Soil bulk electrical resistivity and forage ground cover: nonlinear models in an alfalfa (Medicago sativa L.) case study

Roberta Rossi,1 Alessio Pollice,2 Gianfranco Bitella,3 Rocco Bochicchio,3 Amedeo D’Antonio,4 Alaa Aldin Alromeed,3 Anna Maria Stellacci,5 Rosanna Labella,3 Mariana Amato3

1Research Unit for the Extensive Animal Husbandry, Council for Agricultural Research and Analysis of Agricultural Economics, Bella (PZ); 2Department of Economics and Mathematics, University of Bari Aldo Moro, Bari; 3School of Agricultural, Forestry, Food and Environmental Sciences, University of Basilicata, Potenza; 4Department of Agricultural, Food and Forestry Policies, Campania Region, Naples; 5Research Unit for Cropping Systems in Dry Environments, Council for Agricultural Research and Analysis of Agricultural Economics, Bari, Italy

Abstract

Alfalfa is a highly productive and fertility-building forage crop; its performance, can be highly variable as influenced by within-field soil spatial variability. Characterising the relations between soil and forage-variation is important for optimal management. The aim of this work was to model the relationship between soil electrical resistivity (ER) and plant productivity in an alfalfa (Medicago sativa L.) field in Southern Italy. ER mapping was accomplished by a multi-depth automatic resistivity profiler. Plant productivity was assessed through normalised difference vegetation index (NDVI) at 2 dates. A non-linear relationship between NDVI and deep soil ER was modelled within the framework of generalised additive models. The best model explained 70% of the total variability. Soil profiles at six locations selected along a gradient of ER showed differences related to texture (ranging from clay to sandy-clay loam), gravel content (0 to 55%) and to the presence of a petrocalcic horizon. Our results prove that multi-depth ER can be used to localise permanent soil features that drive plant productivity.

Introduction

Alfalfa (Medicago sativa L.) is one of the most productive forage legumes in terms of feed protein and quality of forage, it is widely used in rotation as a fertility-building crop due to its high biological nitrogen fixation (BNF) capacity. Within field spatial variability plays a key role in BNF rates, yield and quality of forage, and hence must be considered in calculating N-budgets (Nykänen et al., 2008) as well as for yield forecasting. Over the last decade geophysical sensors based on the non-destructive measurement of soil electrical conductivity (or its inverse resistivity) have been extensively used in precision agriculture (Kitchen et al., 2005; Mora et al., 2010; Peralta and Costa, 2013).

Electrical resistivity (ER) can be used as a proxy of relevant soil properties (Samuelian et al., 2005) such as clay content (Buvat et al., 2014), gravel lenses (Tetegan et al., 2012) and bulk density (Besson et al., 2004). Multi-depth continuous resistivity profiling has been used to delineate permanent soil features at farm scale (Besson et al., 2010; André et al., 2012; Buvat et al., 2014). Deep soil variability might be relevant for deep-rooted perennials such as alfalfa that can fuel regrowth by relying on residual deep soil water reserves in late spring (Annicchiarico et al., 2014). In order to profitably use sensor-based soil information in agricultural management, however, ER variability must be related to crop growth. As argued by Shatar and McBratney (1999) soil uniform zones are not necessarily yield uniform zones and non-linearity often occurs. Among empirical modelling techniques generalised additive models (GAMs) are well suited to represent non-linearity that might exist in soil-yield relationships (Shatar and McBratney, 1999) as well as between ancillary information and soil properties (Bishop and McBratney, 2006). In this work we surveyed within-farm plant and soil variability by coupling a multi-depth automatic resistivity profiler (ARP) (Geocarta, Paris, France) and a radiometric sensor (Greenseeker® derived normalised difference vegetation index (NDVI)). The objective of the analysis was to test the suitability of multi-depth resistivity profiling for identifying soil features relevant...
for plant productivity. Based on the relationship between resistivity and NDVI modelled by a GAM, a limited number soil sampling locations was selected for ground-truth validation.

Materials and methods

Site description

The experiment was conducted in a 7-ha alfalfa (Medicago sativa L. cv. Altiva) stand in Palomonte (SA, Italy) (N 40.613952° E 15.303264°) at 210 m asl South Italy. The soil was classified as a Typic Eutrudept fine, mixed, thermic Calcaric Cambisols (Soil Survey Staff, 1999; IUSS Working Group WRB, 2006).

The average soil texture within the first 0.5 m layer was 41.29% sand, 17.14% silt, 41.57% clay average soil organic matter content was 26 g kg⁻¹. The stand was planted in November 2011 in rows at a seeding rate of 40 kg ha⁻¹, was grown in rainfed conditions and cut at an average rate of 3 cutely.

Automatic resistivity profiling

In this study, we carried out measurements on the whole 7 ha field using the on-the-go multi-depth resistivity meter (ARP©, Geocarta) (Rossi et al., 2013). Rolling electrodes towed across the field enabled resistivity (ER) to be measured simultaneously at three different depths that correspond to the distance between receiving wheels (V1=0.50 m, V2=0.70 m, V3=1.7 m). Data were real-time referenced by differential global positioning system (DGPS). Data were collected on 18 June 2013 along parallel transects at 6 m apart. A total number of 122,460 measurements was taken. The entire area was surveyed in about 40 minutes at an average speed of 9 km h⁻¹. The average soil water content, within the first 0.5 m soil layer, at the time of soil sampling was 27.40%.

Ground cover

Alfalfa ground cover was measured by a handheld NDVI optical sensor GreenSeeker™ on-the-go on 11 September 2013 and 1st November 2013. A third acquisition was carried out on 21 October 2014 (data not shown). The sensor was mounted on a platform and towed by an all-terrain vehicle while data were real-time referenced by DGPS. The system was towed across the field along parallel transects in a serpentine feature using the same distance (6 m) between transects that was used by the ARP system. Following manufacturer’s instructions operating height was kept at 1 m from the ground and the sensor head was oriented in-line with the target. The total number of measurements, for each acquisition, ranged around 210,630.

Statistical analysis

The objective of the analysis was to model the relationship between NDVI and ER. Sensor data were checked for normality and for the presence of outliers. Values above 99th percentile were considered outlying observations and were removed. Data were interpolated onto the same 5x5 m grid using the inverse distance algorithm. To evaluate the effects of geomorphology, point elevation data were rasterised on the 5x5 m grid and slope was calculated and used as explanatory variable. A non-linear relationship between NDVI and ER was modelled using GAM. The GAM was fitted by penalised likelihood maximisation with the function gam in the R library mgcv (Wood, 2006). Smoothing parameters were automatically chosen to minimise an internal Generalised Cross Validation criterion. Models were checked for violation of independence, variance homogeneity and residuals normality by graphical outputs. Starting from a set of candidate models, built having NDVI as a response variable and following a stepwise variable selection process, the final model was selected by comparing the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Both criteria gave a measure of the model goodness of fit penalising for model complexity to control over-fitting (Zuur et al., 2009). Statistical analyses were accomplished within the R environment (version 3.0.2; R Development Core Team, 2013).

Soil sampling

Based on the non-linear relationship between ER and NDVI, depicted by the GAM model (see statistical analysis section above), ground-truth calibration of ARP sensor data was carried out by selecting six sampling sites along a gradient of resistivity. Sampling sites were located in areas of high, medium and low resistivity and in areas characterised by ER threshold values where soil-plant relationship changed. On 18 April 2014, 6 trenches were excavated down to two meters depth. Pedological description was carried out according to the regional guidelines for pedological surveys (Campania Region, 2014). Sixteen soil samples were collected along the profile and the following parameters were lab determined: soil texture (hydrometer), soil organic matter (Walkley-Black methodology), 42 samples were collected to measure gravimetric water content. Root colonisation below 1.20 m was estimated by counting the number of visible roots in a rectangle of the trench wall of 100 cm width × 80 cm height (Walkley and Black, 1934).

Results and discussion

In our data both resistivity (ER) and NDVI showed a large structured variability across the field. ER values ranged from 3.7 to 64 Ohm m with three layers displaying a strong linear correlation (r=0.95 between V1 and V2, 0.92 between V2 and V3 and 0.83 between V1 and V3). The coefficient of variation of ER, increased with depth rising from 40% in V1 to 53% in V3. The NDVI at the first date (September) ranged between 0.33 and 0.89 while in November it approached saturation with values comprised between 0.71 and 0.90. The two readings, showed consistency in spatial patterns and were linearly correlated (r=0.55). A similar pattern was also visible on NDVI acquired a year later (November 2014, data not shown). At a visual analysis, the spatial pattern of NDVI and ER (respectively Figure 1B and A), were similar: many high resistivity (red) areas corresponded to areas of low NDVI, and low resistivity features (blue) corresponded to areas of high NDVI. Exploratory analysis therefore showed that NDVI was negatively correlated with resistivity measured in all of the three layers but mostly with the third layer (r=-0.49), the relationship though was non-linear and was therefore modelled with a GAM (depicted in Figure 1B-left and Table 1). The smoothing function picked up a threshold value of resistivity, approximately corresponding to 12-Ohm m, above which NDVI declined following an exponential decay with increasing resistivity. Below this threshold, however, although data are very scattered, there was a weak (r=0.21) but significant (P<0.05) positive correlation between NDVI and ER, indicating that in areas of very low resistivity NDVI decreases. To model the effect of the geomorphology the terrain variable slope was added as explanatory variable, moreover a smooth function of the geographic coordinates was included to account for the non-linear spatial trend that was detected in the map of residuals. The best model, chosen comparing both AIC and BIC criteria was the one explaining NDVI as a non-linear function of resistivity measured at the deepest layer, plus a
linear additive effect of the slope and a non-linear trend of the coordinates (Table 1). This model explained 70% of the total NDVI variability, model check showed uncorrelated residuals and a high correlation between observed and predicted values. Based on gradients of ER, six trenches were excavated in the field. All sites showed distinct characteristics consistent with both ER and NDVI values: texture in the 0-0.5 m layer ranged from sandy-clay-loam to clay (Figure 1C-left), and in one trench (A3) a large rock fragments content was found (55%). Root counts (RC) below 1.2 m also differed between profiles (Figure 1C-right). The highest values of resistivity (>50 Ohm m) were measured in correspondence of trench A4 and A5 where a petrocalcic horizon below 0.5 m was found. Trench A5 corresponds to the lowest RC value and a low NDVI (0.5). At this site the presence of a hardpan, coupled with a low water content (14% on average at the time of measure-

![Figure 1. Caption report. A) Left: Field map electrical (ER) (Ohm m) measured in the third layer (V3). ER values range from 5 to 60 Ohm m, high values are displayed in red shade while blue shade depicts low values. The trenches position and number is indicated by black letters, red dotted arrows indicate (right side) the corresponding selected soil trenches pictures: A1, A2, A3. B) Left: map of the normalised difference vegetation index (NDVI) measured on the first date (range: 0.44-0.81), red shade indicate high values and blue shade depict low values. Right: Scatterplot of the estimated smoother for the generalised additive model. The solid line is the estimated smoother, the red shaded regions are the 95% point-wise confidence bands. The horizontal axis shows the V3 ER (Ohm m) and the vertical axis is the contribution of the smoother to the fitted values. The smoother is centred around 0. C) Left: bar plot of soil texture measured in the top-layer (0-0.5 m). The values are referred to the fine earth, in trench A3 (asterisked) a 55% of rock fragments was measured. Right: bar plot of root counts on a rectangle on the trenches walls of 100 cm width × 80 cm height below 1.2 m depth.](image-url)
ers variability is relevant for perennials but is also important for crops root hydraulic conductivity (Richards and Passioura, 1989). Deep lay-
soil, in water-limited environments, water must be dried up in a con-
sistently by cultivars growing in different environments regardless of its
adaptation value (Annicchiarico et al., 2011). A large root system would
can access subsoil through pre-existing bio-pores network. Multi-depth soil information is important for deep rooted perennials
such as alfalfa and might be considered also for following crops that
can access subsoil through pre-existing bio-pores network.

Conclusions

ER was correlated to the presence of permanent soil features also related to plant variability. Highest resistivity values matched areas
where a petrocalcic horizon was found, while lowest values (<12 Ohm m) corresponded to a clayey hydromorphic soil. The highest correlation
between NDVI and ER of the third layer supported the hypothesis that
alfalfa was relying on resources in deep strata, and this was also cor-

m. In our survey resistivity proved to be correlated to permanent
soil features, and this is consistent with other studies (Besson et al.,
2010; André et al., 2012). ER variability was related to NDVI, but non-
linearly, and the use of a GAM helped identifying threshold values
where soil-plant relationship changed. A significant correlation
between ER and plant variability was also found by Rossi et al. (2013)
in vine, supporting the hypothesis that perennials tend to develop per-
stantial spatial pattern following soil variability. Plant variability was
mostly correlated with the ER below 1 m indicating that the stand might
be mostly relying on resources in deep strata. Mapping the presence
of hardpans could be used to optimise the choice of the cultivar in preci-
plantation applications. Research on drought-resistant alfalfa vari-
eties has shown that the root system size was a trait expressed consis-
tently by cultivars growing in different environments of its
adaptive value (Annicchiarico et al., 2007). A large root system would
be beneficial in soils with deep water reserves, whereas on shallow
soil, in water-limited environments, water must be dried up in a con-
servatory way: in this case a favourable root trait might be a reduced
root hydraulic conductivity (Richards and Passioura, 1989). Deep layers
variability is relevant for perennials but is also important for crops
following alfalfa. Gaiser and co-authors (2012) found that water extrac-
tion from deep soil layers (90-105 cm) was significantly higher when
wheat followed alfalfa compared to wheat sown after chicory and fes-
tive, indirect evidence that wheat could have extended its root zone by
colonising bio-pores created by alfalfa. Detailed information on root
zone spatial variability can also be used in crop models, which rarely
take into account rooting depth variability, even though neglecting it,
leads to substantial biases in model predictions (Raza et al., 2013).

Table 1. Summary statistic of the best fitted generalised additive model. Alfalfa normalised difference vegetation index was estimated
as a function of one parametric term (terrain slope = SL) and two smooth terms (s): a smoothing function of the electrical resistivity
(ER) (Ohm m) of the third layers (ER V3) and a non-linear trend of the geographic coordinates (easting + northing).

| Parametric terms | Estimated coefficients | P-value |
|------------------|------------------------|---------|
| Intercept (α)     | 0.619                  | <0.001  |
| Terrain slope (SL) | 0.002                  |         |
| smooth terms      |                        |         |
| s (easting + northing) | 28.653              | <0.001  |
| s (ER V3)         | 7.692                  | <0.001  |

Model performance

| Parameter | R² - Adj | nobs |
|-----------|----------|------|
| Deviance explained | 0.698 | 2574 |

NDVI, normalised difference vegetation index; ER, electrical resistivity.

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