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An approach for delineating homogeneous zones by using multi-sensor data

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ABSTRACT

Spatial heterogeneity in soil properties has an impact on crop response. There is a growing demand for rapid and non-invasive acquisition of fine-scale information on soil and plant variation for site-specific management. Proximal sensing (Electromagnetic Induction (EMI), Ground Penetrating Radar (GPR), hyperspectral spectroscopy (HS)) and remote sensing (RS) can complement direct sampling. However, sensor data fusion techniques, jointly analysing data from different sources, are still being developed.

The objective of this work was to define a multivariate and multi-sensor approach by combining EMI, GPR, RS and HS data, without any previous weighing, in order to differentiate an 1.5-ha arable field into homogenous zones.

The multi-sensor data were split into four groups: 1) bulk electrical conductivity (EC) from EMI data, 2) amplitude of GPR signal data, 3) the first principal components relating to five bands (green, yellow, red, rededge, near-infrared (NIR) PCs) of hyperspectral reflectance data and 4) the vegetation indices (NDVI, NDRE and NIR/Green) calculated from the remote sensing image. The data of each group were separately analysed and interpolated at the nodes of a same grid by using cokriging or kriging. To obtain spatially contiguous clusters, a combined approach was used, based on multivariate geostatistics and a non-parametric density function algorithm of clustering, applied to the overall multi-sensor data set of the estimates.

The full approach allowed to identify three homogenous areas. In particular cluster 1, in the NW part of the field, with the lowest values of bulk electrical conductivity and GPR amplitude, and the highest red PC values. The other two clusters were delineated in the SE part of the field, with the highest values of green, yellow, red edge and NIR PCs for cluster 2, and the highest values of bulk electrical conductivity and vegetation indices for cluster 3. The delineation might be related to the intrinsic spatial variability of soil and the health status of plants and be used to produce a prescription map for site-specific management.

1. Introduction

Spatial and temporal variation in soil properties and meteorological conditions may affect crop growth, yield and yield quality. To increase farmers' profitability and environmental protection, management practices then need to be adapted to variable site conditions. Recent research has focused on delineation of management zones (MZs) in precision agriculture which are defined as sub-field regions where the effects on the crop of seasonal differences in weather, soil, management, etc. are expected to be more or less uniform (Lark, 1998). The final target is the production of 'prescription maps' for spatially variable-rate applications (VRT) of inputs such as water and/or fertilizer.

To produce accurate and cost-effective assessment of spatial variation, at the scale required by precision agriculture, there is a growing demand for rapid, relatively cheap and non-invasive acquisition of fine-scale information on soil and plant. The high costs of traditional soil and plant sampling and laboratory analyses suggest a need for soil sensors that could detect critical soil properties on-the-go in every field location (Adamchuk, 2011).

Many alternative methods are being considered to complement conventional survey for estimation of soil and plant properties. Proximal soil sensing, which uses instruments operating very near or in contact with the soil, has recently received much attention (Molin and Faulin, 2011).

Geophysical methods provide indirect fine-scale information on various physical properties both of topsoil and subsoil, whereas remote sensing by satellites as well, as proximal hyperspectral sensors, give fine-scale information on vegetation or bare topsoil at different spectral resolutions.

Geophysical surveying with more than one sensor is expected to become a standard approach, because of the variety of field information required to make proper agricultural management decisions. The current geophysical methods widely employed for agricultural purposes are Electromagnetic Induction (EMI) and Electrical Resistivity (ER), whereas Ground Penetrating Radar (GPR) has been used for

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agriculture applications more recently (De Benedetto et al., 2011), and all of them are integrated with Global Positioning System (GPS) receivers.

However, systems based on the full assembly of more than one geophysical sensor still need to be developed for agriculture management. These multi-sensor systems might even be directly integrated with farm machinery to allow on-the-go decisions regarding precision farming operations (Allred, 2011; Castrignanò et al., 2012; Taylor et al., 2010; Wong et al., 2010).

Some EMI ground conductivity meters have been developed, which are particularly well suited for agricultural applications. EMI has several, well known advantages over other methods, which include speed and ease of use, due to its portability and noninvasive nature (Reedy and Scanlon, 2003). Ground conductivity meters, typically employed for obtaining apparent electrical conductivity (EC_a) measurements in agriculture, have inter-coil spacing of around 1 m and effective investigation depths of 1.5 m or less, when they are positioned near the ground surface (McNeill, 1980). Vertical and horizontal dipole orientations of the transmitter and receiver coils can provide different EC_a investigation depths within an agricultural setting.

Apparent electrical conductivity is usually related to various physical and chemical properties across a wide range of soils (Sudduth et al., 2005). EC_a measurement has been successfully used, for example, to measure soil salinity (Lesch et al., 1992), soil water content and clay or to map groundwater contaminants (Williams and Hoey, 1987). However, it gives an integrated response on the soil profile and then fails to disclose pedological horizons (Castrignanò et al., 2012; Wong et al., 2010).

Ground Penetrating Radar (GPR) is a non-invasive geophysical method that has most often been used as a tool in shallow geophysics (e.g., detection of buried object, mapping stratigraphic units, etc.); more recently, it has also been used for agriculture applications. A method to estimate soil properties from GPR data is to look for the attributes of signal, such as the amplitude of reflected radar waves, that can give us information on lateral continuities and/or discontinuities of the subsoil reflectors, on the geometry of the spatial soil structures and on their characteristics (Sénéchel et al., 2000). Knight et al. (1997) and De Benedetto et al. (2011) used the amplitude values for geostatistical analysis of the GPR data to decipher the link between the radar image and some of the properties (porosity, density, water content and texture) varying along the soil profile at a very fine scale.

Remote sensing of crop vegetation has been widely used as an excellent high-density data source to assess changes in growth environments from location to location. The potential of remote sensing in agriculture is very high, because multispectral reflectance of the crop canopies is related to the important physiological process of photosynthesis. Reflectance data can be converted into estimates of canopy area or plant biomass by calculating different spectral vegetation indices (Rodriguez et al., 2006). Several vegetation indices have been developed by linear combination or ratios of red, green and near-infrared spectral bands (Basso et al., 2004). This is the case of the most widely known Normalized Difference Vegetation Index (NDVI, Drissi et al., 2009), Green Normalized Difference Vegetation Index (GNDVI, Gitelson et al., 1996) and soil adjusted vegetation index (SAVI, Huete, 1988), which can be used to estimate green biomass; whereas the Normalized Difference Red Edge (NDRE), which uses a reference band in the edge band region (720 nm) in combination with a vegetation index, is suitable to estimate nitrogen status (Rodriguez et al., 2006).

Soil reflectance and plant water stress can affect the assessment of canopy status using remotely sensed data in dry environments (Basso et al., 2009). Moreover, water deficiency, in these dry environments, can mask the crop spectral response for nitrogen stress through changes in reflectance patterns in the Near-Infrared (NIR) and middle infrared reflectance (Rodriguez et al., 2005). Therefore, it is expected that Hyperspectral Proximal Sensing (HPS) can be a more exhaustive source of radiometric information for detecting plant stress (Thenkabail et al., 2004).

The HPS techniques, based on reflectance measurements acquired in a high number of contiguous spectral bands, have been successfully used to derive meaningful biophysical variables related to plant status, such as the concentration of foliar pigments, nitrogen concentration (Fava et al., 2009), water content and Leaf Area Index (LAI) (Colombo et al., 2003).

Since a geophysical sensor can give only a partial assessment of soil/subsoil properties and radiometric sensor output is more related to superficial land (soil and crop) features, the single use of a sensor is not ideal to characterize the integrated soil/subsoil - vegetation system. The combined use of different techniques could then enable to map distinct spatially-varying features and then to obtain a more comprehensive knowledge of the soil-plant system, avoiding the high cost of intensive sampling. At present, there are few papers (Castrignanò et al., 2012; Guastaferro et al., 2010; Taylor et al., 2010) that integrate different layers of information, such as proximal and/or remote sensing data and soil data, for the delineation of homogenous zones.To the best of our knowledge, there are no studies specifically focused on collecting multi-sensor data in a Mediterranean area, being submitted to multivariate analysis of geostatistics and clustering for Precision Agriculture applications.

The objective of this study was to define an approach to combine data from different sensors through geostatistical methods, with the target of delineating spatially contiguous homogeneous subfield areas.

2. Materials and methods

2.1. Study area

This study was conducted in an experimental field (41° 30′ N, 15° 33vE, 102.9 m above level sea) located in an agricultural flat area of approximately 700 km^2 (Capitanata plain) in southern Italy, mostly cropped with wheat, tomato and sugar beet. The climate is "accentuated thermo-Mediterranean" (FAO-UNESCO, 1963), with minimum temperatures below 0 °C in winter and maximum temperatures above 40 °C in summer.

The field has a size approximately of 300 m × 30 m. The soil is silty and has a slight depression (at most 2 m) at south-east. The experimental field was cropped in 2010 with winter cabbage and after harvesting the soil was ploughed up to 35-cm depth and then superficially tilled to prepare bed-sowing. Tomato plants were transplanted on May 15th 2010 at a density of 3 plants m^{-2} with a twin-row (1.8 m apart) arrangement and harvested on September 7th.

The irrigation water was supplied at a fixed amount (30 mm) every 5–6 days during the first month and every 2–3 days in the second and third month of tomato season. To differentiate the irrigation treatments, the field was split into two blocks (150 m × 30 m) with Optimal (OP) and Deficit (DE) irrigation: from July 15th to the harvest, the irrigation in the DE block (in the north-western part of the field) was scheduled on the same days but with half amount of water of the OP treatment (in the south-eastern part of the field).

Plant measurements were carried out in three georeferenced points per each irrigation treatment at 2-week intervals. In particular, in each block the following variables were observed:

- Phenology stage of tomato: times of the main phenological stages, expressed with BBCH scale (Feller et al., 1995);
- Leaf Area Index: leaf sampling, as average of 6 readings, was carried out using LiCOR LAI 2000 instrument, that measures the blue light (320–490 nm) in 5 concentric cones (with 148° field of view).