The LIFE+ SOILCONSWEB project: a web based spatial decision support system embedding DSM engines

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ABSTRACT: This contribution aims to refer first results obtained by the SOILCONSWEB (EU LIFE+) project which deals with a web based spatial decision support system embedding digital soil mapping engines. The aim of the project is to develop, to test and to apply a tool to support (stakeholders) decisions on landscape issues aiming at both the best soil conservation/land management and an easy landscape implementation of some important but complex environmental EU directives and regulations. In fact, often environmental directives/regulations (such as those by EU) have an intrinsic complexity because they apply to soils and landscapes which have the well recognized "multiple functions" as a fundamental feature. Then it is not surprising that this decision support system requires to include and to mix many different high quality information, engines and processing units in order to be successfully applied. Moreover the tool will also integrate the classical top-down decisions with the bottom-up contributions towards a sustainable landscape planning and managing. In this paper we employed Digital Soil Mapping procedures to obtain the spatial distribution of soil features/functions but also to incorporate any new (certified) analysis performed and uploaded by farmers. The SOILCONSWEB will automatically include new records by updating spatial models.

1 INTRODUCTION

1.1 *Background*

Nowadays soil science, agriculture and forestry must provide multiple answers to the multiple functions of soils/landscapes to a range of multiple users and stakeholders. Although much of the scientific literature emphasizes these multiple functions/answers/users, very little is actually available to understand the road map to achieve such huge expectations. Moreover, existing agriculture and environmental rules and regulations may further complicate these issues. The outcome results of combining multiple functions/answers/users and legal regulations may easily lead to high difficulties in addressing proper landscape management (Bouma 2010).

In this complex scenario, we believe that soil scientists must provide a much wider and possibly better contributions by establishing a framework to face these challenges.

1.2 *The SOILCONSWEB tool*

One possible framework is the use of a Web Based - Spatial Decision Supporting System (WB-SDSS) as an integrated platform where to address sustainable landscape management (Sugumaran et al. 2010).

Here we report the first results obtained by the EU project LIFE+ named SOILCONSWEB which aims to develop, to test and to apply a tool to support decisions on landscape issues aiming at both the best soil conservation/land management (embedding digital soil mapping engines) and an easy landscape implementation of some environmental EU directives and regulations.

The inclusion of environmental directives/regulations is of special importance because they have an intrinsic complexity since they apply to soils and landscapes which have the well recognized "multiple functions" as a fundamental feature. Then it is not surprising that this decision support system requires including and mixing many different high quality information, engines and processing units in order to be successfully applied.

The SOILCONSWEB makes it possible for geographically dispersed groups to real-time (or near real-time) access critical, accurate, and up-to-date spatial data with the objective of advising and producing detailed spatial documents, reports and maps on a series of questions including agriculture, environment and climate change.

The system, strongly rooted in soil information, is being developing with basic web GIS facilities and with advanced modeling including both Digital Soil Mapping (DSM) and soil-plant-atmosphere engines.

The combination of spatial and functional modeling in our WB-SDSS is of special importance for addressing the complex challenges given above. In our system DSM has its value in itself and especially in instructing other integrated modeling which employ digital soil maps for addressing agriculture/forestry/environmental issues. Then our system can be considered as an extreme implementation of the digital soil assessment procedures enabling the assessment of solutions at the landscape scale.

The WB-SDSS tool integrates the classical top-down decisions (as supplied also in basic web-GIS facilities) with the bottom-up contributions towards a sustainable landscape planning and management. In other words the system enables users to upload their certified soil data in the system.

1.3 *Objectives*

The goal of this contribution is to develop a spatial inference system engine implementing different methods, and to test this specifically tailored software program to cross validate the spatial distribution of the topsoil clay content. The engine automatically includes new records (coming from any new certified analysis performed and uploaded by farmers) by updating and possibly changing spatial models which will adapt to the dynamic database. This characteristic is useful to enhance the local and the global accuracy of the WB-SDSS output.

2 STUDY AREA

The work has been performed in “Valle Telesina”, a 20,000 ha landscape located in the South of Italy (Fig. 1). It has a high soil and climate spatial variability and it is a traditional setting for vineyards producing high quality wines.

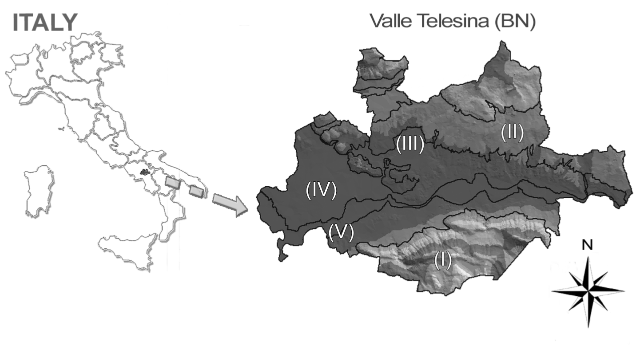

Figure 1. DEM of Valle Telesina and the main terroir systems: (I) mountains, (II) hills, (III) pediment plain, (IV) ancient fluvial terraces, (V) alluvial plain.

The Valle Telesina has a complex geomorphology and it is characterized by an East–West elongated graben where flows the Calore River. Five different geomorphic environments are found, namely (i) limestone mountains having volcanic ash deposits at the surface; (ii) hills constituted by marl arenaceous flysch; (iii) pediment plain constituted by colluvial material of the slope fan of the limestone relieves; (iv) ancient alluvial terraces and (v) actual alluvial plain. Such complexity echoes in 60 Soil Typological Units aggregated into 47 Soil Mapping Units.

3 THE CVSIS ENGINE

The routine query of the WB-SDSS by stakeholders needs that digital soil maps are available to run attribute space inference systems and give a web integrated response. To perform this goal a list of models of spatial inference must be calibrated periodically (within year intervals) to make up-to-date prediction maps according to the core framework of our CVSIS (Cross Validation Spatial Inference System) engine.

More specifically, at any scheduled time step the CVSIS engine starts only if modifications of sample points and/or of covariates occurred, otherwise the most accurate digital map for any soil attribute which was accounted during previous step is retained. This checking node enables to detect the new soil records and their automatic inclusion in the spatial modeling of soil features.

When the CVSIS engine starts it calibrates different types of spatial models each using a leave one out cross validation (L-1-O-CV) procedure. Assuming N is the sample size, the L-1-O-CV procedure requires that (i) any model is calibrated N times, and (ii) the error metric is recursively calculated at all omitted locations. Hence the root mean square error is calculated for any model on the whole available dataset of size N. The less noisy proxy for the soil attribute of interest is selected in the form of digital map.

Different models of spatial interpolation are developed, including the simpler model based on the soil mapping units used as benchmark together with a deterministic and a stochastic model. A brief presentation of these modeling approaches is given below.

3.1 *Soil Mapping Units (SMU)*

In the Telesina valley 47 soil mapping units are condensed fusing 60 soil typological units. The Soil Mapping Unit (SMU) model is fulfilled computing the average value for the parameter of interest by geographically stratifying the soil samples located on different soil mapping units. A level of further aggregation of soil cartographic units is used if the first stratification produces a void average.

The L-1-O-CV procedure is performed calculating the RMSE between the predicted (SMU average excluding the leaved out sample) and the measured value at the leaved out sample.

3.2 *Inverse Distance squared Weighted average (IDW)*

One of the most commonly techniques for spatial interpolation of scattered sample points is the Inverse Distance Weighted average (IDW) method (Cressie 1993). The assumption is that the interpolating surface is influenced most by nearby points. Therefore the weight assigned to each scatter point decays as its distance from the interpolation point increases. As long as prediction depends on the number of retained nearby points, a sensitivity analysis investigates the accuracy pattern with varying neighborhood size (Fig. 2).

The power parameter of the IDW model is equal to 2, and the Euclidean distance is calculated using the spatial coordinates (x, y).

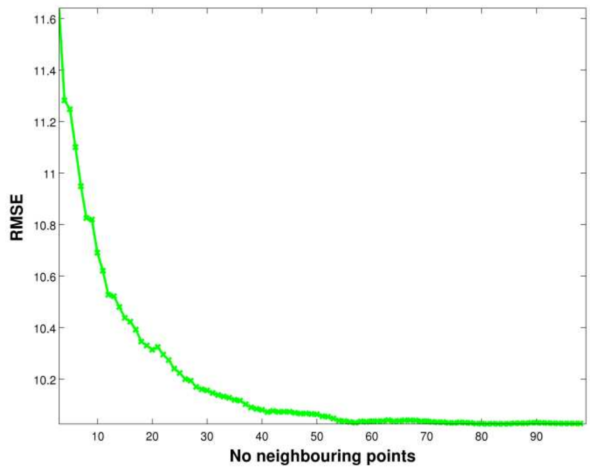

Figure 2. Sensitivity analysis of neighborhood size in IDW.

3.3 *Ordinary Kriging (OK)*

The first step in the Ordinary Kriging (OK) modeling is variography (Fig. 3). The whole dataset is used to build the experimental semivariogram, while interpolation by ordinary kriging is achieved leaving out one sample point per loop. The most sensitive and difficulty phase is the programming of the procedure developed to automatically fit the semivariogram model to the sample semivariogram. The CVSIS implements a nonlinear least squares estimates of the Matérn covariance parameters (Minasny & McBratney 2005) using the iterative Marquardt's method (Nielsen 1999).

4 RESULTS

The IDW method is applied after the neighborhood size yielding the highest accuracy is recognized. The L-1-O-CV procedure applied on topsoil clay yields the highest accuracy using 81 number of neighborhood points (Fig. 2).

The ordinary kriging estimates are calculated using the variance-covariance matrices derived from the fitted Matérn function presented in Figure 3. This approach is flexible because it overcomes the problems concerning the automatic choice of model type (e.g. nugget, spherical, exponential) to be adapted to the experimental semivariogram.

Topsoil predictions of clay content by the three methods of spatial inference are presented in Figure 4. SMU, IDW and OK methods are shown in the top, middle and bottom panels, respectively.

The SMU model is not suited to represent the clay variability within any soil mapping unit, even if it is able to distinguish the average clay value between the main soil mapping units of the Valle Telesina area.

The CVSIS selects the most accurate model by evaluating the RMSE after the L-1-O-CV procedure. It should be pointed out that a similar RMSE is achieved by both the inverse distance method (10.03%) and the ordinary kriging (10.19%). However the engine numerically selects the IDW model to represent the topsoil clay content within the study area spatial domain.

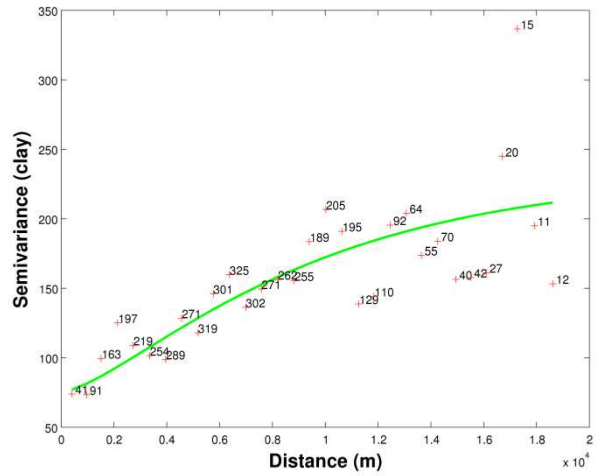

Figure 3. Variography of clay content.

5 CONCLUSIONS

Here we present a preliminary version of the engine of spatial inference that will be further developed during the LIFE+ SOILCONSWEB project. We applied the CVSIS engine on the clay content measured at topsoil. The current CVSIS version demonstrated that any soil property at hand can undergo to spatial inference after a cross validation procedure selects the most accurate model. The procedure can automatically update a digital map of any soil parameter according to new certified soil instances uploaded by farmers.

We expect that further development will be tackled to:

- empower the IDW model weighting also by environmental covariates other than spatial coordinates;
- check the experimental semivariogram and especially its fitted model to flag them as *not good*, *good*, and *check*. Therefore an optional manual checking is warned if the flag is different from *good*;
- enable more models of spatial inference such as multilinear regression, regression kriging and artificial neural networks;
- automatically include a dynamic set of exhaustive auxiliary predictors (e.g. from forthcoming proximal and remote sensed imageries);
- apply the CVSIS to model the soil parameters required by the WB-SDSS system (e.g. horizon thickness, soil texture, organic carbon, pH);
- implement a parallel program running the CVSIS engine in order to shorten the computational time.

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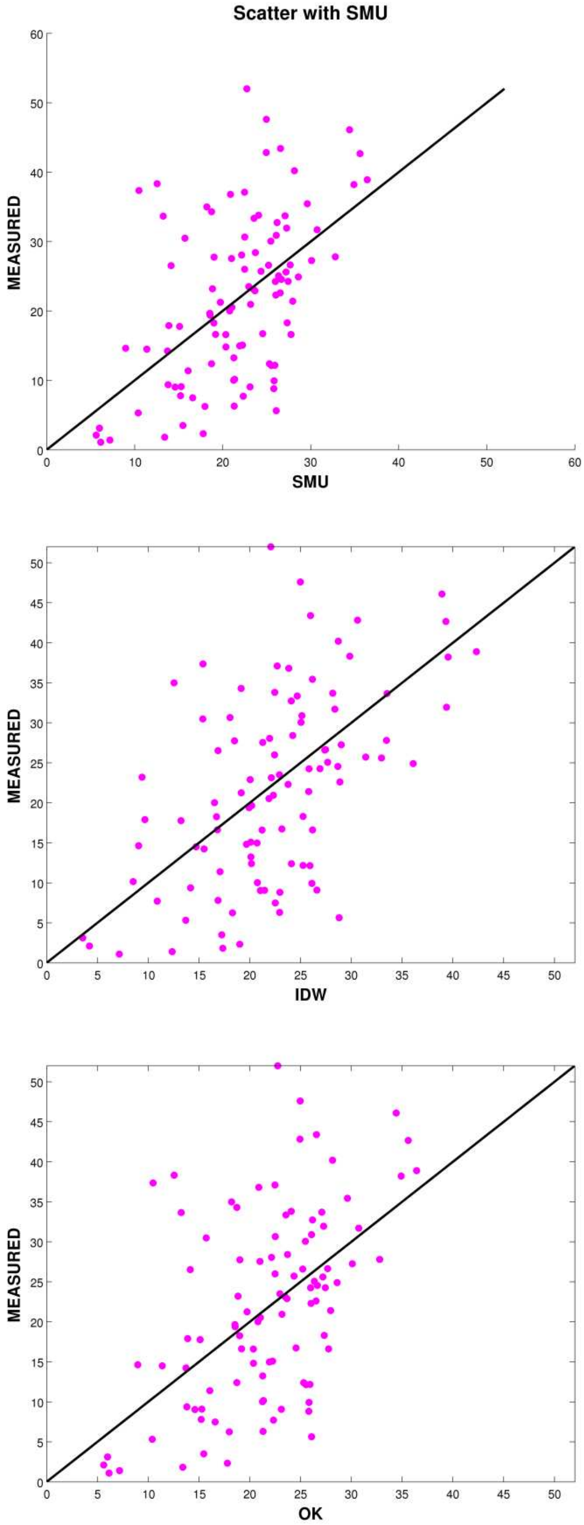

Figure 4. Cross validation predictions of clay content. Top panel: SMU; middle panel: IDW; bottom panel: OK.