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The use of the ARP© system to reduce the costs of soil survey for precision viticulture

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ABSTRACT

The goal of this research was to develop a procedure to minimize the cost of soil survey optimizing ARP© (Automatic Resistivity Profiling) deployment and selecting the best placement of the sampling sites to employ for soil profile description and analysis.
In this respect, devoted tests were conducted in a 3.5 ha vineyard located in Tuscany (central Italy). ARP© produced close-spaced measurements (2335 points) of geo-referenced values of apparent electrical resistivity (ERa) related approximately to 0.5 m depth. A fast soil surface sampling (0.1–0.3 m depth) was contemporarily carried out for analyzing moisture, particle size distribution and electrical conductivity. Relationships between soil properties, elevation and ERa data were analyzed along with a comparative investigation about the cost for soil description, analysis and ARP survey.
The best correlated soil property (clay) to ERa was then employed for evaluating its predictability starting from different combinations of reduced ARP measurements and sampling sites chosen by regression-driven method and the ESAP (ECe Sampling, Assessment and Prediction) software.
It was noticed that the reduction of the soil sample number affects clay map predictability less than the decrease of ARP survey intensity. The regression approach provided higher clay predictability than ESAP for the densest ARP survey and loosest soil sampling.
Such a procedure can be applied to fields once the geoelectrical calibration phase is performed. Given that the study case can be considered representative of many Mediterranean viticulture districts, we are confident that the methodology can be widely used. These findings indicate that ARP on-the-go sensor can fruitfully support traditional soil investigation, allowing the cost reduction for sampling and laboratory analyses.

1. Introduction

It is well recognized that there is an increasing need in agriculture to adopt site-specific management because of economic and environmental pressures (Frogbrook and Oliver, 2007; Ortega et al., 2003). Nevertheless, this management requires accurate knowledge about the spatial variation of soil properties within fields. In viticulture, in particular, the understanding of the nature, extent and causes of vineyard variability may help grape-growers and winemakers to use precision farming tools to improve management practices such as irrigation, fertilization, pruning and harvesting (Bramley and Lamb, 2006).

In this perspective, on-the-go sensors for measuring soil apparent electrical resistivity (ERa) or conductivity (ECa) can be used to assess soil spatial and temporal variability. These geoelectrical properties can be indirectly related to many soil physical and chemical properties such as texture, structure, water content, and salinity (Samouelian et al., 2005). In particular, mobile electrical conductivity sensors are most popular than the resistivity ones. Basso et al. (2010) remarked that reports on the application of the ARP© (Automatic Resistivity Profiling) device to agriculture are still limited in the scientific literature. Actually, such an instrument is not a commercial product and has been mainly applied to archeology prospection (Campana et al., 2009; Dabas, 2006, 2009; Dabas et al., 2000).

The geophysical methods, including both invasive (direct contact: e.g., Veris 3100 Sensor Cart — Veris Technologies, Salina, KS) and non-invasive (electromagnetic: e.g., Geonics EM-38 and EM-31) sensors, are considered very sensitive for describing subsurface soil properties without disturbing the soil in depth. Bramley and Lamb (2003), for instance, found that a traditional soil sampling survey on a 75 m grid was less able to provide an overall understanding of the reasons for vineyard yield and quality variability compared to the same survey chosen on the basis of a high resolution proximal soil sensing. Actually, as observed by Johnson et al. (2001), the maps provided by these field-scale sensors demonstrated to be a good basis for soil-sampling strategies, accurately reflecting spatial variation.

The ESAP-95 software package (Corwin and Lesch, 2005a, 2005b; Lesch et al., 2000) was designed to generate optimal sampling schemes

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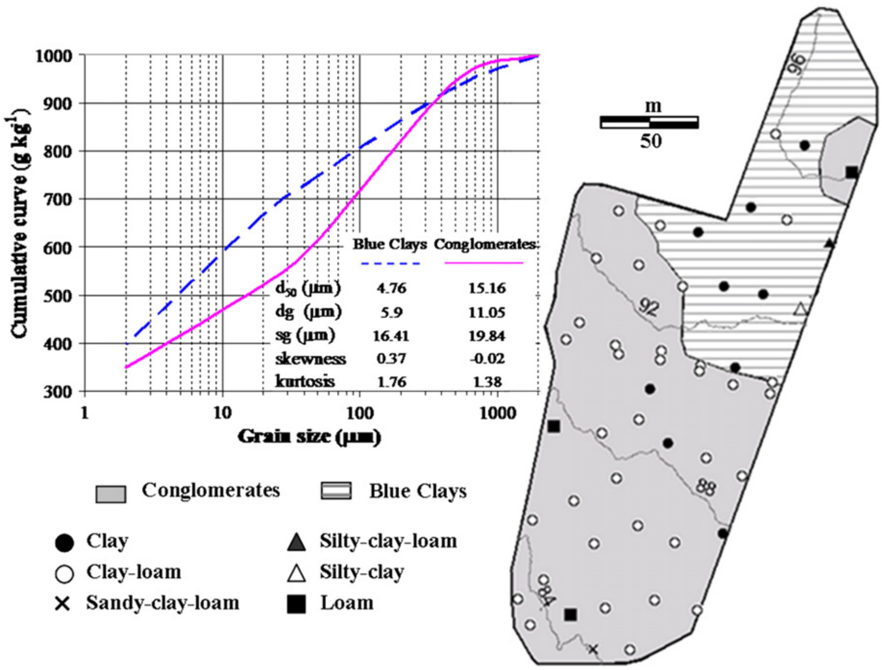

Fig. 1. Geological map, altitude (m asl), and soil sampling points differentiated on the basis of the texture class. Descriptive parameters of the grain-size distributions along with the cumulative curves for both the soils are indicated.

from soil apparent electrical conductivity information. This sampling approach is aimed at minimizing the number of samples, while fully accounting for the spatial variability. The ESAP software provides only three options of calibration/sampling locations per field: 6, 12 or 20. Usually ESAP accepts survey data generated by nearly all types of commercially available geoelectrical instrument and is also able to manage various types of remotely sensed data, such as NDVI (Normalized Difference Vegetation Index).

Wienhold and Doran (2008) employed the software for selecting soil calibration sites starting from apparent soil electrical conductivity data, and in turn for evaluating the spatial variability of some soil properties (soil salinity, clay content, nitrates and pH). Other common uses of the ESAP software are soil sampling design and the successive spatial characterization of soil salinity on the basis of apparent electrical conductivity information (Amezketa, 2007; Amezketa and de Lersundi, 2008; Cassel et al., 2008; Corwin and Lesch, 2003).

Nevertheless, the cost of a mobile sensor survey cannot be considered negligible. To this end, Farahani and Flynn (2007) studied the different qualities of soil ECa maps provided by widening the transect width for the Veris 3100 equipment in a 44.6 ha field. In particular, they demonstrated that map accuracy slightly deteriorated as transect width increased from the initial value of 2.5 m to about 50 m; but when transect widths were equal or more than 80 m, quality declined severely, and field delineations in different ECa zones became highly distorted and the soils wrongly classified.

At the same time, it is well recognized that developing appropriate soil sampling protocol is crucial to obtain useful information (Wu et al., 2009). Several studies investigated how the sampling density affects the accuracy (Bourennane et al., 2004; Frogbrook and Oliver, 2000; Oliver and Frogbrook, 1998) and precision of the resulting map (Iqbal et al., 2005; Oline and Grant, 2002; Sobieraj et al., 2004; Western and Blöschl, 1999).

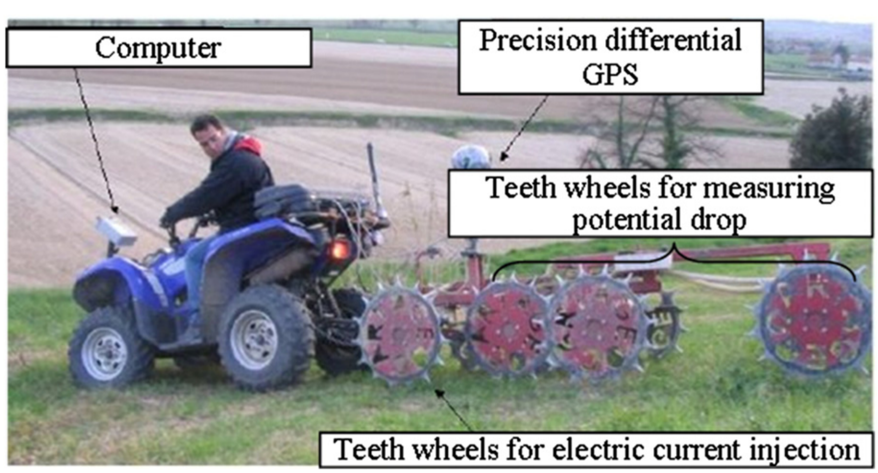

Fig. 2. A view of the ARP© (Automatic Resistivity Profiling) device (photograph by SOING).

Although geo-electrical surveys have been already introduced into viticulture (Bramley, 2009; Bramley et al., 2011a, 2011b; Costantini et al., 2010; Dabas and Cassassolles 2002; Morari et al., 2009), the reliability of different densities of geophysical investigation in supporting conventional soil survey has not yet been investigated. In particular, suggestion provided by Farahani and Flynn (2007) cannot be applied to many Mediterranean countries, where precision agriculture is mainly adopted in high-income agricultural cropping systems such as viticulture for high quality wine production, typically practiced in small vineyards (I numeri del vino, 2008).

With the aim of correctly relate the pattern of ERa spatial variability to soil properties and verify the possibility of reducing the survey cost, this research dealt with the following issues: 1) identify the most influencing soil characteristics on the resistivity and find the mathematical relationship between them; 2) assess the accuracy of the resistivity maps provided by different ARP survey densities; 3) compare the accuracy of soil spatial variability provided by the combined use of ARP with an expeditious soil survey, each with different densities of investigation; 4) address the location of sites for a successive punctual and more exhaustive soil profile description; and 5) compare the results provided by authors' soil sampling design (called from now on regression-driven method) and by ESAP selected sites.

2. Materials and methods

2.1. Study site

The study area, located in Tuscany (central Italy; 43°13′N; 10°38′E), is particularly suited to high quality wine production. The test field (3.5 ha) was placed on a gentle south-west facing slope. The size of the field is representative of vineyards in Italy (ISTAT, 2010) and in many Mediterranean countries.

The geology of the area is represented by two formations (Fig. 1): marine clays of the Pliocene in the upper part of the field, and conglomerates of the Pleistocene dominating the median and lower part: on the former Endostagnic Cambisols (Calcaric, Sodic) (WRB classification system – FAO, IUSS, ISRIC (2006)) or Aquic Haploxerepts (Soil Taxonomy – Soil Survey Staff (2006)) dominate, Haplic Cambisols (Eutric) or Typic Haploxerepts on the latter.

2.2. Mobile resistivity survey

The geoelectrical survey was carried out by employing the ARP© (Automatic Resistivity Profiling) device (Fig. 2). This technique is less common than the other on-the-go sensors, such as Veris 3100 or electromagnetic instruments, as it is not a commercial product.

The ARP© device is an automatic system for geo-resistivity survey able to acquire and process in real-time both electrical resistivity data and GPS information. Horizontal and vertical positioning of the ARP system is obtained with a GPS with differential corrections (StarFire, John Deere). The whole system is controlled in real-time by a PC which enables acquisition, processing (to remove outlying observation and reduce data roughness, as indicated in Rossi et al. (2013)), storage and visualization of the electrical resistivity data by the operator while driving. Horizontal precision is defined by the DGPS manufacturer (for StarFire 30 cm minimum). Vertical precision is of the order of 60 cm. The precision of the resistivity values is 1%.

The mechanical part of ARP system is made of four dipoles: the first one injects a stabilized current into the ground; the following three dipoles measure the related potential. The depth of investigation is a function of the geometry of the electrodes and the soil being probed. Increasing the distance between electrodes will increase the depth while decreasing the measured potential. The distance between the three potential dipoles is respectively 0.5, 1 and 2 m. The amplitude of the current is 10 mA. Whatever the speed of motion, this device can make a measurement at a fixed distance interval (0.2 m) along each transect.

The computer processes all the raw resistivity values by a 1D median filter and then provides a sub-sample of ERa data at points 3 m apart, on average, along each transect. The apparent electrical resistivity of the soil (ERa) is expressed as Ω m and can be easily converted into apparent electrical conductivity (ECa) as follow ($ECa = \frac{1}{ERa}$). The major novelty of the ARP technique, compared to the traditional resistivity arrays, is represented by the employment of a resistivimeter, designed for optimized synchronous measurement of three channels with a quick time response (44 ms) and therefore able to perform up to 30,000 measurements per hectare in continuous. Further characteristics of the apparatus, including its technical development, are thoroughly described in Dabas (2009).

During the survey, the ARP performed 22 transects 6-m spaced, parallel to the vineyard length, along with the delineation of the field boundary. At each measurement point, three soil apparent electrical resistivity values at 0–0.5, 0–1.0 and 0–1.7 m depth were measured and tagged with geographical co-ordinates (UTM) including elevation. In this paper, only the surface (0–0.5 m) apparent resistivity data (ERa_{50}) were employed to be combined with the analyzed soil properties.

2.3. Resistivity map creation

Resistivity and elevation (H, m asl) data were interpolated over the whole study area with the GIS software ArcGIS V.9.2 (ESRI Co, Redlands, USA) by means of the Ordinary Kriging interpolation algorithm, producing raster maps with a 3-m cell size. A detailed description of the geostatistical analysis is provided in Appendix A. Successively, a buffer of 3 m radius was created around each soil sampling point in order to average both resistivity and elevation data. The mean ERa_{50} and H values of the buffered area were then calculated and coupled to the corresponding soil sample data. A correlation matrix was then employed to find out the most significant relationships between ERa_{50}, H, and both soil physical and chemical data.

2.4. Soil sampling and analyses

An expeditious soil survey was carried out in May, contextually with the geoelectrical investigation, with the objective of calibrating the apparent resistivity data. During the survey, soil samples in the 0.10–0.3 m layer were collected by hand drilling at 50 sites located according to an almost regular grid (40 × 20 m) (Fig. 1). A density of 50 sites for an extension of 3.5 ha corresponds to about 14 samples ha^{-1}, which can be considered fitting the standard requirements for a 1:2000 soil map (FAO, 1979). Laboratory analyses included some basic lab determinations for both the variable and inherent soil properties that most affect the resistivity data (Samouelian et al., 2005): gravimetric soil

Table 1
Daily cost of the soil survey activities (reference scale 1:2000).

Activity	Cost per day (EUR)	Work done in a day	Lab analysis (EUR)
ARP investigation	3000	10 ÷ 20 ha	
ARP calibration	300[a]	25 drills	750[b]
Soil profile excavation	500[a]	16	
Soil profile description and analysis	500[a]	3 profiles	1000[c]

[a] Value referred to standard cost of soil survey according to Italian Professional Order.
[b] Average value of the cost required by a private laboratory to determine texture, moisture, and E.C.
[c] Average value of the cost required by a private laboratory to determine texture, moisture, pH, E.C., cation-exchange capacity, exchangeable bases, organic carbon, total and active carbonate.

Table 2
Physical and chemical properties of the 50 soil samples. Reported values are averages, with the corresponding variation coefficient in parentheses.

Drills number	50
Water content % (w/w)	14.47 (20.85)
Sand % (w/w)	35.33 (22.6)
Silt % (w/w)	28.49 (21.17)
Clay % (w/w)	36.18 (14.46)
EC (1:5) (dSm^{-1})[a]	0.40 (22.77)
Elevation (m asl)	90.35 (4.60)

[a] EC: electrical conductivity measured in a 1:5 soil:water suspension.

Table 3
Summary of ERa_{50} statistics for different survey densities.

	Number of transects		
	22	10	5
Transect width (m)	6	12	24
ERa_{50} sampling points per ha	667	417	276
ERa_{50} sampling points statistics			
Minimum (Ω m)	5.2	5.2	5.2
Maximum (Ω m)	58.3	57.6	57.6
Mean (Ω m)	17.3	17.5	17.8
Standard deviation (Ω m)	6.7	7.0	7.7
Variation coefficient (CV)	38.7	40.0	43.2
ERa_{50} prediction over the whole area			
ω value		83%	74%
θ value		0.36	0.36
κ value		73%	59%
Agreement classification		Substantial	Moderate

moisture, particle size distribution by hydrometer method, and electrical conductivity on a 1:5 soil:water suspension.

The evaluation and understanding of the actual soil variability of the field (relation between soil properties and ERa data) permitted the choice of the sites where digging soil profiles to be thoroughly described and analyzed. The number and location of these profiles will be described at the paragraph 2.5.

2.5. Survey strategy set-up

With the aim of simulating the reduction of the ARP survey cost, the operative time was decreased by enlarging transects. The accuracy of predicting ERa_{50} values for different widths (6, 12 and 24 m), equivalent to 22, 10 and 5 passages respectively, was evaluated. The different reliability of the ERa_{50} values provided by each investigated ARP density was compared to the interpolation of the ERa_{50} values obtained by the most intense survey (22 rows). Accuracy analysis was employed to compare the quality of ERa_{50} maps for different ARP transect numbers. ArcView Kappa analysis tool (κ-analysis), which generates a confusion matrix containing categorical similarities between the observed values and the predicted ones, was used. In particular, three equi-quantile categorical classes, which adequately described the soil spatial variability, were employed. The equi-quantile criterion was adopted to ensure major robustness to the statistical procedure of the κ-analysis based on a pixel by pixel comparison over the whole area. In such a way all the three categorical classes had the same weight within the κ-analysis. A detailed description of the accuracy assessment is provided in Appendix B.

To further simulate a reduction of the survey cost, it was necessary to lower the number of soil profiles being dug. Therefore the density and location of the profiles had to be decided according to soil spatial variability. The capability of different sub-sets of soil sites to represent the whole soil spatial variability had to be selected from the 50 drills grid employed for calibrating ERa data, where essential lab analyses had already been carried out.

Two different approaches were employed and compared to select density and number of the profiles: 1) ESAP and 2) regression-driven.

1) ESAP approach is based exclusively on the information provided by the ERa data. For each ARP density (22, 10, and 5 transects) ESAP algorithms selected a fixed set of sampling sites (6, 12, or 20 sites), extracted from the 50 drills, spread over the study area and able, in theory, to optimize the estimation of the prediction model. By

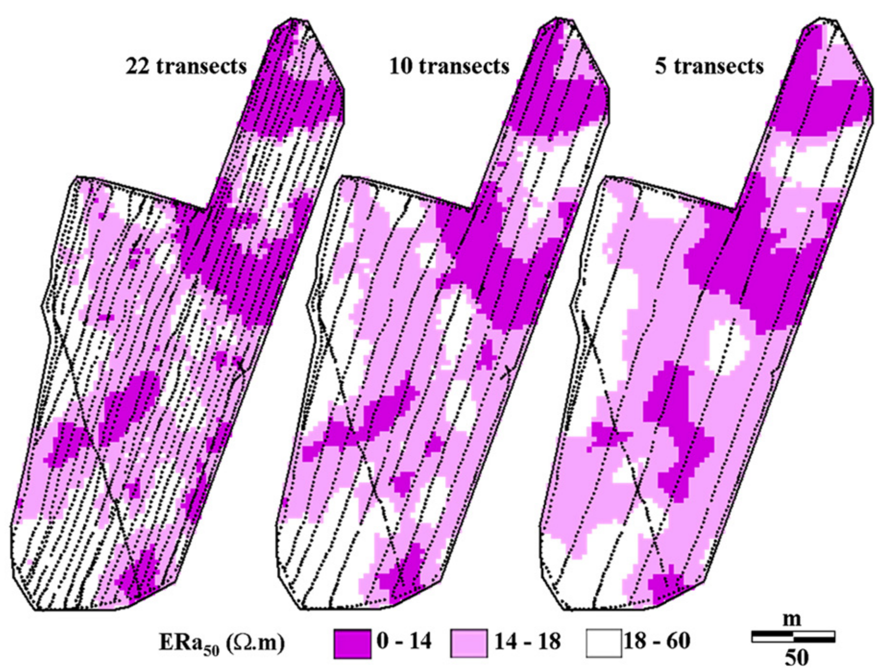

Fig. 3. ERa_{50} maps for 22, 10 and 5 ARP transects.

Table 4
Correlation matrix among soil and site parameters, and mean ERa_{50} values for different ARP survey densities.

	Water content	Sand	Silt	Clay	EC (1:5)	Elevation	ERa_{50} 22 transects	ERa_{50} 10 transects	ERa_{50} 5 transects
Water content									
Sand	0.103 ns								
Silt	−0.234 ns	−0.755***							
Clay	0.111 ns	−0.659***	0.007 ns						
EC (1:5)	0.036 ns	−0.769***	0.555***	0.537***					
Elevation	−0.064 ns	−0.563***	0.362**	0.443**	0.703***				
ERa_{50} 22 transects	−0.258 ns	0.497***	0.035 ns	−0.801***	−0.443**	−0.269 ns			
ERa_{50} 10 transects	−0.164 ns	0.545 ***	0.003 ns	−0.837***	−0.471***	−0.295*	0.968***		
ERa_{50} 5 transects	−0.120 ns	0.525***	0.011 ns	−0.816***	−0.414**	−0.334*	0.891***	0.937***	

ns: non significant.
*** Significant at 0.001 probability level.
** Significant at 0.01 probability level.
* Significant at 0.05 probability level.

design, the ESAP program will try to achieve an as uniform as possible sampling plan, in agreement with the ESAP User manual guidelines (Lesch et al., 2000); however, good spatial distribution uniformity is not always achievable. Therefore, for each set of soil survey density, several ESAP simulations were iterated until the uniformity pattern of the sampling design was maximized across the study area.

2) For the same combinations of soil survey density adopted by ESAP, the regression method addressed the best location of sites for successive soil profile description in two steps. Firstly the choice was guided by the ERa_{50} maps and secondly selecting the sites able to maximize the significance of the regression between H, ERa_{50} and clay content, considering all the possible sets of samples of the same resistivity class.

In order to compare the uniformity pattern of ESAP selection with that obtained by the regression approach, the index of dispersion (ID) was calculated according to Johnson and Zimmer (1985) (Eq. (1)):

$$ID = (n+1)\frac{\sum_{i=1}^{n}\left(d_i^2\right)^2}{\left[\sum_{i=1}^{n} d_i^2\right]^2} \quad (1)$$

where d_i is the nearest neighbor distance and n is the number of the soil sampling sites. Expected value of ID for random patterns is 2, while clustered patterns have values higher than 2, and uniform patterns have values lower than 2.

Clay maps were elaborated implementing regressions in ARC Map starting from ERa_{50}, and H data for the different combined survey strategies, variable in terms of ARP transect density and number and location of the profiles (selected by the two approaches).

It was thus possible to compare, by means of κ-analysis, the results provided by the densest combined survey (22 ARP transects −50 sites) with all the other grouping of soil sites (20, 12, 6) and ARP transects (10 and 5), with both the ESAP and regression-driven approaches.

Clay values were converted into 3 categorical classes, divided according to the equi-quantile criterion, to be used in the confusion matrix. It is to point out that by applying the equi-quantile criterion the thresholds of 345 and 387 g kg^{-1} were automatically fixed; for agronomic purpose these limits were approximated to 350 and to 390 g kg^{-1} respectively without significantly modifying the distribution of the pixels among the classes. The first limit of clay content conveniently separates clayey soil families from the others, according to Soil Taxonomy (Soil Survey Staff, 2006).

2.6. Survey cost analysis

With regard to the possibility of reducing the cost of the whole survey it was first of all necessary to separate the price for soil profile digging, description and analysis, from that for the ARP investigation, comprehensive of the calibration phase (i.e., including the quick soil drilling and basic lab analysis).

Table 1 shows the daily cost for both the investigations, along with the corresponding amount of work needed. The third column in the table indicates the cost for analyzing 6 profiles, assuming the presence of three horizons.

It is to point out that the amount of work done by the ARP may vary along with the topography and geometry of the area being investigated (unevenness, steepness and contiguity), being the survey density equal.

3. Results and discussion

3.1. Soil properties

Fig. 1 illustrates the geological map, location and texture characteristics of the 50 drills along with the particle size distribution curves of both soils. Table 2 shows the statistics of the main soil physical and

Table 5
Summary of ERa_{50} (Ω m) statistics for different numbers of ARP transects and soil sampling sites selected according to a) the regression approach and b) the ESAP approach.

	ERa_{50}-22 transects				ERa_{50}-10 transects			ERa_{50}-5 ransects		
Sampling sites (n)	50	20	12	6	20	12	6	20	12	6
Statistics										
a)										
Mean	17.34	17.98	18.36	15.95	17.92	18.76	18.74	17.38	18.06	18.80
Standard deviation	4.79	6.27	7.10	6.55	6.03	7.48	8.67	6.65	7.73	8.33
b)										
Mean	17.34	18.24	17.60	18.01	18.45	18.51	17.52	18.85	18.22	20.09
Standard deviation	4.79	6.83	6.33	6.74	6.67	6.52	7.97	7.19	6.96	7.68

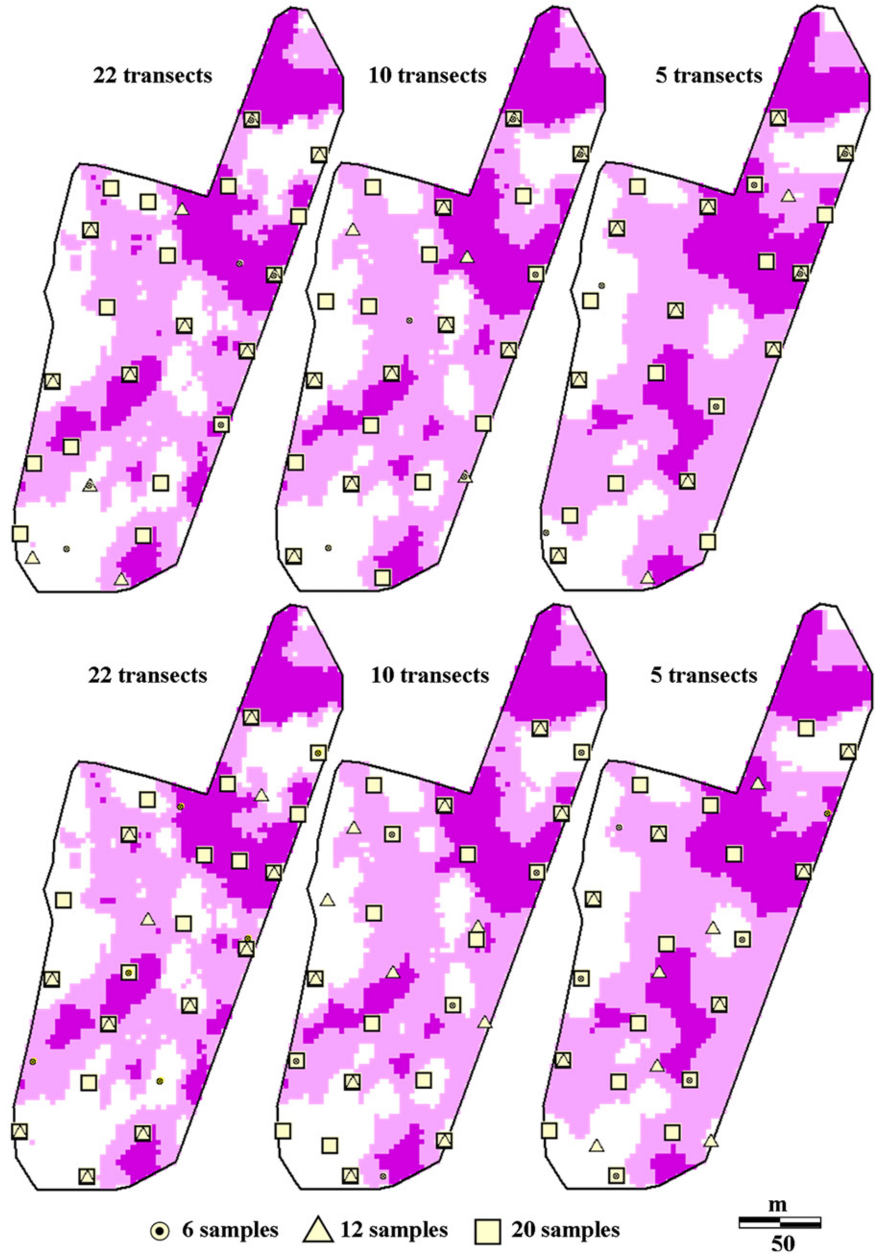

Fig. 4. Location of the sampling points for different soil survey strategies according to both the regression driven (above) and the ESAP (below) approaches on ERa_{50} maps for the three ARP densities investigated.

chemical characteristics indicating that soil EC and sand content are characterized by higher variability with respect to the other features.

In relation to the texture analysis, Fig. 1 indicates that on average the soil on clays was characterized by lower both median (d_{50}) and mean geometric diameter (dg) compared to the other soil; in addition, the two soils were extremely poorly sorted (high geometric standard deviation value) and characterized by a symmetrical shape of the granulometric curve; moreover, kurtosis values indicate a platykurtic distribution for clays and a very platykurtic for conglomerates. The extreme poor sorting of the two soils is responsible for the differentiation of the textural classes found within each geology formation. In particular, on blue clays, the clay textural class represented 50%, whereas the clay–loam textural class represented 33%; the remaining was equally distributed between silt-loam and silty-clay–loam textural classes. On the conglomerates, the clay–loam textural class dominated (81%) and was followed by clay and loam textural classes (almost 8% each).

3.2. Resistivity map quality

The interpolation of the ERa_{50} values using 22, 10, or 5 ARP transects by means of the Ordinary Kriging procedure produced comparable maps (Fig. 3). Each density, in spite of the very different numbers of measurements per ha and transect widths, produced similar basic statistics of ERa_{50} values calculated over the whole area, indicating a high soil spatial variability (Table 3) in agreement with the textural composition of the soils.

It is noteworthy that only the 10 rows grid, corresponding to a reduction of almost 40% of both measurements, provided a substantial agreement, in terms of ERa_{50} predictability, with the result given by

Table 6
Coefficient of determination and significance level of the regressions for different numbers of ARP transects and soil sites selected by both the regression and ESAP approaches. ID values are also indicated.

ARP transects (n)	Soil site number (n)	R^2	Significance level	ID	R^2	Significance level	ID
22	50	0.732	***				
		Regression approach			ESAP selection		
22	20	0.830	***	1.41	0.889	***	1.26
	12	0.901	***	1.42	0.977	***	1.29
	6	0.989	**	3.39	0.853	ns	1.46
10	20	0.877	***	1.41	0.851	***	1.33
	12	0.918	***	2.25	0.890	***	1.31
	6	0.935	*	3.13	0.977	**	1.44
5	20	0.853	***	4.45	0.889	***	1.53
	12	0.906	***	3.16	0.977	***	1.26
	6	0.920	*	3.39	0.853	ns	1.44

ns: non significant.
*** Significant at 0.001 probability level.
** Significant at 0.01 probability level.
* Significant at 0.05 probability level.

the densest ARP survey. In contrast, further reduction to 5 rows reduced significantly the ERa_{50} predictability and produced a moderate agreement with the most expensive strategy.

3.3. ARP soil relationships

3.3.1. Correlation matrix between soil properties and resistivity values

In order to understand the relationship between ERa_{50} values and the soil characteristics, a correlation matrix was produced for the whole data set — 50 samples (Table 4). Moisture content was not related to either soil properties or ERa_{50} values, silt was significantly related to ECa and H only; therefore, these parameters could not be interpolated over the whole study area starting from the resistivity values. Elevation was positively linked to clay content in accordance with the different geological substratum locations within the vineyard (see Study site description). Table 4 shows as clay percentage assumed the highest correlation coefficient versus all ERa_{50} data ($|r| \geq 0.801$) compared to all the other soil properties, and for this reason it was employed to test/compare the performance of different soil survey densities.

3.3.2. Resistivity statistics for different sampling site selections

Before illustrating the comparison of the clay maps provided by the two approaches, it is interesting to have a look at the main ERa_{50} statistics for the various survey strategies and site selection approaches (Table 5). Generally, the various selections provided comparable ERa_{50} mean values with respect to the densest ARP and soil sampling. However, as expected, by lowering the number of both ARP transects and soil samples, the discrepancies increased in terms of standard deviation values. Fig. 4 indicates, for the three ARP survey densities, the different selections of soil sampling sites obtained according to the regression (Fig. 4 above) and the ESAP criteria (Fig. 4 below).

3.3.3. Regressions between H–ERa_{50} data and clay content

As previously stated, for each sampling site selection strategy, obtained by either the regression or by ESAP approach, regression equations were calculated starting from H and ERa_{50} data for the various soil and ARP survey densities. These equations were then implemented in GIS technologies to map clay content over the study area. The coefficients of determination and the significance levels of the regressions are reported in Table 6, along with the dispersion index (ID) values.

The values in the first row in Table 6 refer to densest combined survey (50 samples — 22 ARP transects) representing the common comparison term.

It is to point out that the elevation improved the coefficient of determination, for instance from $R^2 = 0.690$ (value not shown) to 0.732 for 22 ARP transects combined with 50 sites, and most of all the levels of accuracy of clay map over the whole area.

Generally, both approaches provided comparable significant relationships with the exception of the loosest sampling design (6 sites combined to 22 or 5 ARP transects) where ESAP did not give significant regressions. On the contrary, as expected, ESAP selections gave lower ID values providing higher uniformity patterns than regression sites, as illustrated in Fig. 4. In particular, for the regression sites only, the reduction of the density for both the surveys promoted the clustering patterns generation (as highlighted by the ID values increase).

Actually, the ESAP procedure minimized the ID, whereas the regressions approach maximized the predictability of clay content. In particular, in the case of the ESAP selection, the regressions which involved 6 samples with 22 or 5 ARP transects were not significant ($p > 0.05$).

Conversely, all the regressions involving at least 12 sites selected by the regression approach were highly significant, and only further reduction to 6 sites deteriorated the significance at 0.01 and 0.05 levels, for 22 ARP transects and 10 or 5 ARP transects, respectively. Therefore, the reduction of soil sample number to 1.71 ha^{-1} affected more the predictability of clay than the lowering of the ARP transect number.

3.4. Comparison between regression and ESAP approaches in terms of clay predictability

Table 7 illustrates the accuracy of the clay estimates for the different survey strategies over the study area, provided by the regression and ESAP approaches. The results obtained by non significant regressions have been excluded.

The regression approach provided higher clay predictability than ESAP for the densest ARP survey and loosest soil sampling. Comparable results are observed with 10 ARP transects. It may be noticed that, as a rule, the reduction of the soil sample number affects clay map

Table 7
Results of the confusion matrix for the clay accuracy determination on the basis of both the regression and ESAP approaches.

		22 ARP transects (667 points ha^{-1})			10 ARP transects (417 points ha^{-1})			5 ARP transects (276 points ha^{-1})		
Soil samples (n)	Sample density (n ha^{-1})	ω value	κ value	Agreement class	ω value	κ value	Agreement class	ω value	κ value	Agreement class
Regression approach										
20	5.71	91%	86%	Almost perfect	83%	73%	Substantial	73%	58%	Moderate
12	3.43	92%	87%	Almost perfect	74%	60%	Substantial	73%	58%	Moderate
6	1.71	76%	63%	Substantial	81%	71%	Substantial	72%	57%	Moderate
ESAP approach										
20	5.71	85%	76%	Substantial	81%	71%	Substantial	74%	60%	Moderate
12	3.43	79%	68%	Substantial	77%	64%	Substantial	74%	60%	Moderate
6				–	80%	69%	Substantial			–

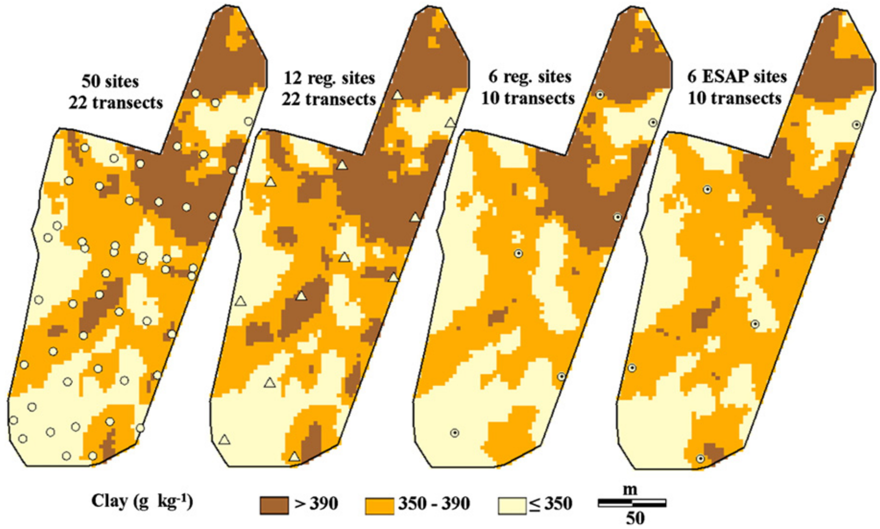

Fig. 5. Clay maps and corresponding location of the soil sites relative to some convenient combinations of soil and ARP survey densities, all providing at least a substantial agreement.

predictability less than the lowering of the ARP survey intensity, and that 20 sampling sites are never necessary in all the ARP densities (Table 7), because it is possible to achieve the same accuracy level with a lower soil sample number (12 or even 6).

Fig. 5 shows some of the clay maps obtained starting from the regression equations listed in Table 5. As a comparison, clay grid values provided by 22 ARP transects and 50 soil samples are also shown. The location of soil sampling sites is also displayed. In particular, as indicated in Table 6, the map given by 22 transects — 12 sites chosen with regression method is more similar to the reference one (almost perfect agreement) than the other two maps, providing a substantial accuracy. The comparison between the latter two grids outlined that the 6-sites regression showed a good reproducibility in the upper part of the map, while 6-site ESAP gave a good similarity in the lower part of the map; in the remaining area the two maps are comparable.

3.5. Comparison of the survey costs

The costs of some possible combinations of survey density (number of ARP transects and soil sites) are compared in Table 8, along with a sketchy description of each activity.

Taking in mind that the ARP employs a day to cover an average surface of 15 ha (Table 1), it is possible to hypothesize several alternatives to the densest density, equivalent to 667 points ha^{-1}. The reduction of the ARP survey density to 10 or 5 transects (417 or 276 points ha^{-1}) could allow to cover nearly 30 and 60 ha per day, respectively, at the same cost of 3000 EUR (Table 8). In such hypotheses the number of drills, located according to a regular pattern, required for calibrating the ERa data, does increase by enlarging the area. In particular, the minimum number of drills can be obtained from the maximum values (78 m) of the effective range of the semivariograms described in Appendix A. Therefore, supposing a drill every about 6000 m^2 (78 × 78 m assuming an omni-directional semivariogram), it is possible to calculate the corresponding number for the hectarages indicated in Table 8. The price for drilling and lab analyses is also indicated in the same table. Going on to the cost for the soil profile excavation, description and analysis, it is to point out that, although all the indicated sites are supposed to be excavated and observed, the complete description and analysis are typically restricted to one tenth of the profiles, the choice depending on the characteristics of the entire soil section.

4. Conclusions

The most influencing soil characteristics on the resistivity data in the study area were the clay content. The relationships we found out between H–ERa$_{50}$ and clay might be considered constant over time, since the moisture conditions were almost homogeneous and not related to the resistivity values during the survey.

With respect to the possibility of lowering the survey cost the regression procedure offered several possibilities of reducing survey intensity with different accuracy levels: if an almost perfect agreement was required, it would be convenient to dug 3.43 profiles ha^{-1} in combination with the densest ARP survey. Otherwise, if a substantial agreement might be considered acceptable, even 1.71 profiles ha^{-1} and 417 ARP points ha^{-1} would be enough. A moderate agreement might be achieved with the scarcest combined survey density.

Table 8
The costs of some possible combinations of the survey density.

Area (ha)	Survey density (points/sites ha^{-1})	Activity							Tot (EUR)	Tot/ha (EUR)
		Calibration				Profiles				
		ARP survey (EUR)	Drills (n)	Drills (EUR)	Lab (EUR)	Profiles (n)	Escavation (EUR)	Description and analysis (EUR)		
15	667/5.71	3000	25	300	750	85	2677	4283	11,009	734
15	667/3.43	3000	25	300	750	51	1608	2573	8230	549
15	667/1.71	3000	25	300	750	26	802	1283	6134	409
30	417/1.71	3000	50	600	1500	51	1603	2565	9268	309
60	276/1.71	3000	100	1200	3000	103	3206	5130	12,386	206

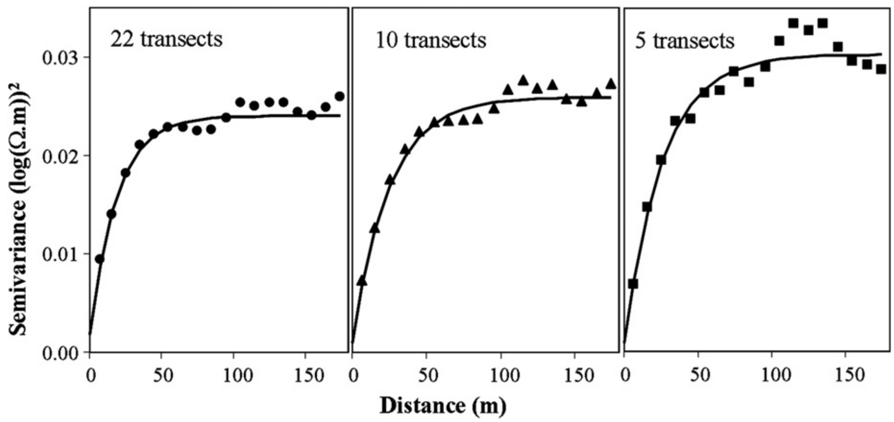

Fig. A.1. Experimental (dots) and fitted (line) omni-directional semivariograms for a) 22 transects, b) 10 transects and c) 5 transects.

Conversely, ESAP selections provided at the most a substantial agreement with the combined survey of 1.71 profiles ha^{-1} and 417 ARP points ha^{-1}. A moderate agreement might be conversely provided by 3.43 profiles ha^{-1} at least with the lowest ARP survey density.

Going on to the choice of the best/convenient survey strategy, it is useful to distinguish the farm type and requirements. If a wide area has to be investigated in a day, then a looser ARP survey has to be chosen, 417 ARP points ha^{-1} for extension of around 30 ha and 276 points ha^{-1} for areas of around 60 ha, each combined with the loosest soil sampling density (1.71 points ha^{-1}). These combinations provide a substantial and a moderate accuracy, respectively at the reasonable cost per ha of 309 and 206 EUR. If the farm is small (around 15 ha) so it can be completely covered with the densest ARP survey in a day, then it is possible to adopt either a soil sampling density of 3.43 or 1.71 points per ha, in relation to the accuracy level required: almost perfect or substantial, respectively, spending approximately 549 or 409 EUR/ha.

It goes without saying that such a procedure can be applied to fields provided that the geoelectrical calibration phase is carried out. However, as the study case can be considered representative of many Mediterranean viticulture districts, we are confident that the methodology can be widely used.

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Appendix A. Geostatistical elaboration

A.1. Set-up of the variogram model and cross validation results

Starting from the measured resistivity data, collected during the three different ARP surveys with decreasing density (22, 10 and 5 transects) (Fig. A.1), the experimental omni-directional semivariograms have been elaborated by means of Surfer 8.0 Geostatistical Software (Golden Software, Inc.) (See Fig. 1a, b and c, respectively). For that purpose, the field resistivity data have been converted into Log values for guaranteeing the normality of the data (Table A.1). Actually, a first attempt to differentiate the experimental semivariograms according to the main directions of the plot, 45° and 135° (data not reported), demonstrated that a clear anisotropy did not occur, therefore isotropy was assumed.

Given that all the semivariograms seem upper bounded, the stationary was assumed. By applying an iterative fitting procedure, aimed at minimizing the sum of the squared residuals, it was possible for each of the survey densities to choose the best semivariogram model, whose characteristics are described in Table A.2.

Table A.1
Descriptive statistics of measured resistivity data before and after conversion into Log values.

ARP transects (n)	Measured data (n)	Skewness field data	Skewness Log(field data)	Kurtosis field data	Kurtosis Log(field data)
22	2633	1.389	0.032	5.694	0.335
10	1458	1.276	0.045	2.123	0.219
5	965	1.289	0.134	1.736	0.022

Table A.2
Parameters of the fitting models for all the ARP survey densities.

ARP transect (n)	Model	Nugget variance (Co)	Structural variance (C)	Total sill (Co + C)	Spatial ratio Co/(Co + C)	Number of lags	Effective range (A) [a]	Max lag distance
		$(\text{Log}(\Omega\ \text{m}))^2$				(n)	(m)	(m)
22	Exponential	0.0018	0.0222	0.0240	0.08	18	57	180
10	Exponential	0.0009	0.0250	0.0259	0.03	18	75	180
5	Exponential	0.0008	0.0295	0.0303	0.03	18	78	180

[a] The effective range is given by the distance at which the semivariogram achieves 95% of the asymptotic sill.

Table A.3
Cross-validation results expressed as statistics of the residuals.

ARP transects (n)	MinE (Ω m)	MaxE	ME	RMSE	MSE	σ^2SE	α coefficient	R^2
22	−19.93	15.16	−0.19	2.79	−0.069	1.00	0.97	0.80
10	−15.47	10.88	−0.15	2.45	−0.060	1.00	0.98	0.86
5	−15.59	11.04	−0.16	2.59	−0.061	1.00	0.98	0.88

MinE = Minimum error; MaxE = maximum error; ME = mean error; RMSE = root-mean-square error; MSE = mean of the standardized error; σ^2SE = variance of the standardized error; α is the slope of the regression between measured and predicted data; R^2 is the related coefficient of determination of the regression.

For all the ARP densities the fitted semivariograms were described by the same combination of the nugget effect plus exponential model, characterized by similar spatial ratio value. This fact indicates that all the models are affected by a strong spatial dependency while a scarce influence of the nugget variance upon the total sill is observed anywhere. A certain raise of the nugget value and a decrease of the effective range value were also registered by increasing the ARP densities.

In order to evaluate the performance provided by the fitted models, the cross validation procedure was employed. Applied to all the respective data set of points (2633, 1458, and 965 points) and basing on the leave-one-out technique, such a procedure evaluated the residuals (errors) along with a detailed statistical summary illustrated in Table A.3.

All the statistical parameters appear quite similar among the ARP survey densities, despite a slight deterioration of the performance is observed in the densest investigation (lowest coefficient of determination and highest RMSE value), probably related to the occurrence of some outliers, not investigated by the other two looser surveys (see both MinE and MaxE values).

The cross-validation results along with the parameters of the fitting models demonstrated that the Ordinary Kriging procedure, adopted to interpolate the resistivity data, provided comparable accuracy in all the ARP survey densities. The parameters of the fitting models for the three ARP survey densities have been successively imported into ARC GIS software to create the related resistivity maps.

Appendix B

B.1. Map accuracy assessment

To compare the results provided by different densities of the ARP and soil survey in terms of ERa_{50} and clay predictability, the technique of the confusion matrix was employed. Such an error matrix compares, on a class-by-class basis, known reference data (ERa_{50} or Clay class provided by 22 ARP transects and 50 sites) and the corresponding results of classification (predicted values) given by the other looser surveys.

In such matrix ($n \times n$) the predicted classification is given as rows, while the reference one (given by 22 ARP transects combined with 50 sites) is along the columns. The diagonals represent agreement maps and the reference data, while the off-diagonal elements represent different mis-classifications.

Starting from this table it was possible to calculate the most common error estimate, that is the Overall accuracy (ω) given by:

$$\omega = \sum_{i=1}^{n} {}^{e_{ii}}/_{T} \quad \text{with} \quad T = \sum_{i=1}^{n} \sum_{J=1}^{n} e_{ij} \tag{B.1}$$

where e_{ii} represents the sum of diagonal pixels, e_{ij} is the sum of all row and column elements (T = the total number of the matrix elements) and n the number of categories being considered.

The results were then expressed in terms of κ value, calculated according to the following equation (Landis and Koch, 1977), and agreement class.

$$\kappa = (\varpi - \theta)/(1 - \theta) \tag{B.2}$$

where θ is the proportion of pixels which agree exclusively by chance, that in turn is given by:

$$\theta = \left(1/T^2\right) \sum_{i=1}^{n} e_{i+} e_{+j} \tag{B.3}$$

with e_{i+} and e_{+j} being the marginal total of row i and the marginal total of column j, respectively and T the total number of the elements of the confusion matrix.

Therefore, the estimate of κ is the proportion of agreement after chance is removed from consideration. If all the pixels are in complete agreement then κ is equal to 1; conversely, if there is no agreement among the pixels (other than what would be expected by chance) then κ is equal to 0. In particular, Landis and Koch (1977) identified five equi-spaced classes of κ values ranging between 0 and 1.0 associated to different agreement classes.

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