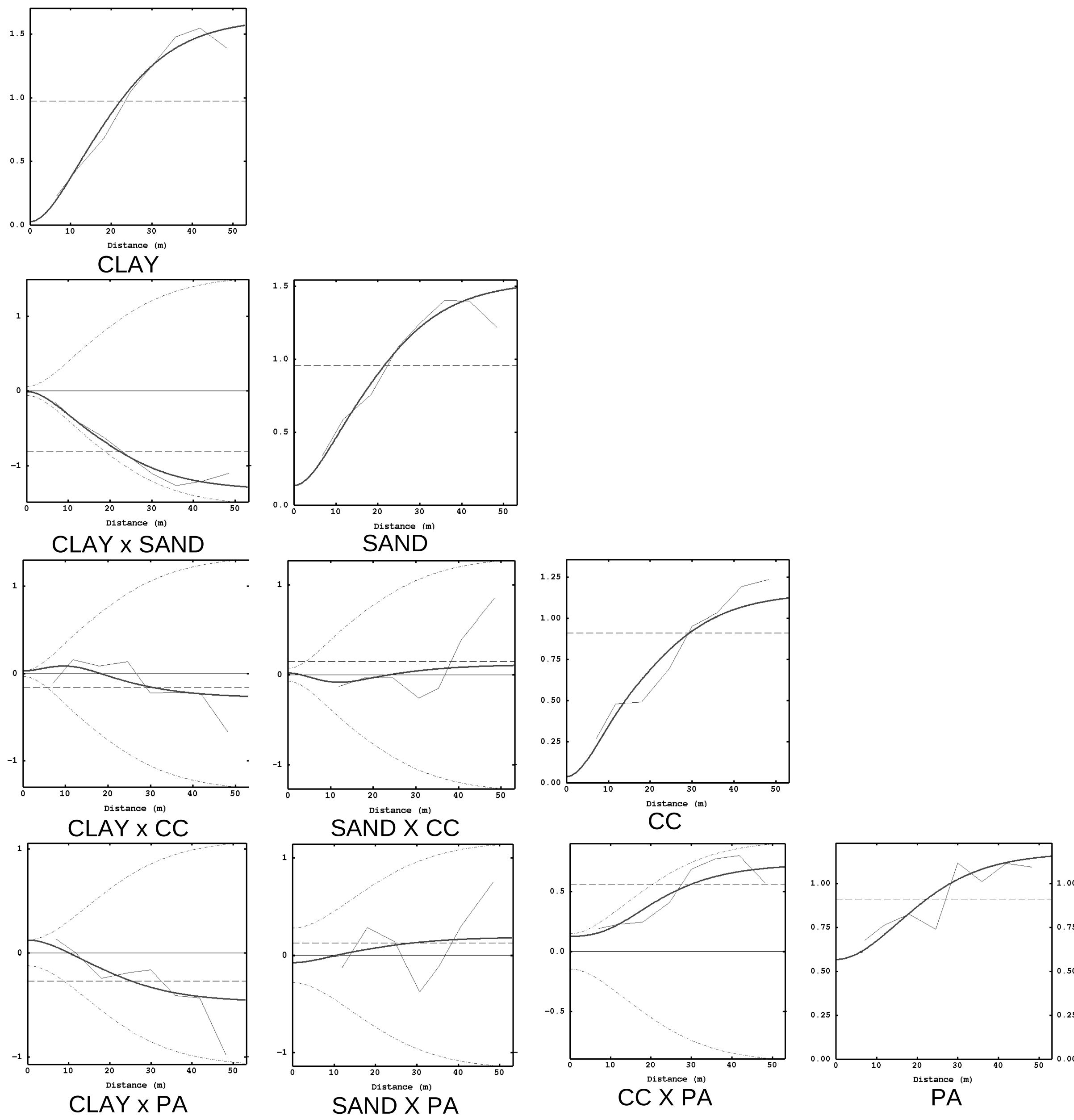


Fig. 2. *Scattergram plots between Normalised Difference Vegetation Index (NDVI) measurements and LAI (top) and between NDVI and total plant nitrogen (bottom).*



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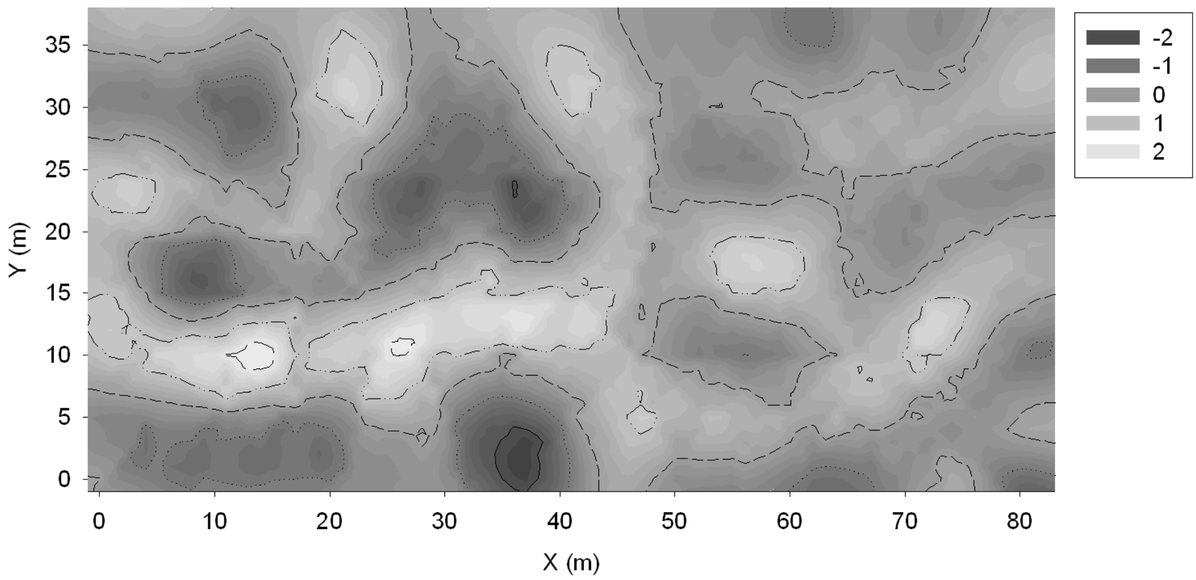

Figure 4. *Cokriged map of the first factor at short range (15 m). Values on the grey scale are factor scores.*

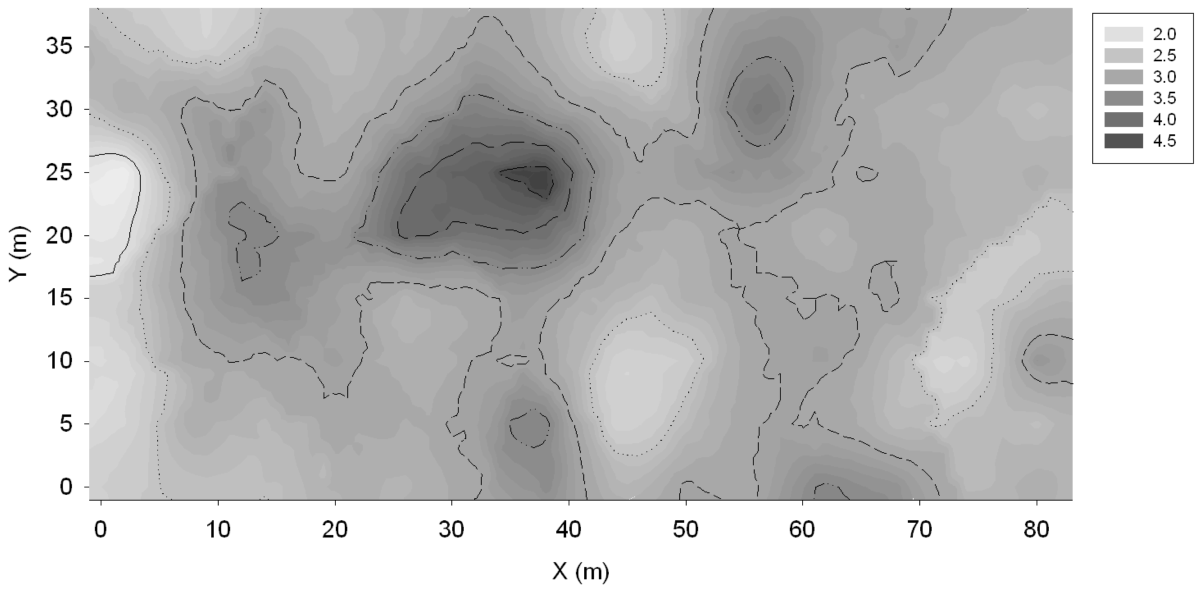

Figure 5. *Cokriged map of grain yield (Mg ha^{-1}).*

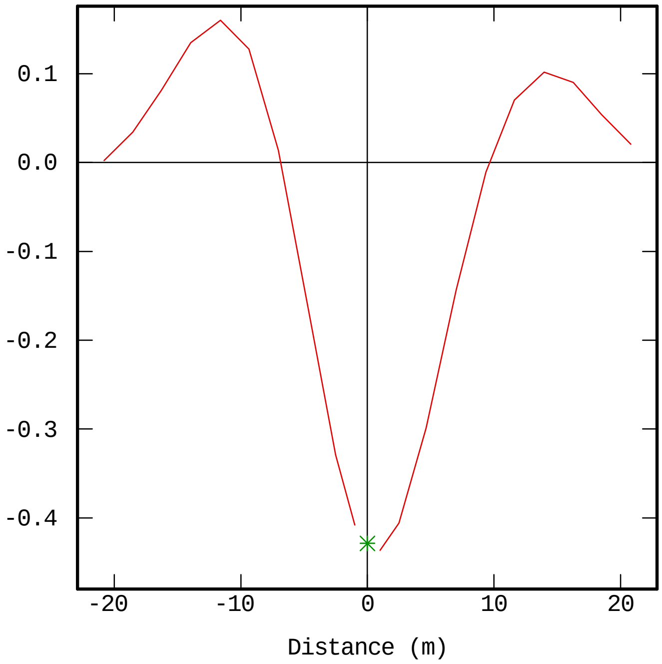

Fig.6. *Cross-correlogram between the first factor at short range (Fig. 4) and grain yield (Fig. 5).*

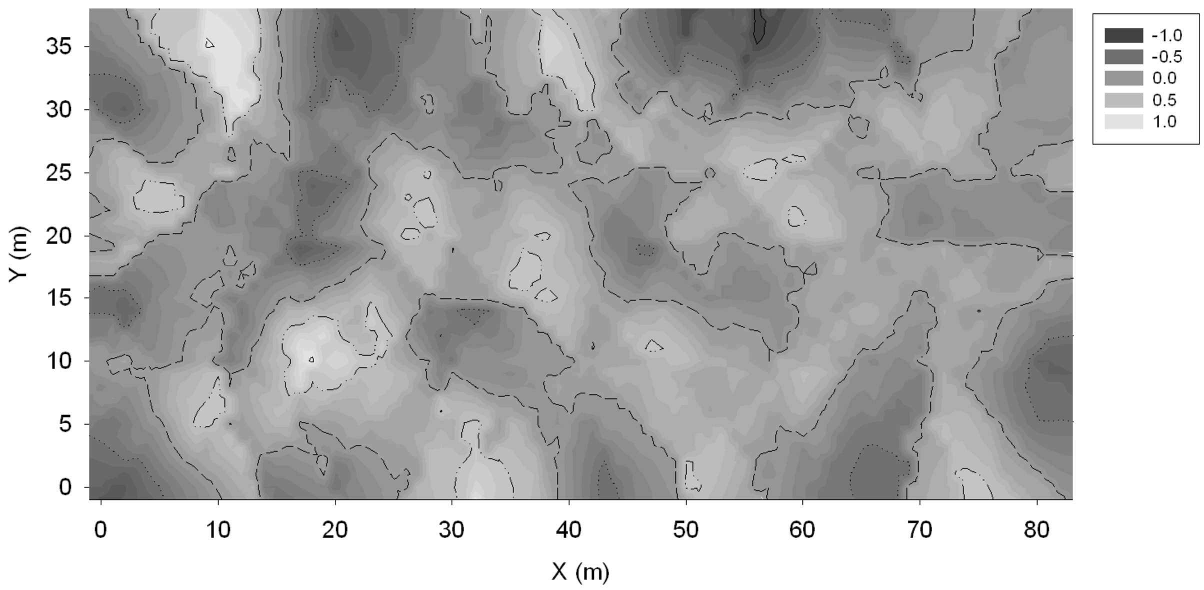

Figure 7. *Cokriged map of the first factor at long range (45 m). Values on the grey scale are factor scores.*