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Identification of different potential production areas for corn in Italy through multitemporal yield map analysis

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Abstract

In order to optimize production factors, farmer has to know production variability and its origin at both the farm level and the field level. Improving Nitrogen management for cereal crops, which need high amounts of the element during the whole production cycle requires, as precision agriculture states, that within-field variability is accurately identified and interpreted. This is particularly difficult in those situations where agronomically significant variability is detected and even in small fields, as is generally the situation in some European countries.

The present study is aimed at defining an integrated methodology to process production data which, through the combined use of hardware (GPS, grain sensor) and software (GIS, geostatistics) allows for acquisition, analysis and representation of information related to the variation of production potential within the field.

Data on grain yield and 1000-grain weight obtained during a 4-year period from a corn (*Zea mays* L.) field were acquired and analysed to study spatial and temporal variability through geostatistical techniques.

Synthetic maps of attitude and stability of production were obtained by combining individual production maps in a GIS environment. These results may prove to be very useful to identify isomanagement areas in precision agriculture.

Keywords: Precision agriculture; Spatial and temporal variation; Geostatistics; Yield map; Educational research farm

1. Introduction

Most cultivated soils present significant variabilty in their chemical, physical and biological features: part of this variability is natural, part is a result of agrotechniques. The complexity of such variability is due to spatial and temporal elements (Bocchi et al., 2000; Pierce and Nowak, 1999; Castrignanò et al., 2002).

Crops react to this variability in different ways; nevertheless, the traditional approach is to apply agrotechniques by assuming that the soils, and consequentely the crops, are uniform. In agricultural systems characterized by high intensity and high level energy inputs, generally typical of developed economies, where large quantities of chemicals and high levels of mechanization are used, inefficient use of this input, can lead to increased risk of contamination of the environment as well as reduced income for the farmer (Verhagen and Bouma, 1997). Some recent papers on precision agriculture have focused on nitrogen as an important production factor, demonstrating the possibility of applying the *N* leaching and economic analysis package computer model to evaluate the potential of site-specific management zones to reduce NO_3–N leaching in an irrigated crop (Delgado et al., 2005; Link et al., 2006; O'Neal et al., 2004).

Local knowledge of the genesis and the physico-chemical features of agricultural soils therefore becomes vital in any agronomic research (Castrignanò et al., 2000). However, such knowledge is in itself no guarantee of effective agronomical results, both for tactical choices made in the short-term and strategical choices made in the medium–long-term, because the variability of each soil parameter rarely corresponds to a different crop qualitative–quantitative response (Pierce and Sadler, 1997). This is particularly challenging in those situations where significant spatial variations exist over small areas: a recent (2001) national census taken in Italy revealed that average farm area is around 5 ha while in some regions, such as Lombardy or

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Veneto, the farms located in the plains reach mean sizes of about 14 ha; only 6% exceed 50 ha of cultivated land. In that contest, it seems feasible to attempt to adopt a new analytical strategy, no longer considering soil as the origin of the time–space variability of the crops, but treating the crops themselves as the synthetic biological indicators of the environmental features and the productivity potential of the soil (Blackmore and Larscheid, 1997; Sadler and Russell, 1997; Stafford et al., 1998). Managing variability at scales that are within fields involves, as precision agriculture states (Stafford et al., 1998) ''the targeting of inputs to arable crop production according to crop requirements on a localized basis.'' The main objective of precision agriculture is then to match agricultural inputs and practices to localised conditions within a field, i.e. ''to do the right thing, in the right place, at the right time, and in the right way'' (Pierce and Nowak, 1999). Therefore, precision agriculture goes well beyond the mere application of advanced technologies, but it is based on the management of spatial and temporal variability. More precisely, precision agriculture is the application of an integrated approach to manage spatial and temporal variability related to any component of production system in order to improve crop performance and environmental quality. The basic components of precision agriculture are: assessing variation, managing variation and evaluation of procedures. The knowledge and understanding of variability is then the critical first step, since it is clear that one cannot manage what one does not know (Pierce and Nowak, 1999). Almost all processes and properties affecting crop growth and production vary in space and time and adequately assessment of this variability is a necessary condition for successful implementation of precision agriculture. As crop yield is a basis for recommendations of managed inputs in precision agriculture, since the early 1990s some researchers, agrobusiness and farmers in the USA have presented trial results based on yield monitor in the form of yield maps supplied with traditional descriptive statistics and subjective interpretation. Monitoring the yield of a corn field gives rise to spatially referenced observations which cannot be treated as a random sample of corn yields: first the sample locations are not chosen at random, since the combine collects samples at systematic intervals and second the observations may not be independent as a random sample would imply. We would indeed expect relationships between spatially distributed yield data and the strength of such relationships is a function of their spatial separation, as Tobler's law of geography (Tobler, 1970) states: ''Everything is related to everything else, but near things are more related than distant things.'' Techniques for assessing spatial variability, taking into account spatial dependence of observations, are now readily available (Cressie, 1993; Goovaerts, 1997; Wackernagel, 2003). Typically they are drawn from geostatistics and allow the interpretation of spatial patterns of crop data and the identification of relationships between the different components of production systems. The interpretation of the causes of variability calls for a deep knowledge of environmental conditions as discussed by Schroder et al. (2000). Techniques for assessing temporal variation also exist (Shumway, 1988), but space-time statistical applications to precision agriculture are still rare (Blackmore, 2000; Blackmore et al., 2003) and need to be better developed and tested. Ultimately, farmers must be able to delineate areas that will respond similarly to inputs in order to optimise crop performance (yield and quality) and reduce environment impact. Therefore, yield maps form one basis for precision agriculture, but to maximize productivity, both spatial and temporal variability must be managed. However, multi-year yield maps can be used to estimate maps of yield potential (or conversely maps of gap to yield potential) which are preliminary necessary to define prescription maps or to estimate soil test levels in mass balance approaches (Pierce and Nowak, 1999).

The aim of the present study is to define an integrated approach of acquisition and processing of spatial and temporal yield data to delineate areas of different productive potential, a pre-requisite for the rationalization of agronomical techniques.

2. Materials and methods

The research was carried out at the ''A. Menozzi'' educational-research farm located in land near Landriano (Pavia, Italy), in a 2-ha field (ranges of sand: 45.2–59.2%; loam: 28.0–38.7%; field capacity: 19.05–22.7%; wilting point: 7.18–10.38; available water content: 9.10–14.24%; carbon: 1.1–1.9%; total nitrogen: 1.2–1.8 g kg^{-1}; C/N: 8.6–10.6; P: 66–148 mg kg^{-1}; K: 119–530 mg kg^{-1}), where corn (*Zea mays* L.) was cultivated in monoculture. The harvest was carried out after physiological maturity with an experimental combine plot machine on each elementary unit of 8.4 m^2 to calculate the spatial variation of grain biomass, the grain moisture content, the 1000-grain weight and the yield (Mg ha^{-1}) over the 4 years: 2000, 2001, 2002, and 2003.

The positions were georeferenced with a DGPS (Garmin GPS with GBR21 DGPS receiver.

2.1. Statistical and geostatistical analysis

A preliminary exploratory statistical analysis was carried out on the data to characterise the sample distributions and to detect any possible significant deviations from the gaussian distribution. Multivariate geostatistical techniques were applied to estimate the values of the studied variables in unsampled positions in order to improve the representation of spatial variability and subsequent cartographic production (Goovaerts, 1997).

The measurement of the combined spatial variability of the two variates (yield and 1000-grain weight) is represented by the cross-variogram, defined as half of the average of the product of the spatial increments of the attributes z_i (yield) and z_j (1000-grain weights) corresponding to a distance (lag) h:

$$\gamma_{ij}(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} \{[z_i(x_\alpha) - z_i(x_\alpha + h)]\,[z_j(x_\alpha) - z_j(x_\alpha + h)]\}$$

The fitting of the n $(n+1)$ experimental, direct and cross-semivariograms related to the n variates, is performed by adapting a matrix of semivariogram models. The main