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Electrical resistivity tomography to detect the effects of tillage in a soil with a variable rock fragment content

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Summary

Electrical resistivity tomography (ERT) is a promising non-destructive tool to characterize agricultural soils where management effects are superimposed on natural variability. The aim of our study was to test whether ERT was capable of detecting stones and tillage effects in a soil with a variable rock fragment content. Field experiments were conducted by performing a set of three two-dimensional (2D) resistivity tomographies across two management systems (tillage/no tillage) replicated twice on each transect, using dipole-dipole configuration and 0.25-m inter-electrode spacing. Soil texture, bulk density and water content were measured destructively. Greater average electrical resistivity (ER) was found in tilled plots, with maximum values of up to 1700 Ohm m. However, when the spatial correlation structure was considered in a mixed-effects model, no significant difference in ER was found between tilled and untilled plots. Empirical semivariograms showed less spatial continuity and more noise in tilled plots. Resistivity was strongly correlated with rock fragment content ($r = 0.68$), with greater average values in ploughed plots, which may possibly be linked to kinetic sieving after ploughing. ERT was able to identify the position of gravel lenses and was also sensitive to the presence of clay ($r = -0.45$): a linear trend in resistivity across the field ($r = 0.80$) was consistent with a decreasing clay content ($r = -0.68$). Resistivity was correlated with rock fragments, clay and an interaction variable (water × rock fragments). There was a poor fit for the tilled plot where resistivity peaks could be linked to the presence of voids, but their detection would have required a resolution greater than that which we adopted.

Introduction

An undisturbed soil is characterized by a large spatial heterogeneity with 'hot spots' of aggregation in the vicinity of organic carbon reserves, a wide range of pore sizes from the water-filled micropores within aggregates to the large biopores created by plant roots and soil fauna, and cracks between aggregates where water and gases diffuse. Soil break-up by tillage modifies aggregate dimension and stability, porosity, residue distribution, surface roughness and biological activity. Tillage effects are subjected to a large degree of spatial and temporal variability depending on soil texture gradients, meteorological conditions and cropping systems; thus any assessment of long-term impacts requires measurements over space and time of the ploughed layer.

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Structural characterization of tilled layers encompasses several methodologies, implemented at different spatial scales, from small scale studies, such as pore-space depiction by image analysis of polished sections and aggregate classification by wet-sieving techniques, to field-scale approaches based on soil profile morphological description, *in situ* measurements of bulk density, and hydrological properties linked to porosity. Traditional techniques are generally time consuming and labour demanding. Some of them are intrusive, preventing future observation at the same site, whilst point source measurements give only local information which is often limited by financial and time constraints (Besson *et al*., 2004).

Over the last decade soil research has progressively invested in the use of complementary geophysical ground-sensing technologies using surface measurements of soil electrical resistivity (ER) or its inverse, soil electrical conductivity, for the non-destructive characterization of soil spatial variability at different scales

(Corwin & Lesch, 2003; Rossi *et al*., 2010). Soil resistivity depends on how soil materials oppose the flow of electric current: if an artificially generated electric current is supplied at the soil surface, identifying its underground distribution conveys information on sub-surface materials. Soil constituents cover a large range of resistivity values from 1 Ohm m in saline soils to several thousand Ohm m for crystalline rocks (Tabbagh *et al*., 2000). In non-saline soils resistivity varies as a function of water content, soil texture and structure, and cation exchange capacity (Samouelian *et al*., 2005), and can be used as a proxy for several soil physical and chemical properties. Two-dimensional and 3D electrical resistivity tomography (ERT) has been widely used to monitor dynamic properties in cultivated soils (Besson *et al*., 2004) and for detecting soil cracks at the centìmetre-scale (Samouëlian *et al*., 2004), and has been recently adopted to map plant root systems (Amato *et al*., 2008). Electrical resistivity is sensitive to soil structure variations, detecting natural and management-induced soil compaction (Tabbagh *et al*., 2000; Besson *et al*., 2004), and has been used for non-destructive characterization of ploughed layers (Séger *et al*., 2009). Basso *et al*. (2010) reported that freshly tilled soils had a more marked resistivity than older tilled soils and demonstrated that the resistive behaviour of tilled soils is linked to bulk density variation. In other studies the effect of tillage on resistivity distribution has been attributed to the seasonal variation of porosity and water storage capacity (Muller *et al*., 2009).

Electrical resistivity tomography imaging depends on the degree of contrast between the target property and the surrounding background matrix (Samouelian *et al*., 2005). Ambiguity in interpretation is a general limiting factor because soil resistivity is influenced by a number of soil properties that fall in the same range of values (Rossi *et al*., 2010). At a given site, though, one factor can be dominating if its electrical response is stronger and if the within-field variation is large enough compared with other properties; prevailing effects must be assessed on a case-by-case basis (Sudduth *et al*., 2001; Amato *et al*., 2008). The effect of tillage on soil resistivity is an increase in the order of 10–100 Ohm m (Muller *et al*., 2009; Séger *et al*., 2009; Basso *et al*., 2010); rock fragments are reported to increase soil resistivity by hundreds or thousands of Ohm m according to mineralogy and abundance (Rey *et al*., 2006). Their presence and their spatial variation, therefore, might partially overlap or even totally mask the effects of tillage. This possible masking effect has not been tested yet: while previous experimental results have shown that ERT is capable of detecting tillage effects in medium-textured soils, the technique has not yet been validated in coarse heterogeneous soils.

The objective of our study is to test whether ERT is capable of discerning the effect of tillage even in a soil with a variable content of rock fragments. Quantitative information on soils containing rock fragments is of great interest first of all because they are widespread in Mediterranean countries, covering a large percentage of the land surface (up to 60%) (Cousin *et al*., 2003), and also because they influence crop yield in many ways, exerting complex effects on soil hydrology and temperature regime (Poesen & Lavee, 1994). A stony soil has at least 40% in mass of particles larger than 2 mm (coarse particles); the modifier 'gravelly' is used in soil classification if coarse particles range between 15 and 30% in mass. Whereas truly stony soils have been generally less used for agronomic production because of poor workability and a generally poor water storage capacity, those with up to about 30% of coarse fragments are used and tilled, and stones play a role in preventing land surface degradation processes, such as surface sealing and erosion (Cerdà, 2001). The localization and quantification of stones in agricultural soils is also important for the correct quantification of carbon (C) and nitrogen (N) stocks (Rytter, 2012). The spatial distribution and abundance of coarse fragments in topsoil and hence their contribution to the processes noted is influenced by tillage (Poesen *et al*., 1997). There is therefore a need to develop new tools to gain information on how to overcome the methodological difficulties that have often limited quantitative research in such soils.

While research on stones with ERT measurements has been mainly limited to natural soils or landfills, and focused on the identification of stony sites or gravel lenses with coarse resolution, research on stone quantification on agricultural soils is limited, and estimation of rock content by ERT has been, until now, a partially unresolved question. Measurements on agricultural soils require greater resolution than that for petrographic research, and have to be at a scale compatible with near-surface variation and the detection of tilled or biologically active layers. They are usually performed at a range of inter-electrode distances, from centimetres in the laboratory to decimetres in the field. Applications of decimetre-scale measurements to plot and field-scale surveys is the object of current studies, and promising approaches are based on multilayer 'on-the-go' settings (Samouelian *et al*., 2005; Basso *et al*., 2010; Tétegan *et al*., 2012) where data are collected with variable horizontal resolution, but vertical resolution permits measurements in the first few decimetres of soil. Tétegan *et al*. (2012) proposed the use of the standard deviation of resistivity measurements as an indicator of rock fragment content, and found that it was strongly affected by soil water content and rock type. Rossi *et al*. (2010) argued that agricultural soils are systems where management effects linked to tillage, fertilizer application or irrigation may create structured variation, which may mask or confound the effect of other features on resistivity. Therefore the potential of ERT for stone research may be diminished in agricultural soils, but so far stone detection across management treatments has not been attempted. Our hypothesis was that ERT was capable of discerning structured variability induced by tillage from natural soil variability and could be used to detect stone lenses even in the presence of management-induced changes in soil structure.

Materials and methods

Experimental system

Field experiments were conducted at the experimental site of Ce.Spe.Vi. (Pistoia, Italy; 43°55′13.32″N; 10°54′31.18″E) on a

Dystric Gleyi Fluvic Cambisol according to the World Reference Base of Soil Resources (IUSS Working Group WRB, 2007). Two management systems (BM = ploughed at 30 cm and SA = set-aside left untilled) were implemented in 2008 on 5 × 5 m plots on a soil that had been left uncultivated for 15 years. Two-dimensional DC resistivity tomography was performed on three transects across two replicates (SA2, SA3; BM2, BM3) of the two management systems (Figure 1) with an Iris Syscal Pro 10-channel receiver (Iris Instruments, Orléans, France) resistivity meter. Electrical resistivity data collection was carried out in the dipole-dipole array. In each transect resistivity data were collected from a line of 72 electrodes spaced at 0.25 m, to give a total length of the line of 17.50 m and an exploration depth of approximately 2.90 m. A total of 2272 resistivity values were recorded.

The value and spatial distribution of resistivity data thus obtained yielded a 2D section of apparent resistivity values, flawed by the implicit assumption of isotropic current distribution, which is only valid in homogeneous soil (Samouelian *et al*., 2005). In order to account for the lack of isotropy of the soil medium, apparent resistivity data were inverted through a 2D finite-element inversion algorithm to solve the forward modelling problem (Morelli & Labrecque, 1996), implemented with the Tomolab inversion software (Geostudi Astier, Livorno Italy), and true resistivity values were obtained. Figure 1 depicts the experimental system, the results of the inversion process and the position of destructive sampling sites on transect 1.

Temperature measurements were made at five locations along the first profile (transect 1): 2.2, 3.5, 6.25, 7.25 and 10.8 m from the left-hand corner of the profile, a thermometric probe (PT100), connected to a data-logger, was inserted at 0.05, 0.15, 0.25, 0.35 and 0.45 m depth. Using the closest thermometric probe, the effect of temperature on measured resistivity at the soil sampling locations, has been corrected to a reference temperature of 25°C, as suggested by Samouelian *et al*. (2005), and using the experimental equation from Campbell *et al*. (1948):

$$\rho_T = \rho_{25^\circ C}[1 + \alpha(T - 25^\circ C)], \tag{1}$$

where ρ_T is the electrical resistivity measured at a given temperature (T), $\rho_{25^\circ C}$ is the electrical resistivity to a reference temperature of 25° C, and α is a correction factor equal to 0.02.

Determination of soil properties

Directed sampling (or model-based sampling) was performed with the explicit goal of optimizing the estimation of a multiple regression model of ER data and soil properties. The spatial locations of the calibration ground samples were chosen on the basis of the observed magnitude of ER data. A target strategy was adopted as suggested by Amato *et al*. (2008) to optimize sampling: on transect 1, locations of contrasting resistivity were identified on the resistivity tomogram, which was available in

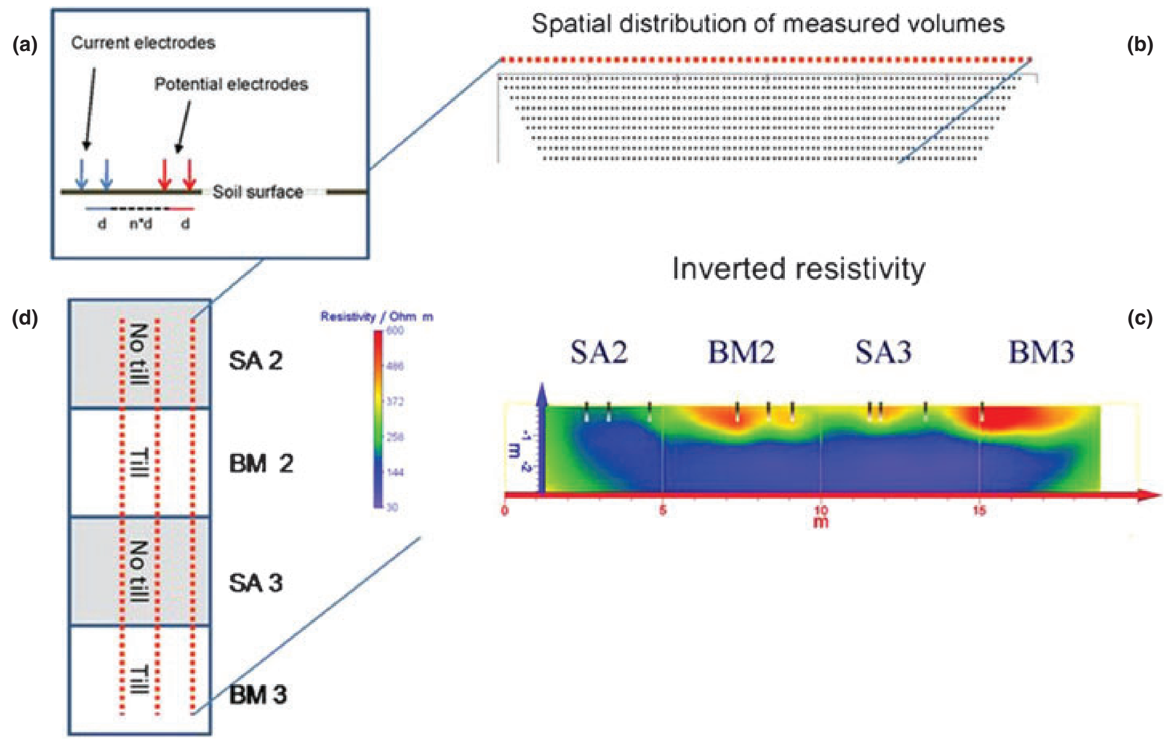

Figure 1 Experimental system: (a) arrangement of electrodes in the dipole-dipole array; (b) arrangement of centres of elementary cells for resistivity; (c) soil electrical resistivity tomogram in transect 1 overlain by experimental plots contours (with their spatial dimensions) and position of destructive soil samples; (d) position of the three multi-electrode arrays on the experimental plots.

the field within 60 minutes of data acquisition, and sampling points were chosen in order to cover a resistivity gradient. Soil cores were taken with a bucket auger of 0.075 m internal diameter on 10 vertical profiles located at 1.5, 2.20, 3.5, 6.25, 7.5, 8.0, 10.45, 10.80, 12.20 and 14.00 m along the electrode array. At each location soil samples were taken at 10-cm depth increments up to 0.50 m. A total of 50 samples were available for laboratory determination. Samples were transported to the laboratory in air-tight containers and used for the following laboratory determinations. Gravimetric water content (GWC g g^1) was determined by oven-drying the soil sample at 110°C until constant mass. The soil sample dry mass was then used to calculate particle size classes. The coarse fragment content was measured after separation from fine earth by sieving on a 2-mm square-meshed sieve. The stone fraction was weighed and the relative amount expressed as mass of rock fragments per unit soil sample dry mass (rock fragment = rf g g^1%). Fine earth materials were separated with the hydrometer method. Fine earth particles were expressed as mass distribution with respect to particle diameter: sand (2.0–0.050 mm), silt (0.050–0.002) and clay (<0.002 mm). Soil paste electrical conductivity (EC) was measured on a 1:2 (w/w) soil water slurry. Soil dry bulk density (bd) was measured by the cylinder method (with 98.125 cm^3 internal volume brass cylinders) at six locations (1.50, 3.50, 6.25, 8.00, 12.20 and 10.45 m) every 0.10 m up to 0.50 m. In 50% of cases coring was impossible, because of stoniness, and therefore 15 samples were collected.

Statistical analysis

Statistical analysis will be presented in two parts. In Part 1 overall ER data collected in the three transects were analysed through a mixed effects model to assess if there was any significant systematic effect of tillage on resistivity. In Part 2 quantitative relationships between ER and soil properties at destructive sampling locations were analysed by multiple regression analysis.

Part 1. Analysis of overall ER data. Resistivity data were collected up to 2.91 m depth but only the first two layers of ER data corresponding to 0.30 m (ploughing depth) were retained for this analysis. Ploughed plots were replicated at different field positions but not randomized, therefore the presence of pre-existing pedological gradients may offset treatment effects; moreover, resistivity data have an inherent spatial correlation. Both these factors thus prevent the use of a classical analysis of variance approach. In order to test the effect of tillage, ER data were analysed as a spatial random field with a mean structure given by the two levels of the treatment (tillage or no tillage) and a positive gradient along the transects, spatial correlation among observations was modelled by an exponential spatial covariance structure implemented through a mixed effects model (R package – nlme; Pinheiro *et al*., 2011), and a random term for the combined effects of the transect and the depth layer was included. A further analysis to identify any differences in the spatial dependence structure between the two treatments was carried out by computing experimental variograms for two treatments (R Package – gstat; Pebesma, 2004).

Part 2: Analysis of correlation between ER and soil variables. A sub-set of resistivity values was used for this analysis: those corresponding to destructive sampling locations on the first transect. The correlation between ER and soil variables was assessed through multiple regression analysis. A first sub-set of soil variables, used as predictors of resistivity in the multiple regression model, included soil properties with strong correlations only, in order to prevent structural multi-collinearity between fine earth components. The best set of covariates was chosen with backwards elimination and goodness of fit was assessed through the Akaike information criterion (AIC). Residuals analysis was carried out and the presence of correlated errors was verified with the Moran's I test for spatial auto-correlation. Spatially correlated errors, arising from observations collected at consecutive depths, were treated as nested errors and handled within the framework of the generalized least square (GLS) regression; the error component was modelled by assuming a first-order auto-regressive process. All analyses were carried out using the 'R software environment for statistics' (www.r-project.org).

Results

Analysis of overall ER data

Soil resistivity as imaged in the tomograms (Figure 2) showed a strong spatial variability in all of the transects. The largest variability was concentrated in the first 100 cm, where values ranged from below 100 to over 1700 Ohm m; below this depth the soil was more homogeneous and conductive (purple-blue shade). Greater average resistivity was found in tilled plots and peaks of resistivity were localized at various positions, with maximum values of up to 1790 Ohm m, as found in the third transect. In all of the transects resistivity showed a linear increase from the left to the right of the survey line, with linear coefficients, respectively, on the first, second and third transects of 15.32, 21.00 and 21.05 Ohm m increase in resistivity for each metre moving from the left to the right corner of the transects. The treatments were not randomized, and the data show an inherent spatial auto-correlation, both factors preventing the use of a pooled t-test. Overall resistivity values collected in the three transects were analysed as a spatial random field with a mean structure given by the two treatments and the linear trend along the transects. Spatial auto-correlation between ER measurements was taken into account when fitting a mixed effects model (Table 1).

The estimated range for the exponential covariance structure, chosen to model the residual spatial dependence, was 1.287 m; the model summary (Table 1) shows that there was no difference in ER mean values between tillage treatments ($P = 0.61$), whereas the fixed effect exerted by the gradient was significant. The spatial structure of both treatments was analysed separately from the experimental variograms (Figure 3) and differences appeared in

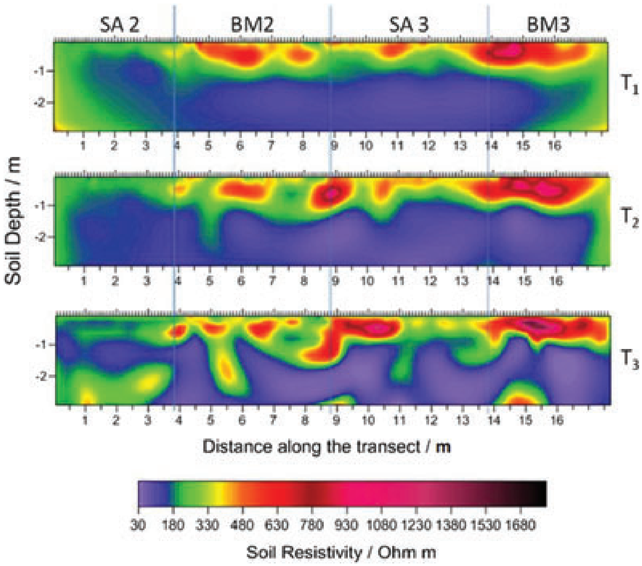

Figure 2 Inverted electrical resistivity 2D tomograms obtained in the three transects (T1, T2 and T3). Vertical blue bars mark plot boundaries.

Table 1 Mixed-effects model results: residual spatial covariance structure parameters and significance levels associated with fixed effects

Response variable = soil electrical resistivity / Ohm m				
Fixed effects:	Value	Standard error	t value	P value
(Intercept)	247.44	42.71	5.79	0.0000
Tillage	−8.09	16.82	−0.50	0.6174
x-coordinate	15.40	4.06	3.79	0.0002
Residual spatial correlation structure: exponential spatial correlation				
Parameter estimate: range 1.29				

x-coordinate = position along the transect / m.

their spatial structure. The empirical semivariograms show that in untilled plots ER had a greater spatial continuity and in the tilled plots the ER data were noisier, as can be inferred from the larger nugget value.

Analysis of correlation between ER and soil variables

Soil variables from destructive sampling and resistivity at the corresponding locations are summarized in Table 2 and the correlation matrix in Table 3. Rock fragment content was greater in the tilled plots (12.72% on average) than in the untilled plots (4.97% on average). The best correlations with resistivity (Table 3) were found with rock fragments and clay content. These were also the variables with the largest variability, especially the stone content, with samples ranging from a practically stoneless silt loam to a gravelly silt loam.

An area that had good conductivity in the untilled plot SA2 (blue-shaded region above 1 m in Figure 2) corresponded to the sample with the largest clay content. In locations corresponding to peaks of resistivity, a greater stone content and a smaller soil

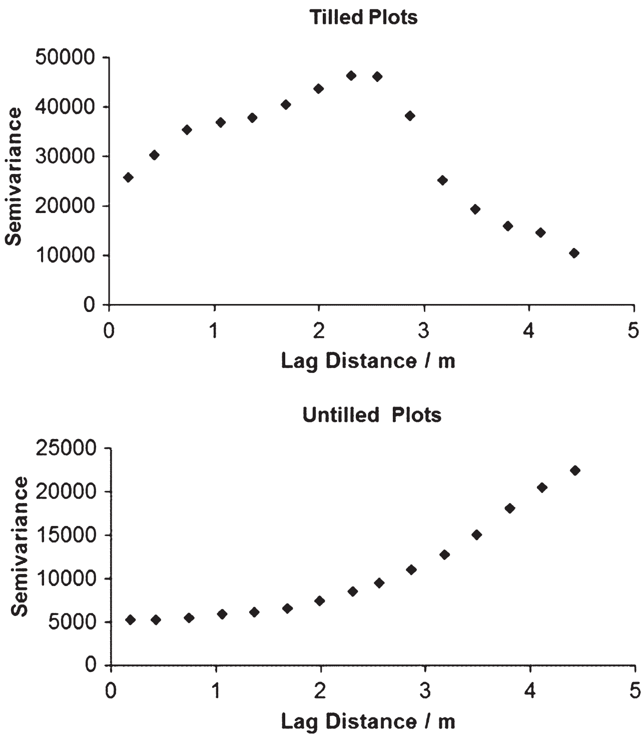

Figure 3 Directional empirical semivariograms of ER overall data under tilled (top) and untilled (bottom) plots.

water content were found. The univariate relationship between rock fragment content (RF) and ER was

$$\mathrm{RF} = 0.0361 \times \mathrm{ER} - 1.7398;\ R^2 = 0.456.$$

Bulk density was not included in the overall analysis because fewer data were available than for other variables and they were not correlated with resistivity. As found for the whole dataset, an increasing linear trend in electrical resistivity along the transect was also detected in the subset of ER data corresponding to the sampled locations; the percentage of clay showed a corresponding decreasing linear trend (Figure 4a,b). Water content was correlated with resistivity only in tilled plots ($r = -0.61$ and -0.93, respectively, in BM2 and BM3). Data from the two plots cannot be pooled as such because of the spatial trend in ER. When ER data were de-trended from the positive gradient along the transect and pooled, a highly significant quadratic relationship between ER residuals and water content in tilled plots was found (Figure 5)

$$(y = 8\mathrm{E}-05x^2 - 0.039x + 23.85;\ R^2 = 0.52).$$

Resistivity variation was best explained as the multivariate response to soil variables. Residual analysis from ordinary least square regression revealed the presence of correlated errors. For the Moran's I test for spatial autocorrelation, the null hypothesis of non-correlated residuals was rejected with $P < 0.05$. The linear model equation was then fitted by using the generalized least

Table 2 Descriptive statistics of ER and soil variables in destructive samples

	ER / Ohm m	GWC / %	rf / %	Sand / %	Silt / %	Clay / %	EC / dS m^{-1}
Mean	271.8	23.7	8.1	53.2	36.4	10.4	0.23
Median	257.6	22.5	6.8	52.9	36.5	9.2	0.22
Standard deviation	116.79	4.26	6.24	8.90	5.91	4.33	0.08
Kurtosis	0.76	0.89	−0.35	−0.52	−0.01	−0.06	1.05
Skewness	1.02	1.15	0.73	0.21	−0.18	0.59	1.09
Minimum	123.84	17.83	0.62	36.21	22.84	3.45	0.12
Maximum	597.50	36.66	24.06	73.65	50.96	22.32	0.46
CV/ %	42.97	18.00	77.34	16.72	16.25	41.68	32.91

N = 50.
ER = *in-situ* soil electrical resistivity; GWC = gravimetric water content; rf = rock fragment content.

Table 3 Correlation matrix of ER and selected soil variables in destructive samples of gravimetric water content (GWC), rock fragments (rf), sand, silt, clay and soil paste conductivity (EC)

	ER / Ohm m	GWC / %	rf / %	Sand / %	Silt / %	Clay / %	EC / dS m^{-1}
ER / Ohm m	1	—	—	—	—	—	—
GWC / %	−0.18	1	—	—	—	—	—
rf / %.	0.68	−0.05	1	—	—	—	—
Sand / %	0.35	0.39	0.39	1	—	—	—
Silt / %	−0.19	−0.27	−0.28	−0.91	1	—	—
Clay / %	−0.45	−0.43	−0.43	−0.82	0.50	1	—
EC / dS m^{-1}	−0.04	0.53	0.22	0.46	−0.34	−0.48	1

N = 50.
ER = *in-situ* soil electrical resistivity; GWC = gravimetric water content; rf = rock fragment content.

squares model, which accounted for correlated errors with the x-coordinate and depth. The significant predictors were clay content, rock fragments and the interaction between rock fragments and water content (Table 4). Figure 6 depicts the observed resistivity along the transect, with GLS predicted values superimposed. A poor fit can be observed in both tilled plots and especially in plot BM3, where the predicted values were less than observed values and under-estimated resistivity by several hundreds of Ohm m.

Discussion

Our experiment showed qualitative and quantitative relationships between ER and soil properties: a clayey lens was clearly mapped as an area of small resistivity, and this is in agreement with previous findings (Samouelian *et al*., 2005). Electrical conductivity in soil is largely through electrolytic effects, and therefore is sensitive to the ion concentration on the surface of clay particles. A trend in ER corresponded to a trend in clay content and resistivity was also strongly correlated with rock fragments. Quantitative research in stony soils has been severely limited by methodological difficulties despite the importance to soil hydrology and effects on land degradation processes (Poesen & Lavee, 1994). Electrical resistivity tomography has advantages over other non-destructive surface penetration methods that have a limited spatial scale and are inaccurate whenever rock fragments are not randomly distributed within the profile but have a systematic lesser or greater content at the soil surface. Bias in estimates can be worsened because stones tend to be arranged with the larger area facing upwards (Eriksson & Holmgren, 1996). Electrical resistivity tomography allows several layers of stones to be imaged: 3D applications would also allow volume estimates. The correlation of resistivity values with stone content is widely documented in petrophisycs (Rey *et al*., 2006). Rock fragments are reported to increase soil resistivity by hundreds or thousands Ohm m according to mineralogy and abundance (Rey *et al*., 2006). Morari *et al*. (2009) integrated the use of electro-magnetic induction with ER survey to delineate field spatial variability in a gravelly soil. As in our case, both electrical conductivity and ER maps predicted rock fragment spatial distribution, and association with rock fragments and gravel material gave resistivity values in the order of 400 Ohm m. Beresnev *et al*. (2002) used 2D resistivity tomography in gravel exploration and reported that seasonal variation in soil water content caused a shift of gravel resistivity from 1500 to 300 Ohm m; nevertheless, the strong contrast between the highly resistive rock fragments and the surrounding fine-textured material was stable enough to allow gravel lenses to be identified at any time of the year.

In our study, rock fragments were the prevailing factor affecting resistivity. A quantitative univariate relationship was found between rock fragments and ER, with correlation values similar to those found in a stony soil by Morari *et al*. (2009). Better than typical relationships of many other soil properties with ER or its

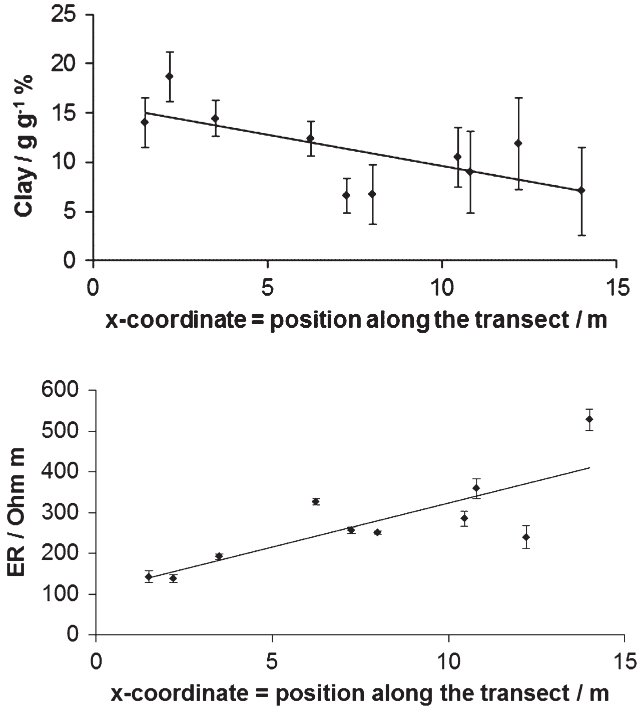

Figure 4 Average values over the 0–0.50 m depth of clay content (top) and ER (bottom) along the transects; vertical bars represent the standard deviation. Black line = linear trend models: clay = $-0.6306x + 15.8976$; $R^2 = 0.47$; ER = $21.497x + 108.105$; $R^2 = 0.64$.

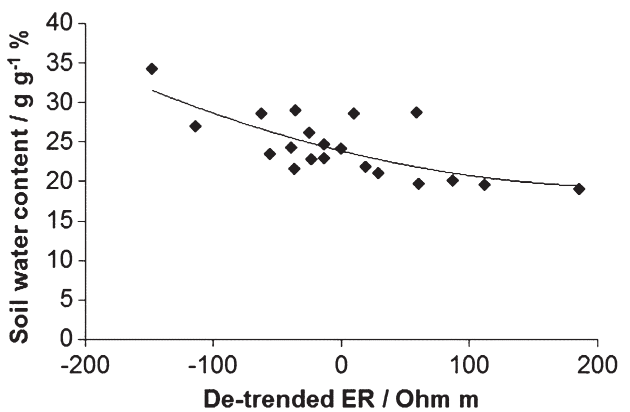

Figure 5 De-trended electrical resistivity data versus water content in tilled plots. Black line = model $y = 8\text{E} - 05x^2 - 0.039x + 23{,}85$ $R^2 = 0.52$.

Table 4 Summary statistics for the generalized least square multiple regression model of electrical resistivity and selected soil variables (rock fragments (rf), clay and gravimetric water content (GWC))

Model: ER = rf + clay + GWC + rf × GWC	Value	Standard error	t-value	*P*-value
(Intercept)	224.67	87.24	2.57	0.013
rf	22.54	9.37	2.40	0.020
Clay	−5.86	2.03	−2.89	0.006
GWC	1.81	2.87	0.63	0.532
Rf × GWC	−0.66	0.36	−1.81	0.076

Residual standard error: 63.08 on 45 degrees of freedom.
Residual spatial correlation structure: AR(1).
Parameter estimate Phi = 0.6.
AIC = 529.024; BIC = 539.865; logLik = −258.512.
ER = *in-situ* soil electrical resistivity; GWC = gravimetric water content; rf = rock fragment content.

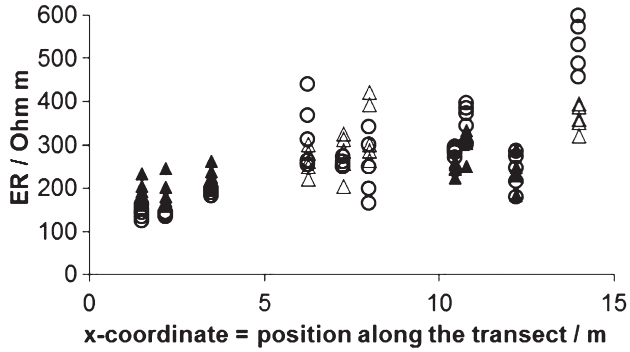

Figure 6 Observed electrical resistivity (ER) values along the transect (empty circles) overlaid by predicted values from the GLS model (full triangles = untilled plots, empty triangles = tilled plots).

reciprocal, electrical conductivity, have also been found in other geophysical studies (Banton *et al*., 1997; Corwin *et al*., 2006). This confirms the strong effect of stones on soil ER, and that rock fragments can be quantified by ERT. Because our study was conducted on a site with different sources of variability (natural and linked to management) we are able to show that resistivity is best modelled as the multivariate response of different soil variables and their interactions. Therefore practical applications of the method require *in-situ* calibration of the relationship with other variables (clay content and soil moisture) and/or that all reasonable steps to ensure uniformity in other field conditions to minimize interactions, such as making measurements in dry soil, are taken. Even under our conditions, ERT provided useful semi-quantitative or qualitative information on coarse fragments, including the position and extension of the gravel lens. This type of information can improve sampling efficiency through surface-response sampling schemes (Rossi *et al*., 2010).

In our study local stone lenses were independent of tillage, but a greater average stone content in ploughed plots was also found, perhaps as the result of a possible indirect effect related to particle sorting. This effect of kinetic sieving occurs during tillage and large fragments are raised and move toward the surface while finer fractions move downwards, falling through spaces between coarser fractions. Inter-particle percolation results in tilled layers being generally enriched by coarse fragments (Nyssen *et al*., 2002). Oostwoud Wijdenes *et al*. (1997) studied the effect of tillage on rock fragment redistribution in a stony soil profile under dry soil conditions and demonstrated that after a few tillage passes coarse fragments accumulated in topsoil. Such stone displacement, however, varies according to water content and texture (Oostwoud

Wijdenes & Poesen, 1999). Our results indicate that kinetic sieving may lead to a resistive response of tilled soils that is independent of variations in soil structure, and results from the accumulation of coarse fragments in tilled layers. This effect has not been strong enough to cause significant differences in average ER between tilled treatments in our case, but it might be in other specific settings. Tétegan *et al*. (2012) found that electrical resistivity signal noise measured at the decimetre scale increases with the proportion of stones in soil. In our case, empirical semivariograms had greater noise (larger nugget values) in tilled soil, and this may be linked to the larger percentage of rock fragments in addition to changes in aggregation geometry. Therefore effects of stones linked to kinetic sieving on ER and on its spatial structure cannot be neglected because (i) there is a possible confounding effect in research aimed at detecting soil structural changes with ERT, and (ii) it is a further way to explore methods for the detection of tillage effects in soils.

The resistive response of tilled soils in the absence of stones has been attributed to porosity and large voids created by tillage (Basso *et al*., 2010). In our experiment the correlation of ER with bulk density and water content was poor: resistivity was strongly correlated with water content only in the tilled plots. Electrical resistivity is affected by many soil properties, and the effect of variables with the strongest effect on soil electrical behaviour or with the greatest variability will prevail (Amato *et al*., 2009). An inverse relationship between soil water and ER is documented in the literature, but Amato *et al*. (2008) point out that strong relationships are found in cases where measurements are repeated at the same soil location with different soil water content and therefore the variability of other soil properties is minimized. In other instances, where relationships are studied in a series of samples encompassing global soil variability, relationships are weaker or even non-significant if there are other soil properties that dominate the electrical behaviour of the system (Amato *et al*., 2009).

A decrease in bulk density is expected to increase ER because of the volumetric increase in air-filled spaces (Besson *et al*., 2004) but Rossi *et al*. (2010) report a non-significant correlation because of the greater variability in other properties. Basso *et al*. (2010) report a variation in bulk density of 0.52 g cm^{-3}, corresponding to a variation of about 200 Ohm m, with a significant relationship but with a R^2 of only 0.38. They also reported that ER was better able to differentiate between tillage treatments than single soil properties such as penetration resistance measured at a point. It is not surprising therefore that in our case the effects on ER of a variation in bulk density of the same order as in Basso *et al*. (2010) was at least partly masked by changes in stone content corresponding to variations in ER of about 300 Ohm m. Nevertheless, water content improved the correlation as an interaction variable (water $\times$ rock fragment content), and therefore may be considered as an auxiliary variable in explaining the soil electrical behaviour. Multiple regression helped to explain the factors of electrical behaviour of our soil; the problem of correlated errors was approached by re-fitting the regression equation within the framework of the generalized least square model. This improved the fit by supplying information on spatial dependence between observations but still the available set of explanatory variables in the model fails to predict resistivity in tilled plots accurately (Figure 6). There was a poor fit in tilled plots, and more specifically a large dispersion in plot BM2, and the model under-estimated resistivity in plot BM3 by several hundreds of Ohm m. Therefore, a variable that was not identified or included in the model resulted in large values of resistivity in tilled plots. The missing variable might be linked to presence of tillage-related voids that were not water-filled at the time of measurement and would be reflected in a smaller bulk density, but also to larger voids at the interface between soil and rock fragments created through the displacement of stones by the plough. Such voids would not result in a reduced bulk density in core samples and would have needed destructive sampling methods at scales that were not compatible with the need to reduce disturbance to the experimental plots.

Electrical resistivity is very sensitive to the presence of voids (Samouëlian *et al*., 2004) and the delineation of voids, their position and geometry would have required a resolution greater than that adopted in our system, with therefore a smaller inter-electrode distance. Moreover, ERT imaging ability is linked to the choice of the data inversion scheme. Every inversion method makes assumptions about resistivity distribution in subsoil, and implements them in the form of constraints. The accuracy of the inversion results thus largely depends on how such assumptions meet actual sub-surface resistivity distribution. The routine that we used is based on a smooth inversion method that is ideal for modelling complex geometries where resistivity is expected to vary arbitrarily in any direction and in a smooth manner, as it is with fluid migration; where there is a sharp interface between soil features this approach tends to smear out the boundaries (Olayinka & Yaramanci, 2000). Séger *et al*. (2009) studied the effect of tillage on a previously compacted soil with ERT and proved that even small voids were capable of altering resistivity distribution even though they could not be detected in the tomogram because of the poor sensitivity of the inversion routine to abrupt variations in resistivity, as happens with voids.

Surface ER tomography with finer spacing is used in selected cases for soil tillage research with inter-electrode distance from 0.05 m (Muller *et al*., 2009) to 0.10 m (Besson *et al*., 2004), thus allowing features such as compacted zones to be detected with greater resolution but covering smaller areas. Centimetre-scale methods used in laboratory applications are able to detect single stones or voids (Samouëlian *et al*., 2004). Coarser (metre-scale) spacing is more common for petrographic or landfill research, which explores larger areas and deeper layers but would not be capable of analysing the tilled layer.

In our experiment no significant difference in average ER was found between tilled and untilled plots. This is related to a large within-plot variation, mainly linked to areas of large resistivity at various locations in the plots. The short range (<2 m) of auto-correlation effects that might be linked to local gravel lenses makes ER predictable from the values at nearby locations with no need for further information. Therefore tillage, which is a spatial process itself but exerts effects over a larger spatial scale, becomes a redundant predictor.

Nevertheless, when the spatial dependence was analysed separately for the two treatments, clear differences emerged: in untilled plots there was a greater continuity in the spatial structure than in tilled plots that had a smaller range and a larger nugget, and both findings conform to expectations because ploughing breaks up the continuity of soil structural features.

Conclusions

Resistivity tomography was capable of detecting and quantifying stones across tillage treatments, but ER was best modelled as the multivariate response of different soil variables and their interactions, because of natural soil variation in clay and gravimetric water content. The technique has therefore a great potential but quantitative applications require calibration or care to ensure uniformity of other soil variables and to minimize interactions. Nevertheless, even uncalibrated ERT can provide useful semi-quantitative or qualitative information on coarse fragments, such as position and extension of the gravel lens, and allows imaging of gravelly areas at several soil depths. Its extension to 3D imaging would also allow volume estimates. Such information can greatly improve sampling efficiency through surface-response schemes and understanding of the system's dynamics.

Tillage effects were not strong enough to overcome within-plot variation at a smaller scale, probably because of stone lenses, and therefore there was no significant difference in ER between treatments. However, the spatial structure of ploughed plots showed less continuity and more data noise compared with untilled soil. This may be ascribed to fractionation of soil structural units through ploughing but also to a greater percentage of stones found in till plots. The results of this research on the relationship between ER and coarse fragments, and reports on the effects of stones on data noise in agricultural soil, lead to the hypothesis that kinetic sieving may have an effect on the electrical behaviour of tilled soils. In stony fields this effect may confound electrical responses related to structural effects of tillage, but it may also open the way to new methods for their detection.

Decimetre-scale electrode spacing as used is this experiment proved to be able to detect stone lenses in spite of superimposed tillage treatments. This situation allowed us to study the tilled layer and is non-invasive and less time consuming than any destructive sampling technique. Moreover, our scale of measurements lends itself to a rather immediate extension to fast plot scale and field scale extensions through systems for continuous measurement of ER on-the-go, which measure the top few decimetres of soil and cover hectares in a day of work, and therefore provide measurements relevant to the tilled layer in a very short time and over large areas.

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