Szent István University

Doctoral School of Environmental Sciences

Possibilities for integrating Hungarian legacy soil data into international databases

Theses of doctoral (Ph. D.) dissertation

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1. BACKGROUND AND OBJECTIVES

There are less and less opportunities for carrying out new soil surveys with harmonised methodologies on both global and local levels. Therefore there is an increasing attention focusing at the effective use and preservation of already existing data. Since these archive datasets were often compiled using different methodologies and classification systems, their harmonization has become a necessity..

The World refrence Base for Soil Resources (WRB) was been endorsed by the International Union of Soil sCience (IUSS) as its official correlation system in 1998. The system is based on a diagnostic approach, with well defined, quantitative requirements (IUSS Working Group WRB 2007). In contrast, many national classification systems – including the Hungarian one – follow different principles, therefore they do not contain all the adequate data required by WRB.

In the last decade there have been several publications related to the use and digital utilization of legacy soil datasets. However, there is still no harmonised, nationwide database that would be in harmony with the current international terminology of soil science, the WRB.

The main objectives of my research were:

1. Assessment of the data structure and WRB correlation possibilities for legacy the soil datasets with the greatest spatial and thematic coverage of Hungary..
2. Development of a detailed methodology for the WRB correlation of the three Hungarian legacy soil datasets with the greatest national coverage..
3. Development of a methodology for the spatial extension of the correlated data using digital soil mapping techniques.
4. Evaluatione and validationof the results from the applied methods.
5. Development of methodology for the nationwide integration of Hungarian legacy soil data.

2. MATERIALS AND METHODS

Materials

Since the primary object of my work was to develop a methodology that can be applied nationwide, the essential foundations for my work were the following three soil data sources:

- The Kreybig Soil Survey and the Digital Kreybig Soil Information System (Kreybig)
- Data from the Géczy Soil Survey (Géczy)
- Data drom the 1:10 000 scale farm level soil surveys (Farm Level)

For spatial analysis and digital soil mapping I have used the soil data provided by RISSAC for the Gyöngyös area. Because I had no point data available for the Géczy maps, and the kriging of categorical variables would have significantly increased the processing power required, I have decided to exclude the dataset. Therefore, only the two remaining data sources were included in the digital soil mapping process as training data.
For the analysis of the spatial lallocation of the observed WRB units I have also used elevation and remote sensing information.

The primary selection criteria for elevation data was its free availability, thus I have eventually decided to use SRTM data.

Besides the elevation data I have used information from the LANDSAT 5 Thematic Mapper(TM) as remote sensing information. This data source is also freely available. The Landsat TM records in 7 wavelength-bands, at 30x30m resolution with the exception of band 6 (120x120m) :

1. 0,45-0,52 μm (blue)
2. 0,52-0,60 μm (green)
3. 0,63-0,69 μm (red)
4. 0,76-0,90 μm (near-infrared)
5. 1,55-1,75 μm (mid-infrared)
6. 10,4-12,5 μm (thermal-infrared)
7. 2,08-2,35 μm (mid-infrared)

Since the remote sensing information is significantly influenced by vegetation, I have used data from multiple dates:

- 23 October, 2000. (autumn)
- 1 February, 2001. (winter)
- 23 June, 2002. (summer)
- 22 March, 2003. (spring)
- 17 September, 2007. (autumn)

Based on the available data I have analyzed the WRB correlation problems at two levels:

1. A talajszelvény szintjén
2. A talajtérképek szintjén.

Data from the first level is mostly available in tabular format; therefore the applied methodology is only different at the database management level.
In case of soil profile data, also considering the criteria of the WRB it was plausible to use the algorithm-based approach suggested for descriptive soil data by Eberhardt & Waltner (2010). These algorithms, after their development can be applied relatively easily for the individual datasets, thus enabling the mass WRB-harmonization of soil profile data.

Applied methods

Correlation algorithms (profile data)

In view of the fact that a significant part of legacy soil information is available in digital databases, the main data sources for my work were three such Hungarian datasets. Using their methodologies I have assessed the rate of information navailability for international harmonization. At the focus of my analysis was the WRB, as the internationally recognized tool for soil correlation.
An important property of the system is that it allocates soils into categories based onthe presence or absence of well defined, so called diagnostic horizons, materials and properties.

The WRB (IUSS Working Group WRB 2010) uses two main levels:

1. At the reference soil group level it defines 32 main soil types, allocating based on a key using information from field- and laboratory analysis.
2. At the level of qualifiers, there are 179 further descriptive units based on additional criteria. There are so-called prefix and suffix qualifiers.

The basis of the methodology were the simplified WRB algorithms developed by Michéli et al. (2011). These selected the critical criteria for each WRB unit, with fundamental role in its identification. At the Huingarian adaptation of these algorithms the Hungarian Soil Information and Monitoring System (TIM) was considered as a basis.

Out of the 65 diagnostic horizons, properties and materials, 28 does not occur under Hungarian conditions. I have excluded these from my study since the Hungatian datasets does not contain the information required for their definition.

I have developed correlation procedures for the remaining 28 WRB diagnostic criteria and 30 qualifiers, separately of all three studied data sources.

The three data sources used different survey and sampling methodologies, and in some cases different laboratory methods..
During the development of the correlation rules in some cases expert knowledge had to be applied to judge the applicability of legacy data in case of modern datasets. Due to this, in some cases only very limited data was available to derive WRB diagnostic units from.

On the use and evaluation of the developed correlation rules it needs to be noted that they are aonly 'best approximations" by using Hungarian datasets, and should not be mistaken for one-to-one matches.
Figure 1 shows the methodological role of the developed algorithms.

Trough example applications of the developed algoriths I have compared the three legacy datasets available at the test area. At the focus of my analysis was the spatial allocation of WRB units and their changes with different data sources.
For the visualization and processing of geographical information I have used the SAGA geographical information software (System for Automated Geoscientific Analyses 2008). One of the benefits of this programme is that it is open-source, thus freely available. This way the reproduction of the results from this study is easier. SAGA also conatins several easy to use modules for the processing of raster data, including elevation and satellite information.

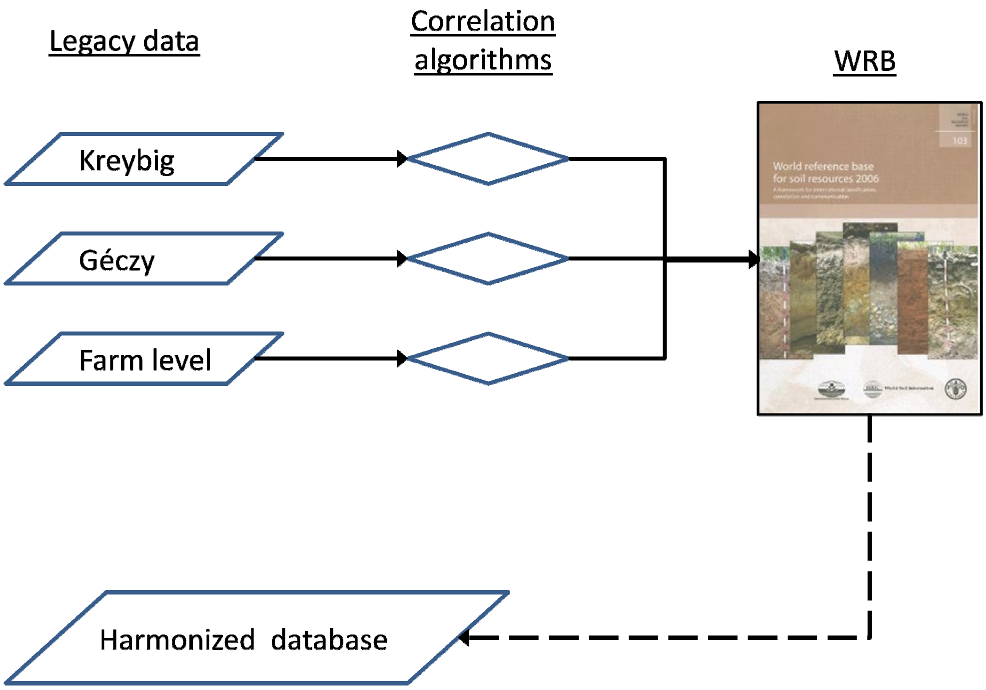

Figure 1. Flowchart of the application of the developed correlation algorithms

For the proper analysis of the spatial extension of harmonized data the WRB units selected must bee available in most datasets and should have a spatial variety considerable enough for differentiationg between certain areas.
For the analysis of the spatial distribution of points I have used the complete spatial randomness method (CSR).

Digital mapping

Preprocessing of predictor variables
Terrain data
Terrain and/or elevation are the most widely used environmental predictors in digital soil mapping. However, not only the "raw" elevation information is used, but several derived terrain attributes are also frequently applied (Dobos & Hengl 2009). Therefore it was logical to apply some such attributes in the present study as well. Using the modules of SAGA the following terrain attributes were calculated:

- slope
- convergence index
- curvature
- flow accumulation
- mass balance
- topographic wetness index
- vertical distance to channel network
- surface roughness

Landsat satellite imagery
Since the seven bands of the Landsat 5 TM carries too much correlated information, I have applied principle component analysis thus reducing the information to four principal components.

I have also calculated the NDVI vegetation index as an additional layer.

After applying the above processing methods, five raster layers were derived for each of the five dates, thus altogeather providing 5x5 = 25 layers in total.

Geostatistics, regression kriging

Geostatistics, the different kriging methods in particular are one of the most widely applied tools of digital soil mapping.

In the case of digital soil mapping, geostatistics generally means that based on a soil attribute observed at point locations, with the application of mathematical models we are trying to describe the same attribute at previously unsampled locations. To achieve this, quite often different environmental predictors are applied which can be more easily and less costly sampled than the original attribute.

Kriging as a geostatistical method calculates the value of the observed attribute at an unsampled location $\mathbf{s_0}$ by applying a linear interpolation function based on sampled locations ($\mathbf{s_1, s_2, \ldots s_i}$), by minimizing the variance at the target location.

There are several geostatistical methods that can be applied for mapping environmental variables. One widely used is regression kriging. Most other kriging methods could be considered a special case of regression kriging (Hengl 2011).

When applying regression kriging, regression analysis is used to calculate the deterministic part (trend) of the spatial distribution function. Then, removing the deterministic part, the variogram is only calculated for the residuals, after which the deterministic part is added.

For the regression kriging I have applied a total of 34 input predictor variables (20 LAndsat principal components, 5 NDVI, 9 terrain attributes) for two WRB units: the **calcaric material** and the **clayic qualifie**r. They both provide significant information for agriculture, the former mostly about soil chemistry ($CaCO_3$ content), while the latter about soil texture

The methodology of the applied regression kriging is mostly based on Hengl (2011), with modifications necessary based on the data and the goals of the study.

Spatial analyses were conducted via the SAGA GIS software, while statistical and geostatistical analyses were applied with the R software (R Development Core Team 2012) and its packages.

The input datasets and their use are presented in a simplified form in Figure 2.

The actual working steps were the following:

1. Resampling of the raster datasets to a common, 100 x 100 m cellsize.
2. Separating the data into learning and test populations.
3. Preliminary statistical analyses of the data.
4. Reducing the multicollinearity of the predictor variables trough principal component analysis.
5. Fitting a logistic regression model to the learning dataset trough the derived principal components, for both WRB units.
6. Reduction of the number of used principal components with stepwise regression.
7. Fittign a variogram model to the residuals, and for ordinary kriging to the input data.
8. Running both kriging methods (OK and RK).
9. Exporting data into a format accessible by geographical information softwares.
10. Evaluation of results trough both spatial and statistical methods.

Evaluation of results

The statistical analyses of the results was done after Baldi et al. (2000), by applying the points of the previously separated test population and the six point from the TIM database.

Based on the test and source data, I have calculated Qα and Pearson's correlation coeffitient for five different membership values.

In case of the TIM data, only a simple contingency matric could be presented.

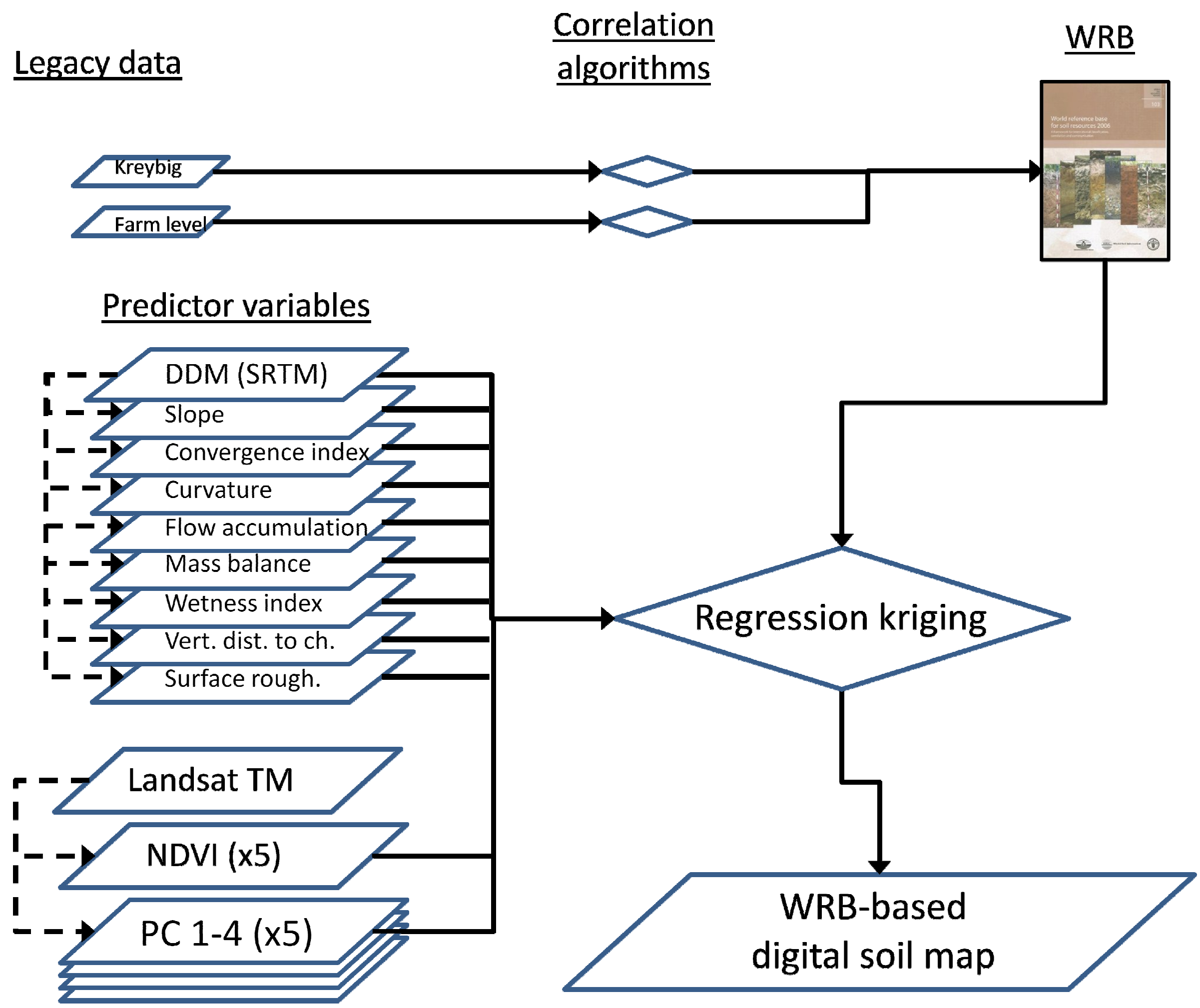

Figure 2. Scematics of input parameters and their use for digital soil mapping

3. RESULTS

WRB-correlation of legacy data

During my research I have studied the possibilities of extracting information from legacy data for the determination of WRB diagnostics and qualifiersm using the developed correlation rules.

There were several cases when the actual data type required was not available. However, there were other parameters (categorical, or derived) from which, although not in an exact, numerical way, the observed attribute can be determined. The most common problem with the data was the limited availability of depth information. All three legacy datasets handled some of its data in a topsoil-subsoil system, that often makes the pecise determination of WRB depth criteria difficult or impossible.

Figure 3 summarises the possible correlations for the observed 28 WRB diagnosrics and 29 qualifiers. For better presentation, the datasets are ordered by time of original survey.

There is a sort of temporal trend considering the amount of WRB-compatible data. The most likely explanation for this is the development of the methodologies. It can also be observed that while in itself none of the datasets provide enough information to determine all WRB units occurring in Hungary, a significant improvement can be achieved with their combined use, particularly in the case of the qualifiers.

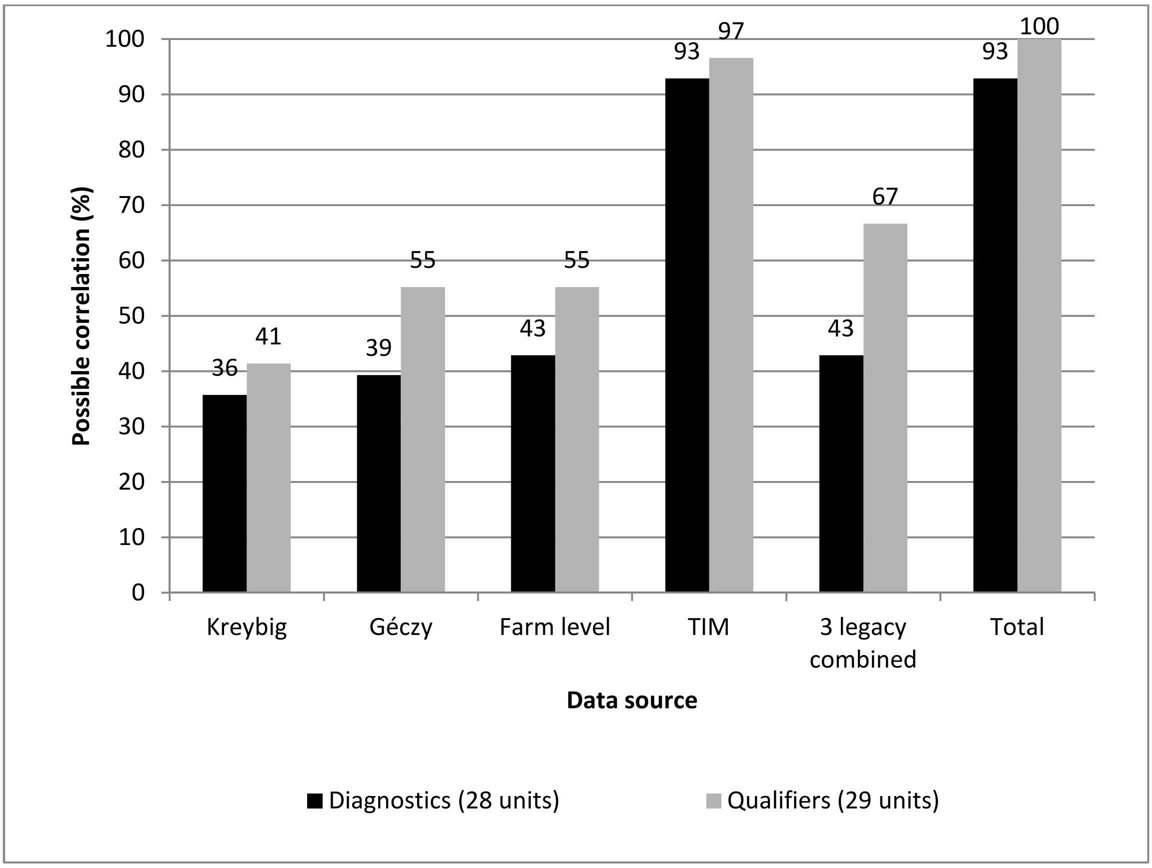

Figure 3. The “best” achievable correlation with the WRB requirements for the different databases

The algorithms developed for each database for WRB units

Hereinafter I will present the decision-trees developed for the WRB units for all three data sources, based on the simplified algorithms of Michéli et al. (2011). Since for the proper presentation the original WRB definitions are essential, these are non-official translations from the original document (IUSS Working Group WRB 2007). Decision-trees were developed for all cases, however in the teses only the calcic horizon is presented as an example.

In light of the fact that due to the different survey methodologies other sources of error can occur besides the difference in data types – different categorical thresholds, laboratory methods – ideally it would be necessary to provide a proper, numeric description of the reliability of the methods. Unfortunately, due to the nature of the data it is impossible at this point, since the different data sources are so different in time and methods that without a monitoring system (running from the early 1900s) or a new national survey only qualitative analyses of the reliability is possible. Due to this, all decision trees (or their main branches if necessary) are provided with a "reliability indicator" provided in bold, capital letters in parentheses the following way:

(HIGH) – The decision-tree evaluates the presence of the WRB unit with high accuracy. In these cases the required laboratory and/or field data are available, thus the decision can mostly rely on these.

(MODERATE) – The decision-tree is moderately reliable for the WRB unit, errors are possible since the decisions are to some extent relying on expert judgement.

(LOW) – Due to missing data, the decisions can almost exclusively rely on expert judgement. The input categories does not represent clearly the criteria required by WRB. They should only be applied with care.!

At the individual WRB units I have only listed the legacy datasets that contzain the required information for determination.

Calcic horizon **(EXAMPLE)**

WRB:

A calcic horizon has:

1. *a calcium carbonate equivalent in the fine earth fraction of 15 percent or more*

and

2. *5 percent or more (by volume) secondary carbonates or a calcium carbonate equivalent of 5 percent or more higher (absolute, by mass) than that of an underlying layer*

and

3. *a thickness of 15 cm or more.*

Kreybig **(EXAMPLE)**

Since the original survey included laboratory measurements for selected profiles, the presence of the calcic horizon can be determined from the calcium carbonate (figure 4, decision point 1) **(HIGH)**. However, it should be noted that differences in the laboratory methods may cause some errors. If no laboratory measurements were conducted for the profile, than field measurements are generally available. These tests identify carbonates by the application of HCl solution, and assess the content based on the strength of effervescence. In case of profiles marked with "+++", the calcic horizon could be present, since it indicates more than 8 % carbonates. (figure 4, decision point 2). However, this approach might carry significant error, since the category can indicate carbonate content much lower than the threshold of calcic horizon **(LOW)**. The presence of secondary carbonates can be indicated by filaments, coatings or concretions (figure 4, decision point 3). The thickness criterium can generally be determined trough the thickness of the sampled soil horizon, or the combined thickness of overlaying horizons. (figure 4, decision point 4).

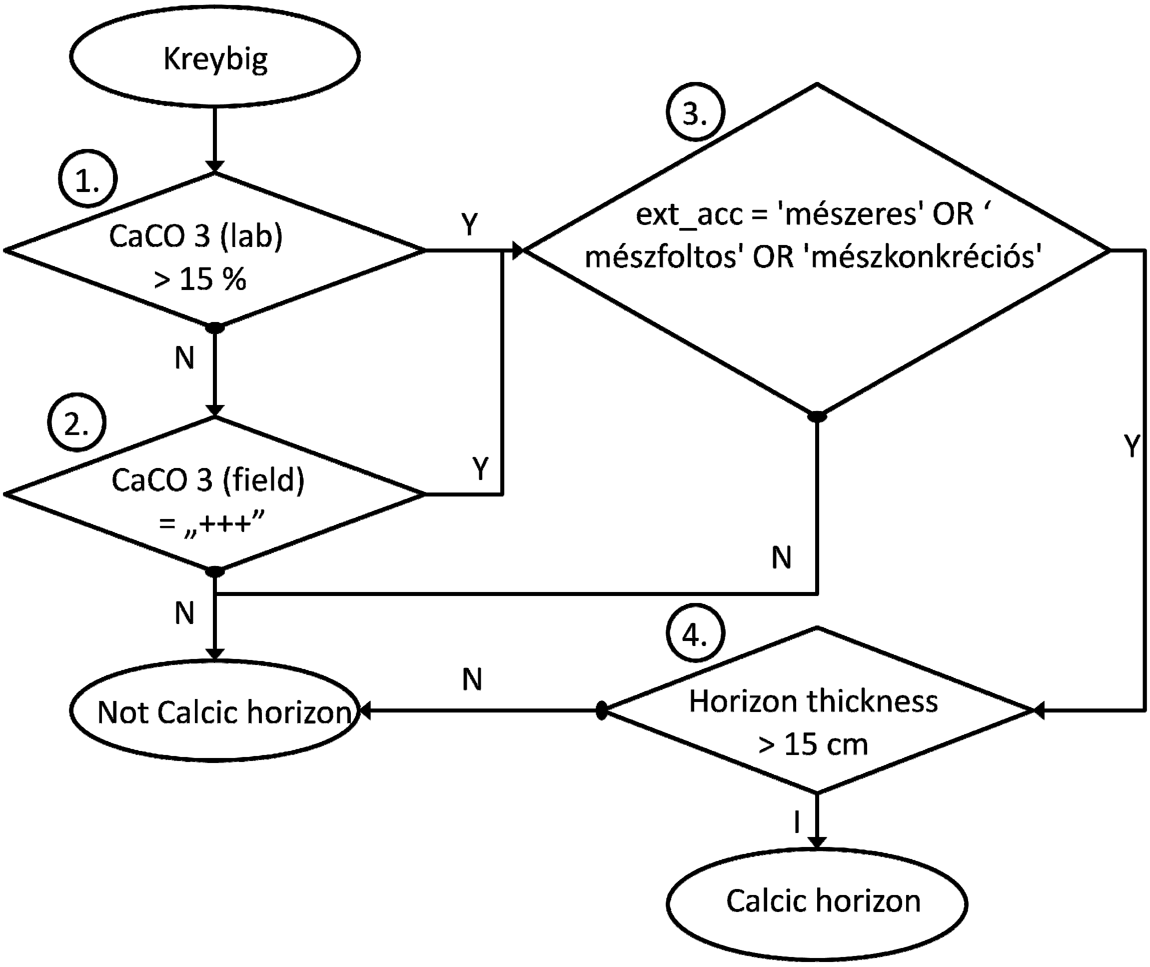

Figure 4. Determination of a calcic horizon from the Kreybig data **(EXAMPLE)**

<u>Results of the preliminary analysis</u>

When separating the originally available point data into training and test populations, I have selected ten percent of the data for the later. Both of the two sub-populations preserved the original distribution of the data, and therefore could be considered representative of the total population.

For the analysis of the distribution of the data I have calculated the average spacing between points, and found that the mean distance of nearest neighbours is 277 m. The differences between the maximum and minimum distances are quite high on the other hand. This could be the result of the combination of points from different surveys, and the poor samling of the hilly and mountaineous and fores-covered regions. The first could explain the minimum while the later ones the maximum values.

The sampling design was also tested for Complete Spatial Randomness (CSR). The results showed that within about 150 m the point are more or less randomly distributes, while above this they tend to form clusters. This could have more, occasionally connected explanations. The point density of the Farm level mapping is higher, due to the large scale methodology. In certain areas of the observed area – mostly due to terrain, land use or other reasons – there were either no, or only very few point observations. However, since most of these areas are not under agricultural use, the point density can be considered sufficient for the areas that are critical in terms of map usage.

By overlaying the raster layers with the point layers it became possible to observe the attribute space as well. This was necessary to evaluate the representativity of the predictor variables at the sample locations to the whole area. For this I have plotted back-to-back histograms to visualize the distribution of every predictor variable for the sampled points and the total area. While the shape of the histograms were generally in agreement, at most variables there were ranges that were under- or over-represented in the point samples.

To compare the distributions of the variable distributions at the points and the total area, I have applied the Kolmogorov-Smirnov test for every predictor. The results reflect those of the visual analysis of histograms, at almost every variable there were statistically significant differences.

The difference can most easily be observed with the terrain-based attributes. This supports the earlier findings that the hilly and mountainous regions are underrepresented in the point samples.
This primarily shows that if we are aiming to maximize the spatial coverage of digital soil maps derived from legacy soil datasets, most likely additional, mostly forestry information will be required.
In spite of that, the data can be utilized, considering that the results are expected to be less accurate for the underrepresented areas.

Results of digital soil mapping

The results of mapping
During the kriging process, exponential theoretical variogram was fitted in case of the calcaric material, while Gaussian in case of the clayic qualifier.
After visual interpretation of the maps derived for the calcaric material, it is clear that the test population shows its occurrence mostly wherethe model also predicted high likelyhood. The results are quite similar for the points with low likelyhood of occurrence.
It should be noted that the likelyhood values are generally low, this could be due to the fact that the predictors do not contain any layer carrying information on the soil parent material.
Considering the variance it can be observed that it is significantly lower in areas where the point density of the training population was lower, as opposed to the low-density, high-evelation or external areas.
It is conspicuous that in the Domoszló area the lack of large scale point did not increase significantly the variance of the model, since the density of the Kreybig points is slightly higher in the area, thus the datasets can compensate for each others shortcomings.

The comparison of the resulting maps from regressionkriging and ordinary kriging revealed that while their spatial pattern is similar, the former one is more detailed, but has slightly higher variance. The spatial distribution of the variance is essentially the same which is to be expected, since both models were prepared using the same points.

In case of the clayic qualifier, both models gave higher probability values. Considering the preliminary analysis, based on the dominance of soils with high clay content it was to be expected that the clayic qualifier would be present in great extent. Figures 5 and 6 show the results of regression kriging and its variance for the clayic qualifier

Numerical evaluation of the results

Since the resulting maps from kriging produce probability maps, membership functions similar to those used in fuzzy sets can be applied. These predict the observed criteria above a probability level set by the user. Based on this, I besides the widely used 50 % threshold I have also applied stricter (60, 70, 80, 90 %) probability levels.

By applying the test data and calculating the Q_α index based on the first- and second-order errors of the models it can be concluded that regression kriging in most cases provides better – if not significantly different – results than ordinary kriging.

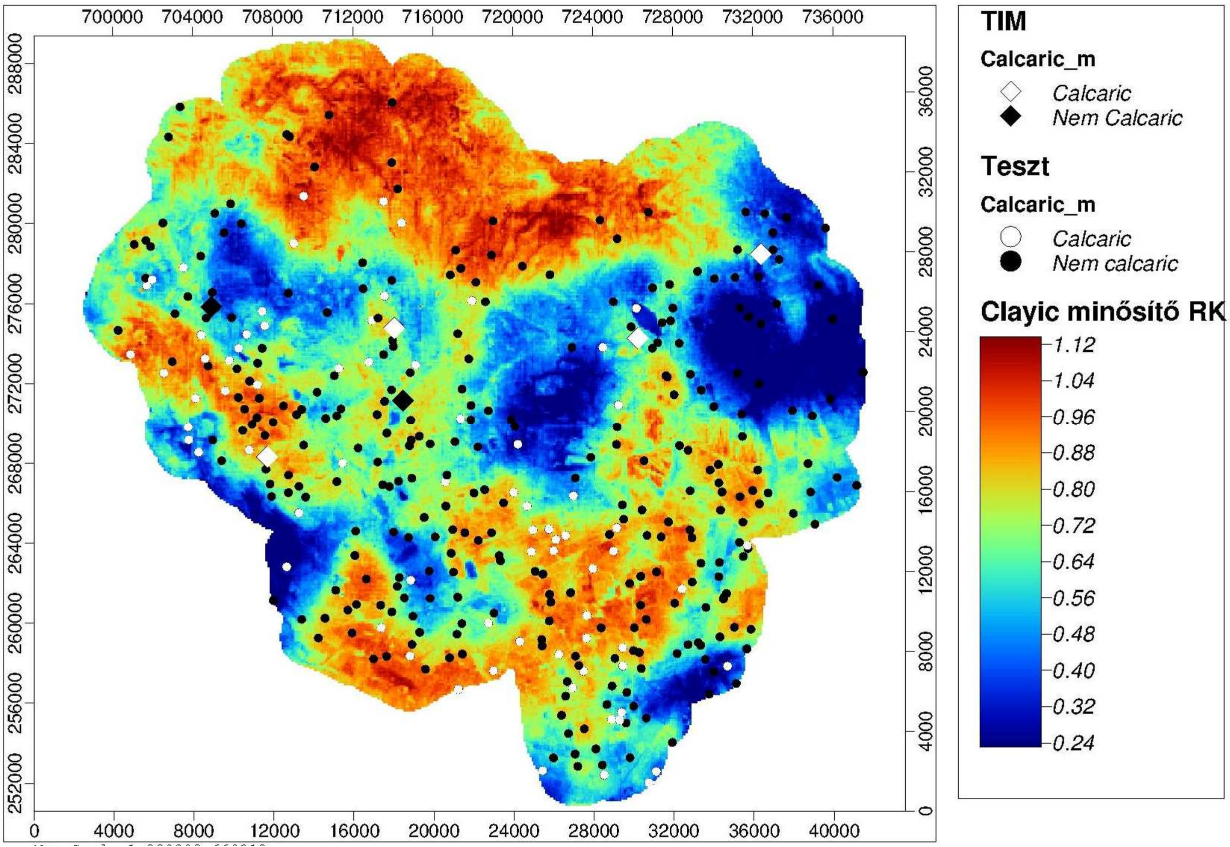

Figure 5. Spatial distribution of the clayic qualifier based on regression kriging in the Gyöngyös area

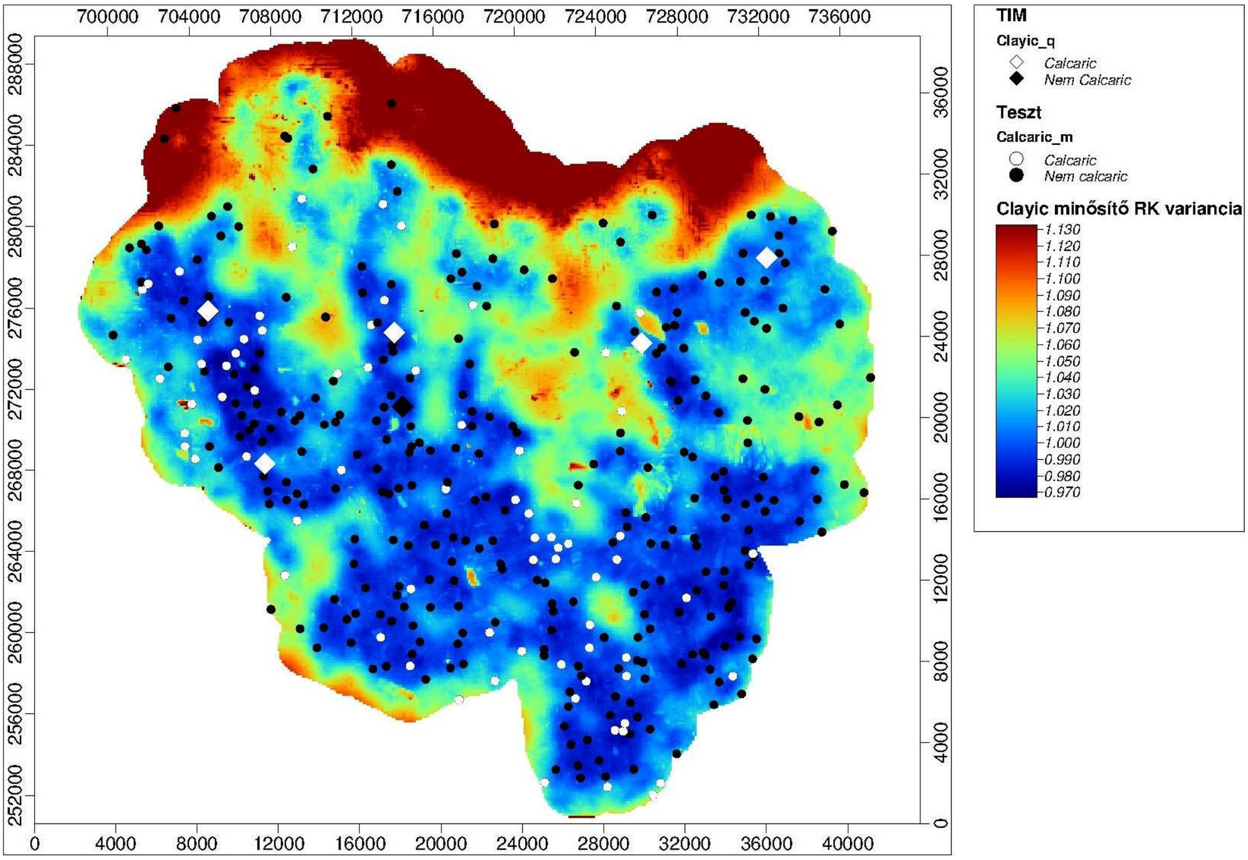

Figure 6. Variance of the regression kriging model for the prediction of the clayic qualifier

Figure 7 presents the changes of Q_α values. It can be observed that in case of the calcaric material the two method produces almost identical results. As opposed to this, in case of the clayic qualifier the regression kriging produced better results at almost every membership levels.

The calculated Pearson's correlation coefficient supports the results of the Q_α indices, the regression kriging performed better in both cases, although without significant difference (Table 1).

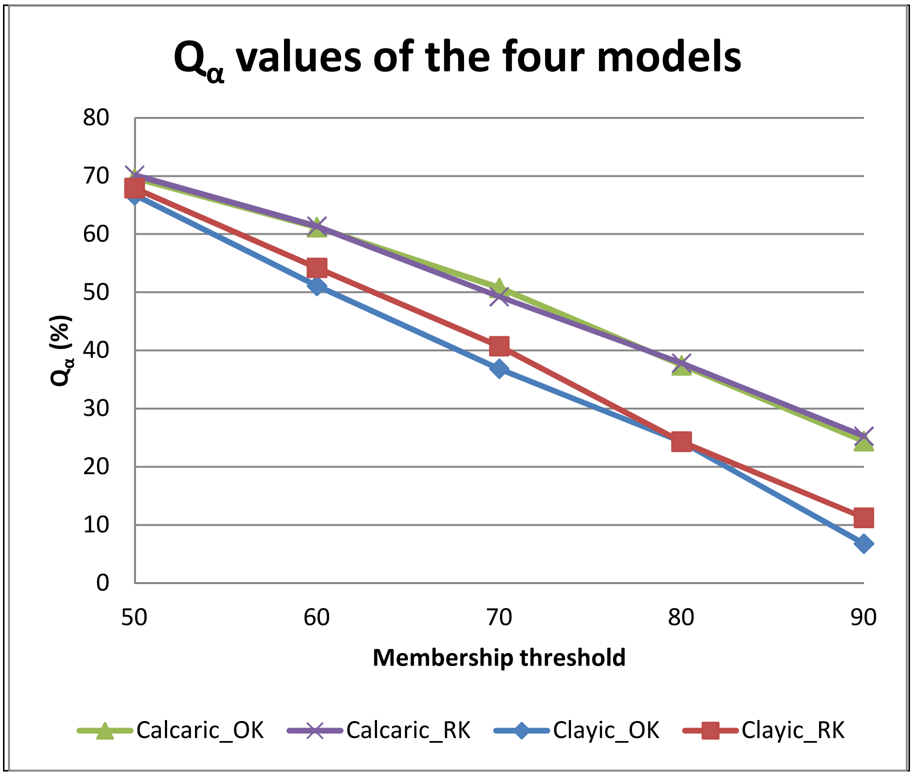

Figure 7. Q_α values of the four models by membership levels

Table 1. Correlation of kriged results with the test population

Pearson's correlation coefficient		
Calcaric	OK	RK
Test data	0,5402	0,5519
Clayic	OK	RK
Test data	0,4384	0,4771

Since there were only six TIM points in the test area, statistical evaluation of the results was not possible. However, it can be observed that both models produced better results in case of the clayic qualifier. This can be explained by the high area covered by soils with high clay content.

New scientific results

1. Based on the available data I have adapted a novel correlation methodology to the data collected by the Kreybig, Géczy and Farm level surveys. This helps the integration of these datasets into other international databases using the terminology of the International Union of Soil Science.
2. I have determined that the changes in the WRB-applicability of Hungarian legacy soil datasets increases with time. (Order of WRB-compatibility: 1. TIM; 2. Farm level; 3. Géczy; 4. Kreybig)
3. On the example of the methodology I have demonstrated that the combined use of the datasets can significantly increase the expected efficiency of correlation works as opposed to their individual use.
4. Based on the methodology I have applied a digital soil mapping technique for the direct prediction of WRB units based on different legacy soil databases.

4. CONCLUSIONS AND RECOMMENDATIONS

The results showed that the legacy datasets with the greatest spatial coverage in Hungary do not individually provide sufficient information for nowadays data requirements.

An increasing trend can be observed in the applicability of legacy data for WRB-use as we are getting closer to the present. It is however clear that the combined use of legacy soil data can (in our case with up to 24 percent) increase the expected efficiency of the harmonization works.

It must be noted that the present study did not cover the increased prediction errors originating in the use of data with limited applicability. Therefore during the use of the data the inaccuracies arising from the differences in methodologies and survey dates should be noted. Based on the results from my research the limited correlation of the three biggest Hungarian soil data sources became possible.

During the study I have proved that the applied methodology can be suitable for the international correlation of Hungarian soil data. The revised national soil classification system is expected to put more emphasis on tangible threshold values at the allocation of soils, therefore it can be expected that certain legacy soil data will require the application of a methodology similar to what is presented in the present study (Michéli et al. 2009).

From the results of the digital soil mapping work it can be concluded that the application of regression kriging produced better results for the test area that ordinary kriging. I have also found that the selection of the proper predictor variables can be critical for the mapping of WRB units.

It is probably even more important that based on the results I believe my work not only provided a chance for the international correlation of Hungarian soil data, but also showed that a similar methodology could be used not only for the WRB-integration of data, but also for the development of a country-wide database beneficial for all Hungarian professionals dealing with soils.

This seems to be supported by the fact that most of the algorithms presented in this study have been used for the development of the OSIRIS (Observation and Spatial Information System for Soil Conservation, osiris.helion.hu) system, which lays the foundations of such a system (Szabó et al.2009).

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6. PUBLICATIONS RELEVANT TO THE TOPIC OF THE DISSERTATION

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Impact factor: 2,318

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