Digital mapping of soil carbon

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Abstract
Digital soil mapping is the creation of a spatial soil information system using field and laboratory observation methods coupled with quantitative spatial prediction techniques. Digital soil mapping follows the advancement in soil and environmental observations using proximal and remote sensing. This paper discusses the methods in digital soil mapping and shows the application for mapping & monitoring soil carbon using two examples. The first example shows the mapping of whole profile soil carbon in Edgeroi, Australia. We combined equal-area spline depth functions with digital soil mapping techniques to predict the vertical and lateral variation of carbon storage across the area. We also show the uncertainty of the prediction using a new technique. The second example is the use of legacy soil data to detect the spatio-temporal changes in topsoil organic carbon in the island of Java, Indonesia.

Key words
Food security, water security, energy security, climate security, soil science, soil carbon, soil assessment, digital soil mapping

Introduction
There is a global demand for soil data and information for food security and global environmental management. This is also a large interest in recognizing the soil system as a significant terrestrial sink of carbon. The reliable assessment and monitoring of soil carbon stocks is of key importance for soil conservation and in mitigation strategies for increased atmospheric carbon. In this paper we discuss the recent advances in digital soil mapping, and show the application for mapping & monitoring soil carbon.

Digital soil mapping is defined as: the creation and population of spatial soil information systems by the use of field and laboratory observational methods coupled with spatial and non-spatial soil inference systems (Lagacherie *et al.* 2007). Digital soil mapping does not just produce a paper map; it is a dynamic process in which geographically referenced databases are created at a given spatial resolution. A digital soil map is essentially a spatial database of soil properties, based on a sample of landscape at known locations. Field sampling is used to determine spatial distribution of soil properties, which are mostly measured in the laboratory. These data are then used to predict soil properties in areas not sampled. Digital soil maps describe the uncertainties associated with such predictions and, when based on longitudinal data, can provide information on dynamic soil properties. The process is summarized in Figure 1.

There are three main steps in digital soil mapping.
Step 1, that of data input, starts with the production of base maps, assembling and calibrating full coverage of covariates from available data [e.g., the 90 × 90 m resolution digital terrain models from Shuttle Radar Topography Mission (SRTM v.3)] for the region of interest. Covariates, reflecting state factors of soil formation, include terrain attributes, gamma radiometric imagery, multi- and hyper-spectral imagery, landuse, geology and prior soil maps.

Step 2 the spatial soil inference system, which involves estimation of soil properties, expressed as estimates and their uncertainties. They are derived by using quantitative relations between point soil measurements and the spatially covered covariates. The model for digital soil mapping can be written as:

$$S = f(s,c,o,r,p,a,n) + e$$

where S is soil properties of interest; s soil and other properties of the soil; c climatic properties of the environment; o organisms; r topography; p parent material; a age (the time factor); n space (spatial position absolute and relative); e: autocorrelated random spatial variation, predicted with a variogram and kriging. This is called the *scorpan* model (McBratney *et al.* 2003).

In **step 3**, spatially inferred soil properties are used to predict more difficult-to-measure soil functions, such as available soil water storage, carbon density, and phosphorus fixation. This is achieved using pedotransfer functions built into a soil inference system (McBratney *et al.* 2002). These soil functions largely determine the capacity of soils to deliver various provisioning and regulating ecosystem services. The overall uncertainty of the prediction is assessed by combining uncertainties of input data, spatial inference, and soil functions.

There is a fourth step which leads to assessment. **Step 4** was recently elucidated by Carré *et al.* (2007). This recognizes that the information should be used to provide information to policy-makers as well as land managers.

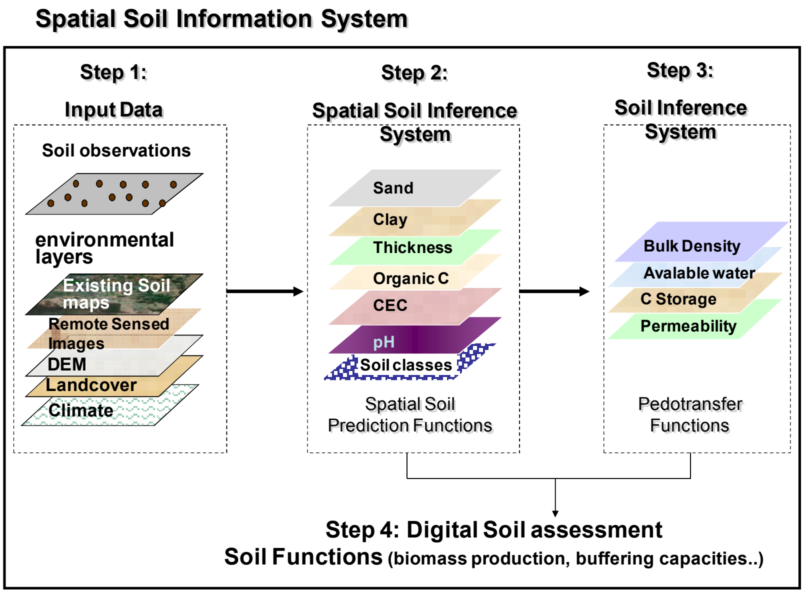

Figure 1. Digital soil mapping

Mapping and detecting changes in soil carbon

Here we provide two examples on the use of digital soil mapping and spatial inference system, for mapping and detecting the changes in soil carbon.

Mapping continuous depth functions of soil organic carbon

The *scorpan* model was expanded to include full-profile prediction at every point, by fitting the covariates to the depth parameters of an equal-area quadratic spline. The so-called continuous layer model provides much more detailed predictions.This results in predictions or maps of soil properties at potentially all depths (Malone *et al.* 2010). Using the Edgeroi district in north-western NSW as the test site, we combined equal-area spline depth functions with digital soil mapping techniques to predict the vertical and lateral variation of carbon storage across the 1500 km^2 area. Neural network models were constructed for soil carbon to model their relationship with a suite of *scorpan* factors derived from a digital elevation model (*r*), radiometric data (*s,p*) and Landsat imagery (*o*). The resulting geo-database of quantitative soil information describing its spatial and vertical variation is an example of what can be generated with this proposed methodology (Figure 2).

We also derived an uncertainty estimates based on a new empirical approach. Uncertainty in this case is treated as the probability distribution of the output model errors, which comprises all types of uncertainty (model structure, model parameters and data). Our approach is based on fuzzy k-means with extragrades (McBratney and De Gruijter 1992), an extension of the method by Shrestha and Solomatine (2006). The concept is to partition the model input (covariates) space into different clusters having similar values of model errors. The covariates used for prediction is partitioned into several classes using fuzzy k-means with extragrades. Each class is then represented by a prediction interval determined from the empirical distribution. The fuzzy k-means with extragrades method is also used to identify and sufficiently penalize those observations outside the domain of the calibration data. Using the class centroids, a new observation can be allocated memberships to each of the established classes. Prediction limits for new observations then can be calculated as a weighted average of the membership values.

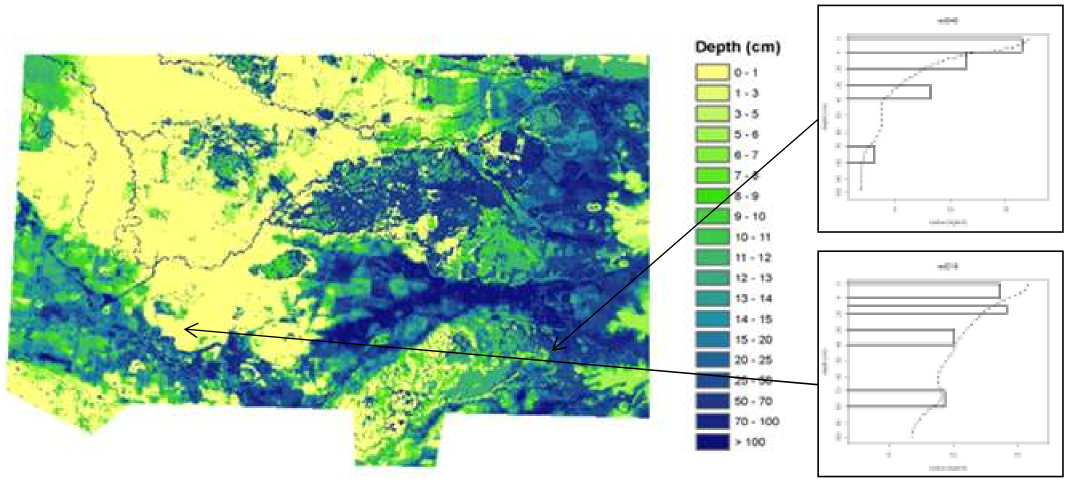

Figure 2. The depth at which soil C < 1%

Using legacy soil data to detect temporal changes in soil organic matter.
The second example deals with the use of legacy data to detect spatio-temporal changes in organic matter at a regional scale. Legacy soil data is mostly used to provide information on the spatial distribution of soil. However legacy soil data can also be used to detect the temporal changes in soil properties (Saby *et al.* 2008). The model here is based on the soil (*s*) and time (*s*) factors. A dataset of soil properties in Indonesia from 1930-1990 was compiled by Lindert (2000). The database contained 2,200 best-detailed soil profiles from Java which has uneven coverage in time, space, and land use. We extended the Lindert database to include new data of 235 profiles from surveys post 1990 conducted by the Soil Research Institute in Bogor. Here we are looking at the soil carbon content from the topsoil (Figure 3).

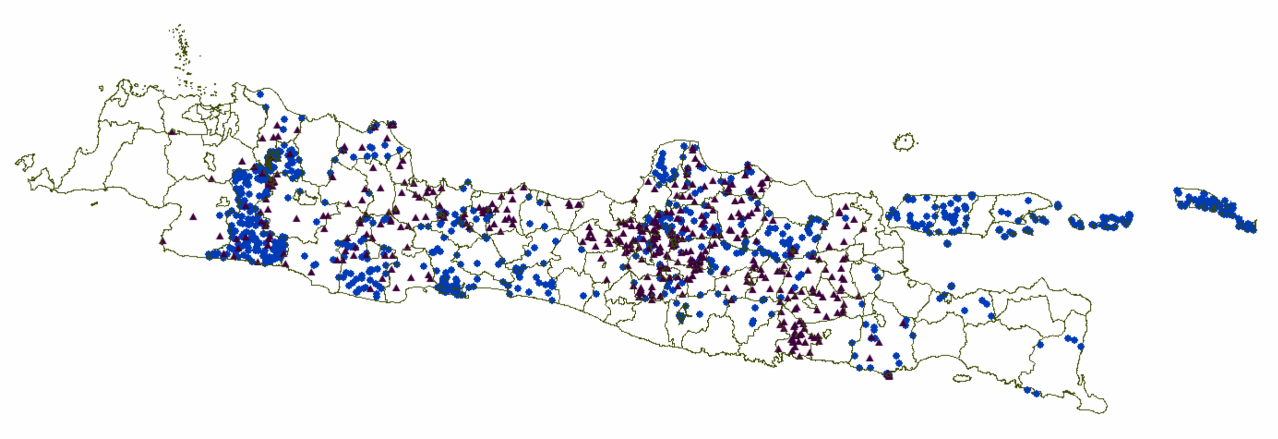

Figure 3. Data density for the period of 1930-1940 (blue dots) and 1990-2007 (red triangles).

Figure 4 shows the topsoil soil carbon content in Java over time, showing a rapid decline of soil carbon from the early 1930s to 1970. Java is the most crowded island in Indonesia, with richest soil from volcanic activities (Inceptisols, Andisols) and large floodplains (Entisols). Its land is most intensively farmed, and thus the organic C trends reflect human activities over time. The median value of C during 1930-1940 is 2.1%, while the median value in 1960-1970 is 0.7%.This rapid drop is due to the high conversion of forests into plantations and food crops. In the early development during the Dutch colonialism, most land development is towards plantations such as tea, rubber, coffee, tobacco etc. This is followed by rapid conversion to food crops in the 1950s, leading to a massive rice production in the 1960s. This resulted in a rapid decline of 1.5% of soil organic C. Following the decline, there is a slight increase of C after 1970s. This is the result of the farmers' effort to remediate the soil fertility by adding fertilizers, returning crop residues, and applying green compost and manures. In the 1990s also there is a large interest in organic farming. We can see the increase of organic C to a level of 1.1% in the 2000s. This trend is also observed in the quality or organic matter in the soil as measured by C/N values (Figure 4).

Legacy soil data come from traditional soil survey with no statistical criteria for sampling. The surveys can be selective and may be purposive and changes with space and time (Figure 3). This may lead to biases in the areas being sampled over space and time. The consistency and accuracy of laboratory methods used is also unknown. However, our empirical analysis is able to show the dynamics of soil organic C over the Java island. We argue that because we have large enough samples, we can represent the average soil C level for each period.

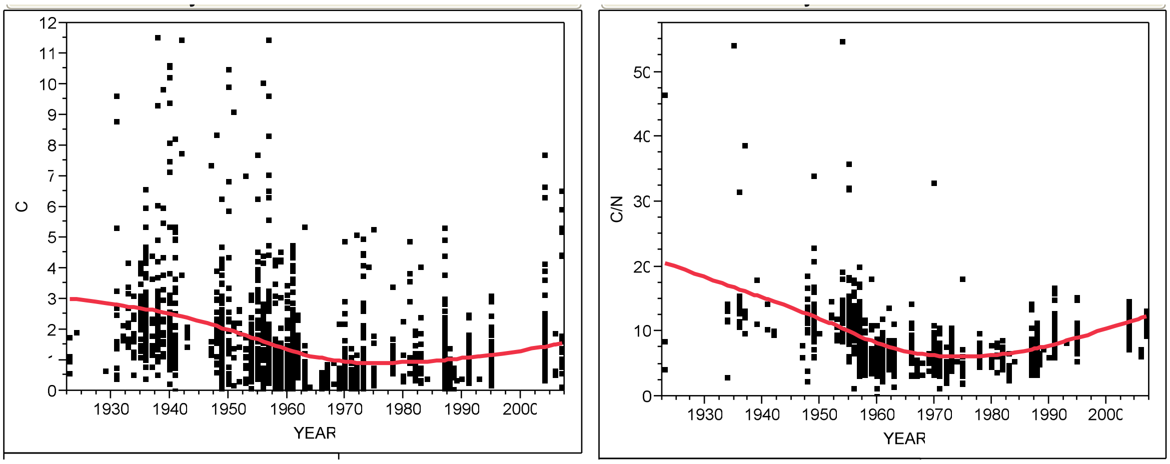

Figure 4. Soil organic C content and C/N ratio over time for top soils in Java.

Conclusions
Digital soil mapping allows the mapping and monitoring the changes in soil carbon. mapping the depth function allows the quantification of soil carbon across large areas. Legacy soil data also allow us to evaluate the dynamics of soil carbon over a large area, as affected by human activities. Although the rates of decomposition and accumulations are affected by various environmental conditions, we are able to detect the trend in Java. There is a lack of data on the accumulation of carbon over large areas; in this study we are able to estimate the average C decomposition rate in the island of Java (topsoil 0-10 cm) during 1930-1950s is 37 kg/m^2/year while the accumulation rate during 1990 to 2000s is 27 kg/m^2/year.

References

Carré F, McBratney AB, Mayr T, Montanarella L (2007) Digital soil assessments: beyond DSM. *Geoderma* **142**, 69-79.

Lagacherie P, McBratney AB, Voltz M (2007) Digital Soil Mapping: An Introductory Perspective. Developments in Soil Science 31 (Elsevier: Amsterdam).

Lindert PH (2000) Shifting Ground, The Changing Agricultural Soils of China and Indonesia. (MIT Press: Cambridge).

Malone BP, McBratney AB, Minasny B (2010). Mapping continuous depth functions of soil carbon storage and available water capacity. *Geoderma* **154**, 138-152.

McBratney A B, De Gruijter JJ (1992) A continuum approach to soil classification by modified fuzzy k-means with extragrades. *Journal of Soil Science* **43**, 159-175.

McBratney AB, Minasny B, Cattle SR, Vervoort RW (2002) From pedotransfer functions to soil inference systems. *Geoderma* **109**, 41-73.

McBratney AB, Mendonça Santos ML, Minasny B (2003). On digital soil mapping. *Geoderma* **117**, 3-52.

Saby NPA, Arrouays D, Antoni V, Lemercier B, Follain S, Walter C, Schvartz C (2008) Changes in soil organic carbon in a mountainous French region, 1990–2004. *Soil Use and Management* **24**, 254 – 262.

Shrestha DL, Solomatine DP (2006). Machine learning approaches for estimation of prediction interval for the model output. *Neural Networks* **19**, 225-235.