NEW CHALLENGES FOR PREDICTIVE SOIL MAPPING

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Topic 1: Introduction & background to digital soil mapping

ABSTRACT:
This paper lists possible developments in predictive soil mapping. Six key tasks are discussed: (1) new spatial prediction algorithms, (2) dynamic modelling of soil genesis, (3) integration of GIS and statistics, (4) use of new technological innovations, (5) use of high-resolution imagery and (6) global modelling of soil genesis. Especially dynamic modelling of soil genesis, use of high-resolution DEMs and development of global thematic soil maps is expected to be a major field of research in pedometrics for the next decade. Solving these research problems requires a joint effort of both pedometricians and pedologists.

1. INTRODUCTION

Every few years some established pedometricians accept the task to write an overview of the new techniques and applications in the field of predictive soil mapping. Webster (1994) wrote the first overview of pedometric techniques. After that, McBratney et al. (2000; 2003) made two extensive overviews, the most recent one listing over 100 soil mapping applications. We should also add to this list Goovaerts' (1999) review of the state-of-the-art of geostatistical techniques in soil science and the overview of predictive soil mapping by Scull et al. (2003). Apart from just trying to summarize what has been done in this field, it is equally important for future research to try to list unsolved methodological problems and suggest possible solutions. From time to time, it is important to free our minds and take 'a look in the crystal ball' to see what will be the future of predictive soil mapping. This is exactly what McSweeney et al. (1994) did a decade ago and what has been systematically discussed by Heuvelink and Webster (2001). Indorante et al. (1996) give even more extensive review of the evolution of soil survey in the USA and present their vision of what to expect in the 21st century.
In this paper we will go beyond a classical review of what is known and what can be done. We will instead try to extrapolate our knowledge and use our imagination, hoping that these ideas will inspire other pedometricians to start new fields of research. This constructive brainstorming brought us up to six quests.

2. THE SIX QUESTS

2.1 Quest #1. New spatial prediction algorithms

"We need tools that will help us understand the soil better and NOT tools that we understand better."

Alex McBratney, Pedometrics 2003 conference in Reading, UK.

Although McBratney et al. (2003) list dozens of possible predictive soil mapping techniques, all accepted quantitative spatial prediction techniques that are used today can be roughly separated based on the three key aspects (a) *amount of geostatistical analysis*: geostatistical and statistical, (b) *amount of temporal analysis*: spatial and spatio-temporal and (c) *amount of empirical and process knowledge used*: pure empirical or expert systems, stochastic and mechanistic approaches. The first and oldest group of quantitative spatial prediction methods relies solely on point observations of the soil property of interest. Predictions are typically made by calculating some weighted average of the observations:

$$\hat{z}(s_0) = \sum_{i=1}^{n} w_i \cdot z(s_i) \qquad (1)$$

where $\hat{z}$ is the predicted value of the target variable, s_0 is the location of the prediction point (in the Cartesian system), w_i are the weights, $z(s_i)$ are the sampled point observations and n is the total number of points. The weights can be optimally solved using the spatial autocorrelation structure, which is what is popularly known as "geostatistical interpolation" (Webster and Oliver, 2001, p. 38).

The second group of spatial prediction techniques uses correlation between the target and auxiliary environmental variables that are mapped extensively over the area of interest. In this case, the predictions are based on some form of the general linear model (GLM), most commonly multiple regression analysis:

$$\hat{z}(s_0) = \sum_{k=0}^{p} \beta_k \cdot q_k(s_0) \,; \quad q_0 \equiv 1 \qquad (2)$$

where $q_k(s_0)$ are the auxiliary predictors available at the prediction location, β_k are regression coefficients and p is the number of predictors. The auxiliary predictors can be terrain parameters, remote sensing images, geological data and other types of discrete and continuous spatially exhaustive information. Underlying assumption of this approach is that the residual of the GLM is spatially uncorrelated.

A step forward is to combine the two approaches above and use a kind of a hybrid interpolation technique. This is done in **regression-kriging**, which in matrix notation looks like this (Hengl et al., 2004):

$$\hat{z}(s_0) = \mathbf{q_0^T} \cdot \hat{\boldsymbol{\beta}}_{\mathbf{gls}} + \boldsymbol{\lambda}_\mathbf{0}^\mathbf{T} \cdot (\mathbf{z} - \mathbf{q} \cdot \hat{\boldsymbol{\beta}}_{\mathbf{gls}}) \qquad (3)$$

where $\mathbf{q_0^T}$ is a vector of predictors at s_0, $\hat{\boldsymbol{\beta}}_{\mathbf{gls}}$ is a vector of coefficients that are estimated using generalized least squares, $\boldsymbol{\lambda}_\mathbf{0}^\mathbf{T}$ is a vector of kriging weights and $\mathbf{z}$ is a vector of n observations. This method is also known in the literature by the term "Universal kriging" or "**Kriging with external drift**" (Goovaerts 1997). Although kriging with external drift and regression-kriging are computationally slightly different, they give the same predictions under the same assumptions (Hengl et al., 2003).

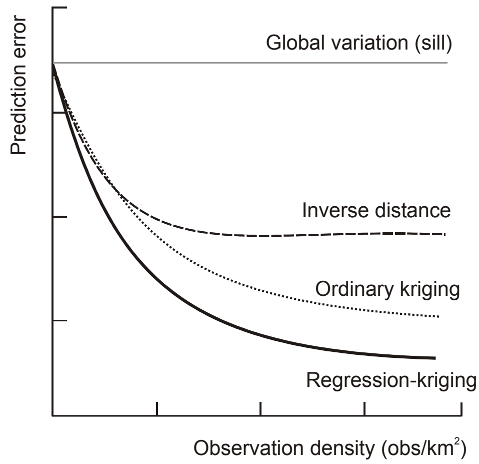

Figure 1. Schematized relationship between prediction efficiency and observation density for different interpolation methods. More sophisticated spatial prediction methods have proven to be better predictors (in general, not in all situations), but only to a certain extent. After Bregt (1992, p. 49).

Regression-kriging is increasingly popular because it (in general) achieves lower prediction errors at the control points (Figure 1) and because a multitude of explanatory variables is available today at high resolutions. A second advantage of regression-kriging is that it uses explanatory variables that are recognised by pedologistst as causal factors, also known as **CLORPT** (CLimate,Organisms, Relief, Parent material, Time) factors. Regression kriging is, however, handicapped because the way in which the explanatory variables appear in the trend is highly empirical, i.e. it does not reflect the actual physical processes. The same can be said for the **Bayesian Maximum Entropy** method (D'Or, 2003), which is another hybrid technique that can employ both the auxiliary maps and information derived from observations nearby.

Apart from purely spatial prediction techniques, **spatio-temporal interpolation** techniques are today used more and more. Most of these follow the general model (Kyriakidis and Journel, 1999; Snepvangers et al., 2003):

$$z(s,t) = m(s,t) + \varepsilon(s,t) \tag{4}$$

where $m(s,t)$ is the deterministic trend (usually a constant) and $\varepsilon(s,t)$ is the spatio-temporally autocorrelated residual. In practice, spatio-temporal interpolation follows the geostastical interpolation principle as explained in Eq. (1), except that here the variograms are estimated in three dimensions (two-dimensional position x and y and 'position' in time). In order for spatio-temporal techniques to yield accurate predictions, dense sampling in both space and time is required. This means that existing soil surveys that have little to no repetition in time cannot be adopted. Also, **dynamic deterministic trend** will be hard to estimate using static auxiliary maps as in Eq. (3), because, again, these maps need to be available in different time lags.

A specific extension of the general model Eq. (4) is to define the trend by the use of simulation models. In this case the soil attribute is predicted from a set of environmental predictors incorporated in a **dynamic model** *f*:

$$z_{sim}(s,t) = f_{cl,r,o,p}(s,t) + \varepsilon \tag{5}$$

where cl, r, o, p are the CLORPT factors and s,t is the position in space and time for which a prediction is made. This means that we can try to predict the soil property z first by using a **simulation model**, and then use real observations to calibrate the model by kriging the residuals. For the latter, we may again use the regression-kriging model:

$$\hat{z}(s_0) = b_0 + b_1 \cdot \hat{z}_{sim}(s_0) + \sum_{i=1}^{n} w_i \cdot \left[z(s_i) - \hat{z}_{sim}(s_i) \right] \tag{6}$$

where $\hat{z}_{sim}$ is the soil property predicted using the simulation model, and b_0 and b_1 are regression (calibration) coefficients. The question remains whether there is an approach that is more attractive than regression-kriging (note that universal kriging was first time described already in 1969 by Matheron!) and whether mathematicians will develop some new system of equations that will prove to be more powerful in prediction.

2.2 Quest #2. Dynamic modelling of soil-genesis

"I often wondered how Einstein could come up with such a simple assumption… the Universe is so trivial that it can be modelled and analysed using a one-dimensional differential equation – in which everything is a function of time."

James Peebles, Princeton, 1990; published in "God's Equation: Einstein, Relativity, and the Expanding Universe" by Amir D. Aczel

In the previous section we have shown how the prediction model might look like if used together with a simulation model. Instead of merely fitting the soil profile data using some (geo)statistical technique, a more promising approach is to make use of physically-based quantitative **models of soil-landscape genesis**. The existing spatial prediction techniques, such as regression-kriging, can then be used to adjust the predictions made by these models (see Eq. (6)). We did not discuss (on purpose) how these mechanistic models might look like and whether we are really able to model soil evolution using only a few inputs such as a DEM and geological data.

Modelling soil evolution in time is becoming increasingly popular. Mitasova et al. (1997) developed virtual soil-scapes that can be visualised as 3D animations. Minasny and McBratney (2001) developed a rudimentary model of soil-landscape evolution, and so did Rosenbloom et al. (2001), Könligel et al. (2002) and Schoorl (2002). Most of these soil genesis models mainly aim to map the distribution of texture fractions, soil mass, organic carbon etc., based on some

mass diffusion model and using a DEM as input (Minasny and McBratney, 2001; Rosenbloom et al., 2001). These properties are then used to make inference about the chemical weathering or development of soil taxa.

Complete modelling of soil evolution, however, is not that simple. The problem is that many soil-forming processes are as yet poorly understood; many of the inputs are unknown or very poorly known. The model will have many parameters that will have to be identified somehow e.g.: process parameters such as hydraulic conductivity, weathering rates, but also stochastic parameters such as variances and correlations. There are enormous challenges. We speak about huge state dimensions: say 40 soil properties at 5 depths for a 100×100 grid give 2 million state variables! Moreover, processes need to be modelled at completely different time and space scales, e.g. podzolization versus event-based erosion. Some of these processes are still poorly understood, some happened suddenly in the past (e.g. overflooding, landslides, movement of glaciers etc.).

The dynamic models might turn out to be as non-linear as with the long-term weather forecast – first real-life proof of chaos theory (Gleick, 1988). It can also finish in a similar dead-end street: although the modelling of deposition/accumulation processes and **meandering water movement** may seem easy, the influence of organisms and climate is often complex and behaves in a non-linear way (Phillips, 1994). Moreover, in many cases we will not actually know how the landscape looked like thousands of years ago. Soils just might be too chaotic and too disturbed for prediction using mechanistic models. McBratney et al. (2003) conclude also that it will be a long time before the mechanistic theoretical approach will be competitive in the prediction sense.

2.3 Quest #3. Integration of comprehensive statistical analysis within GIS

"Eighty percent of the final exam will be based on the one lecture you missed about the one book you didn't read."

Murphy's laws, from www.murphys-laws.com

Another important problem with the use of existing spatial prediction techniques is that, although the new prediction methods are tested and documented, there is still a large gap between what is possible for some and what is available to many. The key problem with GIS packages is that, in many cases, a combination of generalized linear models and kriging cannot be fully employed nor automated. The problem is that every package is specialized for either statistical or GIS operations and there are not many that support both. We have produced a small comparison of popular GIS and statistical packages with interpolation possibilities (Table 1). Note that none of the packages is able to satisfy all of the user needs. Only **Idrisi** seems to be up to the challenge as it covers the most of the sophisticated (geo)statistical operations important for robust spatial prediction, especially due to a recent link to **GSTAT** functions.

The regression-kriging with auxiliary maps can be run in only a limited number of packages. In fact, only GSTAT (Pebesma and Wesseling, 1998) in combination with some raster GIS package such as Idrisi and **GRASS** offers a possibility to interpolate a variable using auxiliary maps together with variogram estimation. But even in the case of GSTAT many operations such as iterative estimation of regression coefficients and step-wise regression are not available and needs to be run in a statistical package like S-Plus or R. Fortunately, a tight link between R and GSTAT has very recently been provided (Pebesma, 2003), but an important problem is that these tools are not easily used by non-experts.

Obviously, a task for the programmers in the near future will be to incorporate statistical procedures normally not available, such as **step-wise regression**, **neural networks**, **automated variogram modelling**, **unsupervised fuzzy classification**, **BME** and others within a **dynamic GIS packages**. This will enhance use of the complex computational frameworks such as the ones discussed in McBratney et al. (2003) and Hengl et al. (2004).

Table 1. Overview of computing capabilities (spatial statistics) of some popular statistical and GIS packages*: × - full capability, O - possible but with some limitations, – - not possible in this package.

	S-PLUS	GSTAT	SURFER	ISATIS	VESPER	GRASS	PC Raster	ILWIS	IDRISI	ArcGIS
Commercial price category: I – >1000 EUR; II – 500-1000 EUR; III – <500 EUR; IV – open source	**II**	**IV**	**III**	**I**	**IV**	**IV**	**III**	**III**	**II**	**I**
Used in soil mapping for: A – statistical analysis and data mining; B – interpolation of point data; C – processing of auxiliary maps; E –preparation and visualization of final maps	**A, B**	**B**	**B, E**	**B**	**B**	**B, C**	**C**	**B, C**	**B, C**	**B, E**
User-friendly environment to non-expert	×	–	×	×	O	O	–	×	×	×
Quality of support and description of algorithms	O	×	O	O	O	O	O	×	×	O
Standard GIS capabilities	–	–	O	–	–	×	O	×	×	×
Standard descriptive statistical analysis	×	×	–	×	–	O	–	×	×	×
Image processing tools (orthorectification, filtering, terrain analysis)	–	–	–	–	–	O	–	×	×	×
Comprehensive regression analysis (regression trees, GLM)	×	O	–	O	–	–	–	–	O	–
Interactive (automated) variogram modelling	–	×	–	×	×	–	–	–	O	×
Regression-kriging with auxiliary maps	–	×	–	–	–	×	–	O	O	–
Dynamic modelling (simulations, spatial iterations, propagation, animations)	–	O	–	–	–	O	×	O	O	O

*Only the computing capabilities of the most recent versions in the year 2004 have been considered.

2.4 Quest #4. Developing and testing new technologies

"If a picture is worth a thousand words – a hologram is worth a million!"

From the www. holograms.bc.ca site.

It is not only new mathematical techniques and new software packages that will make impact on digital soil mapping in the near future – some drastic technological inventions might be a cause of new revolutions as well. Especially the following three groups of technological developments are expected to play a dominant role for digital soil mapping:

1. **New sources of remotely and proximally sensed images** (hyperspectral, radar, gamma-ray spectrometry);
2. **Powerful field-computers connected or integrated with the measuring devices**;
3. **New technologies to visualise soil-scapes and the related uncertainty**;

The remotely and proximally sensed images will be used primarily for calibration of dynamic models. In many cases the theoretical models will fail to explain some random soil features or anomalies in the distribution of soils. This might happen especially in flooded terrains, as a result of human influence or as a result of relic processes. In such situations, remote sensing images, especially the ones that can penetrate soil, will be of great help.

Another development to come is the use of **virtual reality** and **holography** to visualise soil-scapes. There are many examples on how to integrate virtual reality and GIS, both using vector and raster-based structures (Camara and Raper, 1999). 3D computer models can now easily be produced. The remaining task is to develop technology to display such 3D soil-landscape models. One option is to use **cave-like screens** on which anaglyphic imagery is projected (this requires special glasses for 3D impression). Apparently, there are only few tens of Digital Light Processing cave projectors used in the World today. Another option is to work with 3D holographic displays that can replace or supplement 2D computer screens. An idea how such a device might look like in the near future is given in Figure 2. Such **holographic tables** showing both raised relief and draped thematic variables will certainly make soil mapping a more popular business.

Figure 2. In the near future it should be possible to visualize virtual landscapes using hologram technology. Raised relief model is produced interactively as a quasi 3D image.

2.5 Quest #5. Working with finer and finer resolutions

"An expert is a person who knows more and more about less and less until he knows absolutely everything about nothing!"

Murphy's laws, from www.murphys-laws.com site

The grid size in a grid-based soil GIS should ideally be a few metres (i.e. the size of a pedon), which is at the moment a very rare standard. Most digital soil mapping projects belong to the 20 to 200 m range (McBratney et al., 2003), which obviously means that we are ignoring local variation. The use of very detailed (<10 m) terrain parameters and remote sensing images will then also reflect on the efficiency of prediction.

In more than 80 percent of the spatial prediction studies, relief is predominantly used as an environmental predictor (McBratney et al., 2003). Today DEMs are available from a number of sources. Highly detailed and accurate topographic images can now be ordered from remote sensing systems such as SPOT and ASTER. For example, SPOT5 offers a new scanner called the **High Resolution Stereoscopic** (HRS) **scanner**, which can give DEMs at resolutions of up to 5 m. A comparison of a DEM produced using high-resolution satellite imagery and conventional DEMs derived from topo maps is given in Figure 3. Note that the mezzo relief (small channels, ridges and peaks, roads) previously not visible in the conventional DEM become very distinct in the 10×10 m DEM extracted from the HRS imagery.

Even in countries with traditionally low relief like Netherlands, a spatially exhaustive DEM for the whole country has been compiled using **airborne laser-mapping** at a resolution of 4×4 meter (Adviesdienst Geo-informatie en ICT, 2000). We should also mention that NASA and collaborators have recorded most of the World's topography in the **Shuttle Radar Topography Mission** in 2002. From this project, 30×30 and 90×90 m DEMs are available for the USA for free and in the rest of the World for a commercial price (about 0,25 EUR per km^2 in Europe for 30 m DEMs).

Using finer resolutions implies more powerful computational capabilities in our computers. This could be a bottleneck in the coming few years because the PC's that can work professionally with images bigger than 5 million pixels are exceptional, or exceptionally expensive. We should not be afraid of this problem because computing capabilities are still growing exponentially. On the other hand, computational time for matrix calculations will also increase approximately cubically with the sample size (McBratney et al., 2003). We should not expect too much from computers in the shorter period.

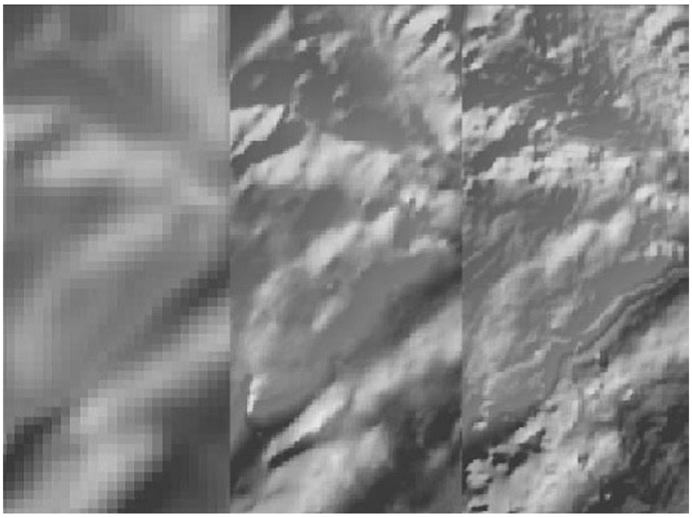

Figure 3. Comparison of three DEMs of the same area: (a) DEM produced from a 1:100K topo map; (b) 30×30 m DEM interpolated from 1:25K topo maps and (c) 10×10 m highly accurate topography derived using the new HRS SPOT scanner (courtesy of SPOT Image ™).

2.6 Quest #6. Global modelling of soil genesis

"We want to develop tools that we can hand-over to other scientists."

Alex McBratney, Pedometrics 2003 conference in Reading, UK.

There are not many environmental systems and ecosystems in the World that can be considered as being completely isolated from each other. This means that soil mappers could benefit if they would integrate their activities and consider a development of a **global dynamic model of soil genesis**. In vegetation science (Bonan et al., 2003), global modelling has proven to be very efficient for explanation of the actual distribution of vegetation and of global changes. In the case of soil data, we can apply dynamic models on the global DEM and then incorporate impact of climate and organism (vegetation) on soil formation. Unfortunately, not many **global profile data sets** to test these models are available today. McBratney and Minasny (2003) fitted variograms from a global data set consisting of 1125 soil profiles from the ISRIC-WISE dataset. As expected, the semivariograms were controlled by the geometric support (grid size), large water bodies and the finite size of region sampled, which gave many computational challenges.

There must be thousands and thousands of high quality soil profile data that can be integrated. We can think of a project with the following phases:

- set-up a **data clearinghouse** (ISRIC) where all soil profile descriptions are uploaded; this can be done by integrating first the national surveys, which can then be uploaded to the international database;
- calibrate different soil variables and laboratory techniques and bring all data to a common standard;
- prepare global auxiliary maps of topography (DEM), water bodies, vegetation and climatic parameters;
- run mechanistic models to produce predictions for the most relevant soil variables: soil texture, solum thickness, chemical variables in the topsoil (30 cm), pH, organic carbon content etc. all at some reasonable resolution (1×1 km);
- calibrate the model using a large number of profile data and adjust the predictions;

These models will be used to represent the **zero stage of World soils**, which can then be used in change detection studies and for ecological modelling. The coarse global soil maps could then be refined on regional scales. Perhaps we can learn from the space-researchers who recently made erosion and landscape evolution models for Mars?

3. CONCLUSIONS

So the good news is there is still a lot of work to do in predictive soil mapping, both to invent and test new algorithms, to use new remote sensing imagery and to work with powerful new gadgets. We foresee that especially dynamic modelling of soil genesis, use of high-resolution DEMs and development of global soil-property maps is definitively going to challenge many researchers, young and old. There will be many case studies in the field of modelling soil-landscape evolution for spatial prediction purposes in the coming decade. Even after we achieve the ambitious quests listed in this paper, many pragmatic questions will remain open. How can specific soil features/processes, such as buried horizons, fossil soils or karstic features be modelled and predicted? Will it ever happen that such advanced predictive soil mapping will replace aerial photo-interpretation and experienced surveyors? Will it ever be possible to fully reconstruct the observed distribution of soils and their properties? How will the soil geoinformation users 'like' these maps? Given the huge challenges and large uncertainties involved, many of these questions will have a negative answer for the coming decades. But this should not stop us from trying. One thing is certain – resolving problems with how to define a mathematical model, where and when to sample and how to interpret the results requires a joint effort of both pedometricians and pedologists, both theorists and experienced surveyors.

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