Integration of EMI sensor data in soil sampling scheme optimization using continuous simulated annealing

Annamaria Castrignanò1, Emanuele Barca2, Gabriele Buttafuoco3, Daniela De Benedetto1 Domenico A. Palumbo1, & Giuseppe Passarella2

1 *Agricultural Research Council Research, Unit for Cropping Systems in Dry Environments, Bari, Italy,* [*annamaria.castrignano@entecra.it*](mailto:annamaria.castrignano@entecra.it)*,* [*daniela.debenedetto@virgilio.it*](mailto:daniela.debenedetto@virgilio.it), *domenico.palumbo@entecra.it*

2 *Water Research Institute (IRSA) - National Research Council of Italy (CNR), Bari, Italy,* [*emanuele.barca@irsa.cnr.it*](mailto:emanuele.barca@irsa.cnr.it)*,* [*giuseppe.passarella@irsa.cnr.it*](mailto:giuseppe.passarella@irsa.cnr.it)

3 *Institute for Agricultural and Forest Systems in the Mediterranean, National Research Council of Italy, Rende CS, Italy,* [*gabriele.buttafuoco@cnr.it*](mailto:gabriele.buttafuoco@cnr.it)

**Abstract.** Soil survey is generally time-consuming, labour-intensive and costly. Optimization of sampling scheme allows one to reduce the number of sampling points without decreasing or even increasing the accuracy of investigated attribute.

Maps of bulk soil electrical conductivity (ECa) recorded with EMI sensors could be effectively used to direct soil sampling design for characterizing spatial variability of soil moisture. A protocol, using a field-scale bulk ECa survey, has been applied to an agricultural field in Apulia region (south-eastern Italy). Continuous spatial simulated annealing was used as a method to optimize spatial soil sampling scheme taking into account sampling constraints, field boundaries and preliminary observations. Three optimization criteria were used: the first criterion (MMSD) optimizes the spreading of the point observations over the entire field by minimizing the expectation of the distance between an arbitrarily chosen point and its nearest observation, the second criterion (MWMSD) is a weighted version of the MMSD, which uses the digital gradient of the grid ECa data as weighting function, and the third criterion (MAOKV) minimizes mean kriging estimation variance of the target variable. The last criterion utilizes the variogram model of soil moisture estimated in a previous trial. The three procedures and a combination of them were separately tested and compared. Simulated annealing was implemented by the software (MSANOS) able to define or redesign any sampling scheme by increasing or decreasing the original sampling locations. The output consists of the computed sampling scheme, the convergence time and the cooling law, which can be an invaluable support to the process of sampling design.

The proposed approach has shown great flexibility in adapting to any field heterogeneity and searching the optimal solution in a reasonable calculation time. The use of bulk ECa gradient as an exhaustive variable, known at any node of an interpolation grid, has allowed the optimization of the sampling scheme, distinguishing among areas with different priority levels. Further optimization criteria should be added to the procedure in the future, as minimization of cokriging variance, in the case of multi-purpose sampling, or maximation of an economic or social objective function.

**Keywords.** Sampling, EMI sensor, bulk electrical conductivity, spatial simulated annealing, spatial variability, soil

**1 Introduction**

Farmers around the world are becoming well aware that agricultural production varies across the landscape due to various naturally occurring, as well as man-induced, differences in key productivity factors (Adamchuk et al., 2011). Implementing efficient management practices requires to identify and interpret these differences so to match agricultural inputs with locally defined crop needs (Pierce and Nowak, 1999). The main target of Precision Agriculture (PA) is to improve management of crop production through spatially-variable within-fields practices, which requires an accurate estimation of spatial variation at very fine scales of resolution. Differences in physical, chemical and biological attributes have been traditionally detected through soil/crop sampling and laboratory analysis. However, data can be difficult or expensive to collect, and both sampling design and data quality may affect final results (Cochran, 1977; Muller 1998). It is then critical to carefully design a strategy of collecting spatial data which usually requires a proper formulation of at least two components: the objective of survey and what is already known in the area (Stein and Ettema, 2003). The aim of sampling, even within PA, can be manifold: assessing the amount of yield, the spatial distribution of weeds or the uniformity of irrigation. Kerry et al. (2010) showed that sampling requirements vary as a function of target variable. In the perspective of PA, the usual objective of sampling is making a spatial investigation such as displayed on a map. With respect to prior information, it may consist of previously sampled data, the presence and shape of boundaries, roads, water bodies or any type of physical obstacle, and of sub-areas with different priority of sampling.

Sampling of soil/crop properties at within-field scales may involve considerable costs (travel, labor time, extraction of soil cores, laboratory analyses, etc.); therefore, for making PA cost-effective, these costs must be minimized. Optimizing sampling scheme means to provide information of the required precision at the minimum cost. At present there are several techniques for optimizing sampling (Marchant and Lark, 2010); a general methodology, survey sampling (Stein and Ettema, 2003), was formulated by Muller (1998) and Van Groningen and Stein (1998) and consists in defining an objective function (optimization criterion) being minimized or maximized while respecting the constraints imposed. Whichever optimization criterion, the costs of sampling and laboratory analysis are such that it is quite difficult to collect enough samples to characterize spatial variability at the accuracy required by PA. This economic constrain generally results in low sampling density which is the major recognized factor limiting PA efficacy. The drive to collect high spatial density data relevant to the soil attributes of interest, so to reduce sampling costs, led to the adoption of sampling methods based on proximal sensing. Differently than remote sensing, proximal sensing involves the operation of sensors close to, or even in contact with, the soil being surveyed. In particular, measuring bulk electrical conductivity (ECa), using electromagnetic induction (EMI) instrumentation equipped with GPS, has become one of the more widely used proximal sensing technologies for soil mapping (Corwin and Lesch, 2005). Geo-spatial measurements of ECa may be used as a powerful tool in site-specific management to direct supplemental soil sampling in these areas where variability is higher (Castrignanò et al., 2006). Moreover, in a geostatistical context, optimizing spatial sampling involves estimation of a model for spatial dependence, usually expressed by a variogram, which can be used to optimize interpolation of an environmental geovariable (e.g. McBratney and Webster, 1983). Van Groenigen et al. (1999) proposed an annealing-based algorithm to optimize sampling schemes on a continuous solution space for different quantitative optimization criteria, taking into account physical sampling barriers and earlier measurements.

The objective of this paper is to introduce a method of optimising spatial sampling in an agricultural field using auxiliary information on the area in the form of ECa maps. The procedure is an extension of spatial simulated annealing (SSA) for optimization, presented by Van Groenigen et al. (1999), which allows the inclusion of objective weighting factors and use of auxiliary information.

The paper demonstrates the application of the software MSANOS for sampling optimization, using three optimization criteria, in a survey of top soil water content over an agricultural field in south-eastern Italy.

**2 Materials and methods**

**2.1 Spatial Simulated Annealing**

The theory of Spatial Simulating Annealing (SSA) is based on the analogy with the organization of the metal atomic network when it undergoes a process of temperature change (cooling process). Following this process, the atoms of the metal change their arrangement to a configuration of low energetic maintenance cost. In the analogy, the configuration of the atoms corresponds to that of the sampling points, while the energy of the system corresponds to the objective function (OF), (Pardo-Igùzquiza 1998, Deutsch and Cockerham 1994). In practice, the SSA performs an iterative random generation of new configurations, each characterized by a value (energy, in the metallurgic analogy) of the selected OF. At any iteration, the current transient optimal solution is randomly perturbed, thus generating the new candidate solution. The decision rule regulating the change or the stay of the current transient optimal solution is the following (Metropolis et al., 1953; Kirkpatrick et al., 1983):

|  |  |
| --- | --- |
|  | (1) |

where:

*ϕ*(·) = objective function;

*S*0 = optimal transient solution;

*S*1 = candidate solution;

*T* = temperature;

*PT* = transition probability from *S*0 to *S*1.

Substantially, whenever the candidate solution is better than the transient one, it always becomes the new transient optimal solution (line 1 of equation (1)); otherwise if the candidate solution is worse than the transient one, it could become anyway the new optimal transient if the value computed by the Boltzmann equation (line 2 of equation (1)), that can be assimilated to a probability, is larger than a Monte Carlo randomly generated probability value. The SSA stops when the Boltzmann equation becomes no longer computable, or, which is the same, when temperature approaches to zero. The variable Temperature is modified during the run according a function called *cooling scheme* after 50 steps. Among all the available cooling schemes, in the present work, it has been chosen the geometric law (Van Groenigen et al., 1998):

|  |  |
| --- | --- |
|  | (2) |

That scheme has been chosen because of its good balance between the success rate of convergence to the global optimum and the time required for reaching the zero temperature.

**2.2 Optimization Criteria**

*2.2.1 Mean of the Shortest Distance (MMSD)*

MMSD (Minimization of the Means of the Shortest Distances)-criterion, which minimizes the expectation of the distance of an arbitrary point to its nearest observation point, has frequently been used in the past (Van Groenigen et al., 1999). This condition should be expressed mathematically, for a scheme *S* of sampling: , where  is the Euclidean distance between the position **x** and the nearest neighbour . When any previous information on the spatial variation over the area of interest is lacking, the most prudent design is an even sampling by applying MMSD-criterion. However, this criterion cannot be the only best one for agricultural fields, which generally have uneven spatial distribution of soil properties. We therefore modified the MMSD-criterion in order to be able to distinguish between areas with different priority levels.

*2.2.2 Weighted Mean of the Shortest Distance (MWMSD)*

The MWMSD (Minimization of the Weighted Means of the Shortest Distances)-criterion is a weighted version of the MMSD-criterion (Castrignanò et al., 2008). A location-dependent weighting function is introduced in the fitness function:

(3)

where: denotes a two-dimensional coordinate vector; w() weighting function; V() the coordinate vector of the sampling point nearest to . The symbol || is used as distance vector.

This function is estimated by:

(4)

where denotes the generic node of a finely meshed grid overposed on the area of interest and *ne* the number of samples being allocated.

Employing a weighting function offers flexibility in the use of auxiliary high-resolution data: when EMI data maps of the area are available, *w*() can be defined as the gradient of ECa, so placing more observations in the area of expected maximum variation. In the absence of a priori information about soil attributes, we assumed that the spatial dependence structure of ECa was similar to the spatial dependence structure of those soil properties influencing within-field soil moisture. We then deemed that a multi-stage sampling design can lead to more accurate site characterization: a preliminary sampling scheme was obtained by allocating 50% of the total number of samples according to the MMSD-criterion; in this way an even distribution of samples was guaranteed. In the second step, the remaining 50% of samples were allocated according to the MWMSD-criterion, so resulting in a coverage of the area that reflected the distribution of areas with different priority of sampling.

*2.2.3 Mean of Average Ordinary kriging Variance (MAOKV)*

This criterion aims at minimization of the average kriging variance estimated at any location of the surveyed domain. It is assumed that prior information is available, as the variogram model of the interest variable. The criterion focuses on the areas of the highest uncertainty in terms of kriging estimation variance, which are the undersampled areas. A limitation of this criterion is that it depends only on the spatial configuration of data points but not on the measured values (under stationary conditions). Therefore, this criterion can be considered as a mere geometrical criterion. It tends to allocate the samples at the borders of the area of interest where kriging variance may become very high due to the scarcity of data in these areas.

Similarly to MWMSD a two-stage sampling design was used by allocating the first 50% of the total number of samples according to MMSD-criterion and the remaining 50% of the samples according to MAOKV-criterion.

**2.3 MSANOS Software**

To realize and compare the different sampling designs according to the three previous procedures, the MSANOS Software was used.

The software MSANOS (Barca et al., 2011) is capable to address a number of issues related to the sampling scheme definition and monitoring network design and/or redesign. In particular, starting from an existing scheme, it can widen or reduce the original scheme in an optimal way according to some specified management objectives and constraints. These are suitably modelled in form of an Objective Function (OF) to be optimized and the optimizing approach is Spatial Simulated Annealing (SSA).

Scientific and technical literature reports a wide number of OFs defined for any specific problem and aimed at improving the accuracy of some statistical index, the spatial network coverage or reducing the overall monitoring costs (Stevens, 2006);. OFs can be grouped in two main classes: model-based or design-based (Brus and de Gruijter, 1997). MSANOS provides both kinds of OFs so as to be able to address a wide range of practical issues (definition of first alert networks, population characterization, sampling and so on), resulting in a very flexible tool for decision making.

The OF kind significantly depends on the optimization problem. MSANOS provides the following OFs:

1. Maximum ordinary kriging variance;
2. Average ordinary kriging variance;
3. Maximum weighted means of the shortest distance;
4. Average weighted means of the shortest distance;
5. Fractal dimension.

The first two OFs quantify the change of ordinary kriging variance produced by adding or removing a location from the network (Barca et al., 2008). The second pair of OFs is designed to achieve an even distribution of the locations over the study area (Van Groenigen et al., 2000). Fractal dimension is an inherently design-based OF, which improves the distribution of the monitoring locations by increasing the fractal dimension through adding new sites (Di Zio et al., 2004). In practice, once the problem and the monitoring objectives have been set, the choice of the specific OF depends on the available information.

**2.4 A Case Study**

The experiment was conducted on a 2.05-ha agricultural field located in the experimental farm of CRA-SCA, Rutigliano-Bari (40°59’48.25’’ N, 17°02’02.06’’ E) in south-eastern Italy. The aim of the soil survey was to predict top soil water content across the field for applying site-specific irrigation under the constraint of a fixed total number of samples set to 100.

Soil is classified as fine, mixed, superactive, thermic Typic Haploxeralfs according to the Soil Taxonomy (Soil Survey Staff, 2010). Soil texture is mostly clayey with the clay content ranging from 30% to 60% by weight and basically increasing in depth. The bedrock is constituted of a layered sequence of Cretaceous limestone with some dolomitic limestone level and occurs at variable depth due to its irregularly shaped boundary.

The data were collected in October 2013 with an EMI sensor (EM38DD, Geonics Limited, Mississauga, Ontario, Canada.), which consists of two single coils positioned perpendicularly to each other: one orientated horizontally and the other one vertically. The instrumentation allows one to measure bulk electrical conductivity (ECa) simultaneously in the two polarisation (horizontal and vertical) modes with a different depth response profile (McNeill, 1980). The sensor was connected with a Differential Global Positioning System (HiPer® 27 Pro, TOPCON) with planimetric and altimetric centimetre accuracies and it was towed across the field by a tractor along 23 parallel N-S oriented transects, approximately 5 m apart.

The system facilitates the collection of fine-scale ECa data in a manageable time interval, thus greatly increasing the spatial resolution of soil information. It is worth pointing out that the absolute values of bulk electrical conductivity may not necessarily be diagnostic but only the variations (gradient) in conductivity can be used to identify soil anomalies (Benson et al., 1988). In the light of the above considerations, the gradient of the horizontal ECa estimates was used as auxiliary variable to optimize location of the sampling points.

**2.5 Geostastical Analysis**

Ordinary kriging was applied to interpolate EMI data. Before applying univariate analysis, the EMI data, which showed departure from Gaussian distribution, were transformed and standardized Gaussian scores by using a set of Hermite polynomials (Wackernagel, 2003). After variogram modelling and cross-validation, ordinary kriging was applied on a 5 x 5m grid and the estimates were then back transformed to the raw variables. The gradient of the horizontal ECa estimates was calculated at the nodes of previous grid and its values were smoothed through averaging within a window of 15m radius. All statistical and geostatistical analyses were performed with ISATIS software, release 2014 (Geovariances, 2014).

**3 Results**

From the descriptive statistics of the very dense EMI data (De Benedetto, 2014), it was evident that ECa data were characterised by large variability and the data distributions looked positively skewed with sensible departure from normal distribution (the hypothesis of normality was refused on the basis of χ2 test at the 5% level of probability). Therefore, the data were transformed by Gaussian anamorphosis and standardized to mean zero and variance one. The variogram of ECa in horizontal polarization was isotropic and included the following basic structures: Nugget Effect, Spherical model (Range = 33.5 m) and Cubic model (Range = 242 m).

The kriged map of ECa (Figure 1a) showed two areas: the north-western area of the field characterised by lower values and the south-eastern corner by higher values. The ECagradient map(Figure 1b) highlighted two halves along the NW-SE direction: the right-hand one with much higher values than the left. The comparison of the two maps shows that the most conductive areas are generally the ones characterized by the largest variability.

**(a) (b)**

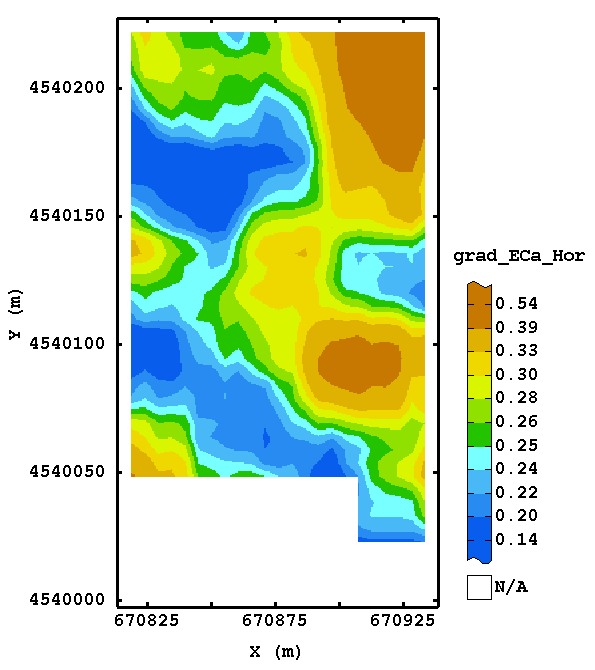
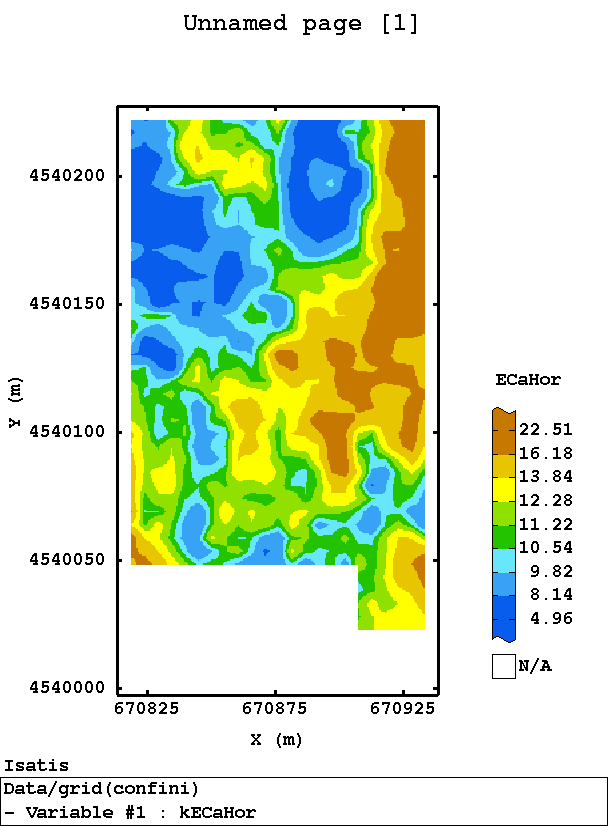


Figure 1. Spatial estimate of ECa in horizontal polarization (mSm-1) (a) and ECa gradient map (b). Colour scale uses iso-frequency classes.

In order to perform MAOKV, a directional nested variogram model of gravimetric soil water content (SWC) was used, consisting of three basic structures: nugget effect, an isotropic exponential model with range of 40m and an anisotropic spherical model along the 130°N direction with range of 100m. The model was estimated in a previous sampling carried out on the same field (De Benedetto, 2014).

Three simulated annealing procedures, corresponding to the three different optimization criteria, were carried out with the starting temperature set equal to 0.1287, 0.0161 and 0.0204 for MMSD, MAOKV and MWMSD, respectively. The cooling down factor equal to about 0.95 and the number of steps before decreasing temperature equal to 50.

To explore and illustrate the different sampling procedures, estimation variance of SWC was calculated, using ordinary kriging with the variogram model above described, at the nodes of the same interpolation grid of ECa. The resulting three sampling schemes overlapped on the kriging standard deviation estimates are shown in Figure 2 which illustrates the impact of optimization criterion on the arrangement of the observation points: the MMSD scheme (Figure 2a) is quite regular; a spatial pattern emerges, that is close to the one of ECa,in the MWMSD scheme (Figure 2b) and the observation points have moved towards the field edges in the MAOKV scheme (Figure 2c). It is worth pointing out that each map reflects the optimization criterion used which, in turn, underlines a particular aspect of uncertainty. It is impossible to judge the best scheme, because each one is useful in a different practical situation. Depending on the particular objective of the survey and the prior information, MMSD will be preferred when no knowledge of the field is available; MWMSD, if the focus is on the high variability zones, and MAOKV when the targets are the most unsampled areas. Moreover, if the purpose is to have the most regular sampling scheme MMSD should be used. MWMSD is useful to reduce the heteroscedasticity observed in most environmental observations whereas MAOKV to increase the overall precision of estimation.



Figure 2. Arrangement of the sample points overlapped on kriging standard deviation for the three optimization procedures: MMSD (a), MWMSD (b) and MAOKV(c).

However, to compare the efficiency of the three procedures in terms of computer time, in table 1 there is reported the time to reach the convergence. It is evident that the introduction of a weight function has speeded up the process of convergence, but the choice of such a function is quite critical, mostly depending on the spatial relationship between target variable and auxiliary information. The current wide use of EMI sensor, or other similar proximal sensors in PA, should then be encouraged to direct efficient sampling of those attributes which are more related to electrostatic properties of the soil.

Table 1: Convergence time for the three optimization procedures

|  |  |  |  |
| --- | --- | --- | --- |
| Objective Function | | Time for convergence (sec) | |
| MMSD | 2649.71 | |
| MWMSD | 1295.65 | |
| MAOKV | 48263.62 | |

Another way to compare the three procedures is to analyse the distribution of kriging standard deviation of SWC estimates (Table 2). From the inspection of the overall statistics, relevant differences do not emerge among the procedures, even if MMSD outperforms in terms of mean and spread of the errors. On the contrary, MAOKV is to be preferred when the target is reducing the occurrence of large errors. Nevertheless, the selection of the optimal sampling scheme is mainly dictated by practical reasons.

The maps of kriging standard deviation of SWC estimates (Figure 2 a-c) show how the spatial pattern follows, as it is expected, the geometrical arrangement of sample points.

Table 2: Basic Statistics of kriging standard deviation of SWC for the three sampling procedures

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Procedure | Count | Minimum | Maximum | Mean | Std. Dev. | Median |
| MAOKV | 835 | 1.04 | 1.98 | 1.70 | 0.25 | 1.75 |
| MWMSD | 835 | 1.04 | 2.42 | 1.71 | 0.27 | 1.74 |
| MMSD | 835 | 1.04 | 2.28 | 1.69 | 0.24 | 1.73 |

**4 Conclusions**

The paper has described three approaches to optimize soil sampling design and explained how they can be adapted to the different practical situations. Three optimization criteria have been defined depending on the main purpose of the survey: a regular arrangement of the sample points (MMSD); better uniformity of uncertainty (MWMSD); and reduction of estimation uncertainty (MAOKV). These criteria cover a large range of practical situations occurring in the reality but, of course, they are not exhaustive. The spatial simulated annealing procedure has shown great flexibility in adapting to the different practical issues reaching the optimal solution in a reasonable calculation time. The ECa gradient map has allowed sampling to be optimized, distinguishing between areas with different priority level. The proposed MWMSD criterion can use any spatial weight function to focus sampling on those areas with by high variability and reduce sampling in the areas with expected low heterogeneity. One of the crucial issues in this approach is the definition of the weighting function. We have preferred to avoid semi-quantitative priority values, based on subjective expert-knowledge and use ancillary variables more formally. However, we think that more research should be dedicated to the best setting of the weighting factors, because attaching priorities to the different within-filed zones result a very effective tool in decision making.

However, further improvement of the software used for sampling optimization should be realized by adding more procedures in the future, aimed at minimization of cokriging variance in multi-purpose sampling and introduction of a loss function. The latter should describe the costs to the former for additional sampling to reduce uncertainty, which is a basis for the rational management of sampling in Precision Agriculture.

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