ON-THE-GO RESISTIVITY SENSORS EMPLOYMENT TO SUPPORT SOIL SURVEY FOR PRECISION VITICULTURE

M.C. Andrenelli, E.A.C. Costantini, S. Pellegrini, R. Perria, and N. Vignozzi
CRA-ABP- Centro per l'Agrobiologia e la Pedologia,
Piazza M. D'Azeglio, 30 50121, Firenze, Italy
andrenelli@issds.it

ABSTRACT

There is an increasing need in agriculture to adopt site-specific management (precision farming) because of economic and environmental pressures. Geophysical on-the-go sensors, such as the ARP (Automatic Resistivity Profiling) system, can effectively support soil survey by optimizing sampling density according to the spatial variability of apparent electrical resistivity (ER).

The aim of this work was to test the sensitivity of the ARP methodology in supporting soil survey for precision viticulture. In particular, an optimization procedure for coupled geoelectrical and soil surveys is illustrated.

The research was carried out in a vineyard located in Tuscany (central Italy) affected by low yield due to soil salinity; the investigation was simultaneously conducted by soil survey and resistivity measurements. The ARP method consists in the electric current injection into the ground and in the continuous measure of the resulting potential, simultaneously providing three georeferenced values of ER related to 50, 100 and 170 cm depths for each point.

Forty-nine soil samples were taken at 10-30 cm depth and analyzed for moisture, particle size distribution and electrical conductivity. The best correlation (R^2 = 0.609; P <0.01) was obtained between clay content and ER referred to the 0-50 cm depth (ER_{50}).

The evaluation of the density reduction effect for both ARP and soil survey was expressed in terms of ER_{50} and clay predictability. Doubling the ARP swaths width (12 m) the ER_{50} accuracy was substantially in agreement with that obtained for the highest ARP survey density (22 swaths 6 m spaced); the further width doubling (24 m) provided a moderate accuracy. With regard to clay content prediction k accuracy values ranged between 0.87 and 0.49 for the 22 swaths/25 soil samples and 10 swaths/12 soil samples combination, respectively.

KEYWORD

ARP – ER – accuracy – precision viticulture – GIS – clay

INTRODUCTION

Viticultural precision farming needs detailed soil information, which can be obtained by means of remote as well as proximal sensors, besides traditional invasive soil survey. The understanding of the nature, extent and causes of vineyard variability may help grape-growers and winemakers to use precision viticulture tools to better target their management (irrigation, rate of fertilizers, pruning and harvesting). Nevertheless, the use of the new technologies is still in its infancy, because of their costs and the lack of knowledge about the detail actually needed for the viticultural husbandry.

Several authors (Bramley and Proffitt, 1999) demonstrated that traditional soil surveys can not succeed in exhaustively explaining the reasons of variability in vineyard performance. The authors find more efficient the evaluation of soil properties by sampling at points selected according to, for instance, electromagnetic measurements (EM38). Actually, soil electrical properties can be considered as an alternative but also complex source of information for assessing the spatial and temporal variability of many soil physical and chemical properties (i.e. structure, texture, water content and salinity). EMI represents the most widespread geophysical technique employed in agriculture, anyway, it is noteworthy that electrical surveys performed by means of this instrumentation require a calibration every time it is used (Taylor, 2004). With this regard, Dabas et al. (2001) prefer electrical current (i.e., device that injects electrical current into the soil) as the calibration is more constant and less sensitive to error from soil heterogeneity, though the limitation regarding the main drawback to the DC sensors (direct current) are problems when the soil exhibits a high contact resistance, that is when it is either very dry or frozen (Dabas and Tabbagh, 2003; Luck and Eisenreich, 2001).

With the aim to reduce the mobile sensor surveys costs Farahan and Flynn (2007) studied the different quality of maps provided by widening the swath width for the Veris 3100 sensor (Veris Technologies, Salina, KS). These authors assess the density effect on the possibility of providing acceptable prediction of the conductivity (ECa) map compared to the densest survey.

Since the density effect of the geoelectrical survey on its reliability to support traditional soil survey in vineyard was not fully investigated, the aim of the work was to statistically test the possibility of combining an optimized strategy for both geoelectrical and soil sampling, able to provide significant information accuracy of the soil spatial variability.

MATERIALS AND METHODS

The study vineyard, sized 3.5 ha, is located in central coast of Tuscany (Central Italy), cultivated with Cabernet Sauvignon and Cabernet Franc in the past. Actually, soil salinity problems strongly reduced the wine production and induced the wine growers to remove the vineyard.

The survey identified three main soil typologies, according to the WRB classification system (FAO, IUSS, ISRIC, 2006): Endostagnic Cambisols (Calcaric, Sodic) on marine clays; Haplic Cambisols (Eutric) and (Calcaric) on conglomerates.

Soil sampling at 10-30 cm was carried out on a regular grid sampling scheme (35-40 m per 20 m), simultaneously to the measurement of soil resistivity executed by the ARP equipment. (a direct current sensor). Laboratory analyses for moisture determination was carried out with the gravimetric method while the texture analysis was performed with hydrometer, identifying five fractions (coarse and fine sand, coarse and fine silt, clay percentages); a 1:5 soil water suspension was then employed for the electrical conductivity determination, expressed as $mScm^{-1}$.

The ARP survey was carried on 22 passages, 6 m spaced from each other. In each sampling point, the device simultaneously provides 3 georeferenced values of electrical resistivity values (Ohm.m) related to different soil depths of investigation (0-50; 0-100 and 0-170 cm). Actually, only the surface ER data (ER_{50}) have been considered compared to the deeper ones provided by the ARP machinery because such value was expected to be more linked to soil properties of 10-30 cm depth.

In order to find a relationship between ARP information and soil properties, resistivity data were spatialized over the whole study area in ARC/VIEW GIS environment (ESRI ArcView 3.2(R)) by means of inverse distance weighted interpolation (IDW2-3) algorithm. Such an algorithm employees 2 neighbours and a 3 power function to interpolate the data. Successively, a buffer of 3 m radius around each soil sample was created and by means of the ArcView tool

Zonal Statistics, the mean value of ER_{50} grids within each buffer was associated to the relative soil sample information. The resolution of the raster layer was 3 meter. Regression analysis was employed to correlate ER_{50} information to soil physical and chemical data.

In addition, to evaluate the possibility of reducing the ARP survey cost, the accuracy of predicting ER_{50} values for the swath widths of 6, 12 and 24 m was assessed. Similar approach was employed to evaluate the opportunity of reducing soil samplings by assessing soil properties predictability for decreasing sampling closeness. Those localizations were in turn selected according to the observed ER_{50} variability for the diverse densities of the ARP survey.

Such accuracy analysis was carried out in ARC/VIEW GIS environment by means of the ArcView tool Kappa analysis which elaborates a confusion matrix containing categorical similarities between the observed values and the predicted ones All the previous statistical elaborations were then implemented in a excel spreadsheet to elaborate graphs and tables.

RESULTS AND DISCUSSION

Before investigating the probable relation between resistivity signal and soil properties it was evaluated the possibility of reducing the costs of the ARP survey. With that aim the spatialization of ER_{50} values for different densities of the geoelectrical survey was compared. In particular, three different swaths width were investigated: actual 6 m, 12 m and 24 m, relative to 22, 10 and 5 passages, respectively (Fig. 1).

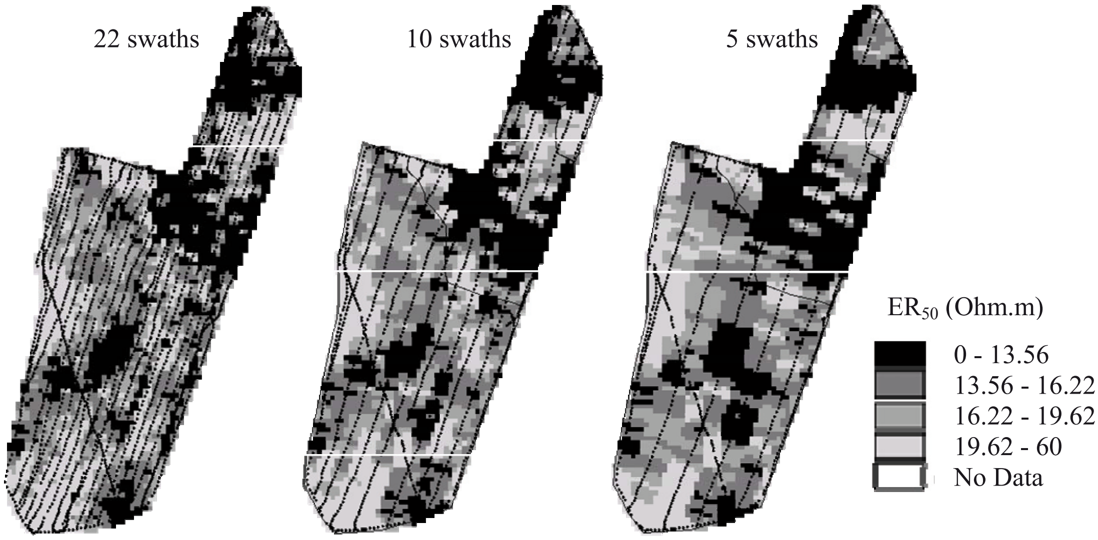
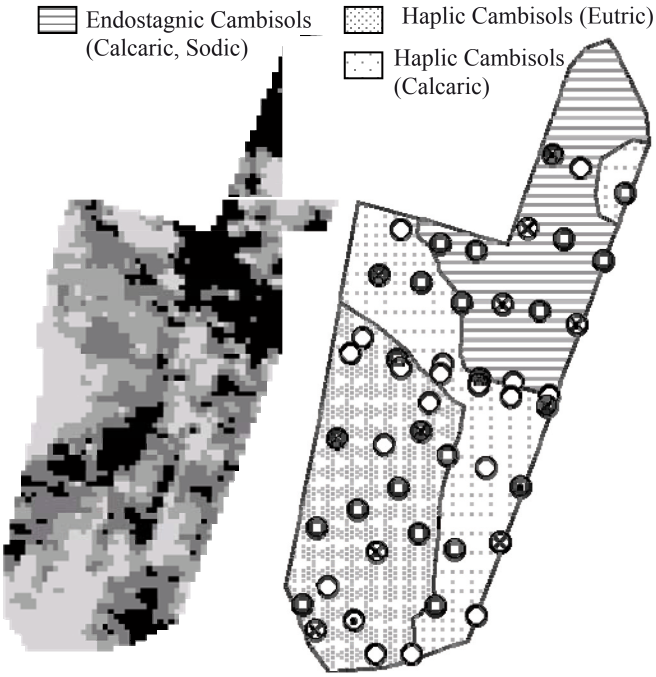


Figure 1. IDW 2-3 interpolation of ER_{50} values for 22, 10 and 5 swaths. (Scale 1:5,000).

The truthfulness of the ER_{50} values calculated for different ER survey densities was evaluated comparing the predicted values with those interpolated starting from the more dense survey (22 rows). In particular, for the K analysis a pixel by pixel comparison was applied; in such a way the evaluation was extended over the whole area starting from the ER_{50} values transformed into four equal dimensional classes. Tab. 1 illustrates for each density survey, expressed in terms of both number of measurements per ha and of swaths width, the statistics of ER_{50} values calculated over the whole area, the accuracy parameters (Landis and Koch ,1977) for ER_{50} prediction.

Table 1. Summary of ER_{50} statistics for different resistivity survey densities.

	Swaths number		
	22	10	5
Width swath (m)	6	12	24
ER sample points per ha	667	417	276
ER_{50} sampling points statistics:			
Mean (Ohm.m)	17.34	17.5	17.78
Standard deviation (Ohm.m)	6.74	7.01	7.72
Overall accuracy of ER_{50} prediction over the whole area		74%	63%
Theta value		0.25	0.25
K value		0.65	0.51
Agreement classification		Substantial	Moderate



Summary statistics of $ER_{50(22\text{-}10swaths)}$ values for different soil survey densities.

	Sampling points (n)			
(Ohm.m)	49 ○	25 □	12 X	6 ●
Minimum	8.82	8.82	8.82	8.82
Maximum	31.59	31.59	31.59	26.93
Mean	17.17	17.99	16.95	16.13
Standard deviation	4.97	6.28	5.60	6.24

Figure 2. $ER_{50(22\text{-}10swaths)}$ grid values, localization of the sampling points (Scale 1:3,500) and $ER_{50(22\text{-}10swaths)}$ statistics for different soil survey density.

It is noteworthy, that only 10 rows, corresponding to a reduction of almost 40% of the sampling points (from 667 to 417 per ha), may provide a reliable accuracy in ER_{50} prediction equivalent to a substantial agreement, compared to 5 rows. Actually, the further swath width enlarging to 24 m reduces significantly the ER_{50} predictability becoming characterized by a moderate agreement.

As rule, the resistivity maps are employed as surrogate information of soil variability to selecting the soil sampling localization. With the aim to obtain a unique ER_{50} map representing the resistivity variability of the study area, the mean value of ER_{50} grids among 22 and 10 swaths $ER_{50(22\text{-}10\ swaths)}$ was calculated to identify three different densities of soil survey (25, 12 and 6 points), which in turn had to be compared with the denser scheme (49 samples) (Fig. 2).

Actually, ER_{50} grids provided by only 5 swaths were excluded from the successively elaboration because of its moderate agreement respect to 22 swaths results. For all the soil survey intensities, the procedure of sample localization/identification consisted in selecting points uniformly distributed over the area and able to explain the whole ER variability.

For that purpose, a buffer of 3 m radius was created around all the soil sampling points and the mean value of $ER_{50(22\text{-}10\ swaths)}$ grids was calculated within each buffer. In such a way the interpolation effect was averaged and the resistivity attribution to each sampling point became more reliable respect to soil properties distribution.

The results illustrated in Fig. 2 outline that each selection guarantees the whole ER variability along with the uniformly spatial distribution of the diverse soil selections.

In order to assess the reliability provided by the different soil survey densities in terms of characterization of soil properties variability over the study area, the possibility of discovering a relation between ER_{50} values and some of soil properties was investigated. For that purpose, once again, the mean values of ER_{50} grids provided by the different ARP survey densities was averaged within each soil sampling buffer and related to the soil properties.

Among all the analyzed soil parameters only the clay content was always linked to the ER_{50} values (i.e., separately provided by 22 and 10 swaths) with an high level of significance($p<0.001$) (Tab. 2); therefore the clay content was employed to test/compare the performances provided by different soil survey densities.

Table 2. Correlation coefficient among soil parameters versus the mean values of ER_{50} for two ARP survey densities and for all the soil samples (49).

	ER_{50} (22ARPswaths)	ER_{50} (10ARPswaths)
W	-0.270 N.S.	-0.205 N.S.
E.C.(1:5)	-0.408 **	-0.498 ***
Clay	-0.750 ***	-0.818 ***
Total Sand	0.446 **	0.565 ***
Fine Sand	0.370 **	0.487 ***
Coarse Sand	0.154 N.S.	0.124 N.S.
Total Silt	0.059 N.S.	-0.038 N.S.
Fine Silt	-0.04 N.S.	-0.149 N.S.
Coarse Silt	0.244 N.S.	0.283 *

*** Significant at 0.001 probability level; ** Significant at 0.01;* Significant at 0.05 probability level; N.S. Non significant.

All the relations between ER_{50} and clay for the diverse densities of soil and ARP surveys assumed the exponential form. Here after, Tab. 3 illustrates the parameters of the regressions employed to assess the clay content starting from the resistivity signal, for different soil and ARP survey densities.

The cells depicted in grey colour represent the comparison term respect to all the other combinations between soil survey points and ARP swaths. Despite the high value of the determination coefficient, all the regressions involving solely 6 samples are less significant because of the few degrees of freedom (df).

Table 3. Parameters of the regressions.

Soil sample number	22 ARP swaths			10 ARP swaths		
	R^2	df	Significance level	R^2	df	Significance level
49	0.610	47	***			
25	0.670	23	***	0.755	23	***
12	0.799	10	***	0.902	10	***
6	0.828	4	*	0.906	4	**

In order to evaluate the consistency of the clay content assessment over the whole study area only the more significant regressions (***) were implemented in ARC View GIS environment, starting from ER_{50} values for different ARP survey densities. In such a way it was possible to compare the results provided by 49 samples-22 ARP swaths on the one hand, with all the other combinations of soil samples number and ARP swaths and therefore evaluate the corresponding clay predictability. Once again clay values were transformed into categorical classes being employed into the confusion matrix for accuracy analysis (Tab. 4).

Table 4. Results of the confusion matrix for the clay accuracy determination.

	22 ARP swaths				10 ARP swaths			
soil samples (n)	Overall accuracy	theta value	K value	Agreement class	overall accuracy	theta value	K value	Agreement class
25	0.92	0.37	0.87	Almost perfect	0.76	0.37	0.62	Substantial
12	0.80	0.33	0.70	Substantial	0.65	0.32	0.49	moderate

The predictability of clay content ranged between 0.87 and 0.49, 22 ARP swaths provided always excellent accuracy for both the analyzed soil sample sizes. Conversely, the more spaced ARP survey guaranteed a substantial accuracy only with 25 soil samples.

CONCLUSIONS

For optimizing the use of ARP technology to support soil survey for precision viticulture two possible strategies were indicated. With the highest geoelectrical survey density the soil samples number may be reduced to twelve, at the most, for assuring at least a substantial accuracy in clay prediction. Conversely a combined reduction of both costs (ARP and soil survey), able to assure the same clay accuracy, may be provided by 10 ARP swaths with 25 soil samples for 3.5 ha, equivalent to less than 3 swaths and 7.5 samples by ha, respectively.

BIBLIOGRAPHY

Bramley R.G.V. and Proffitt A.P., 1999. Managing variability in viticultural production. *Grapegrower and Winemaker*. July 1999, 427:11-16.

Dabas M., Tabbagh J. and Boisgontier D., 2001. Multi-depth continuous electrical profiling (MuCep) for characterization of in-field variability. In: G. Grenier and S. Blackmore (eds.). Proc. Third European Conference on Precision Agriculture. Montpellier, France, 361-366.

Dabas M. and Tabbagh J., 2003. Comparison of EMI and DC methods for soil mapping in Precision Agriculture. In: J.V. Stafford and A. Werner (eds.). Proc. Fourth European Conference on Precision Agriculture. Berlin, Germany.

FAO, IUSS, ISRIC, 2006. World Reference Base for soil resource. World Soil Resource Report n.103, FAO, Rome, Italy.

Farahani H.J. and Flynn R.L., 2007. Map Quality and Zone Delineation as affected by Width of Parallel Swaths of Mobile Agricultural Sensors. *Biosystems Engineering*, 96 (2):151-159.

Landis J.R. and Koch G.G., 1977. The measurement of observer agreement for categorical data. *Biometrics*, 33: 159-174.

Luck E. and Eisenreich M., 2001. Electrical Conductivity Mapping For Precision Agriculture. In: G. Grenier and S. Blackmore (eds.). Proc. Third European Conference on Precision Agriculture. Montpellier, France, 425-429.

Taylor J.A., 2004. Precision Viticulture and Digital Terroir. PhD Thesis. The University of Sydney.