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Quantification of soil textural fractions of Bas-Zaïre using soil map polygons and/or point observations

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ABSTRACT

Reconnaissance soil surveys typically produce qualitative choropleth maps and descriptions of sampled soil profiles. These can be converted to quantitative information directly. Alternatively quantitative predictors can be made by interpolating between the point observations, or the two can be combined.

Three methods to predict the sand and clay content of Bas-Zaïre using a reconnaissance soil map and 151 soil profiles are compared. A cross-validation showed that the combination method produced the most precise predictions with an acceptably small bias. This result was obtained only after verifying and correcting the soil surveyor's estimations of the soil map prediction variances and stratifying the area to acquire a relative pooled within-stratum variogram.

INTRODUCTION

The outcomes of reconnaissance soil surveys are typically qualitative choropleth maps and descriptions of sampled soil profiles. However, many applications require quantitative data. Examples include the estimation of difficult to determine functions, like soil moisture retention characteristics, from basic soil data (Pucket et al., 1985; Wösten and Van Genuchten, 1988; Vereecken et al., 1989), the evaluation of the pollution status of the soil (Lexmond and Edelman, 1987) and quantitative land evaluation (Burrough, 1989; Burrough and Heuvelink, 1992). Several approaches can be followed to derive quantitative information from soil survey.

The simplest method would be to transform the qualitative choropleth soil map into a quantitative map by quantifying the legend. This approach has received considerabe attention in the sixties and seventies (e.g. Morse and Thornburn, 1961; Webster and Beckett, 1970; Beckett and Webster, 1971). Webster and Beckett (1968) assessed the quality of soil maps by the intra-

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class correlation. This approach will be in particular suitable when important abrupt changes are present. Then the between-classes variance will be much larger than the within-class variance. However, most shortcomings associated with choropleth maps (Burrough, 1986) remain.

A second method would be to use kriging to predict continuously between the available point observations. This requires (i) a sufficient number of observations to estimate the variogram accurately (Van Meirvenne and Hofman, 1991a; Webster and Oliver, 1992), and (ii) a sampling covering the entire study area. Unfortunately, reconnaissance soil surveys rarely meet these conditions.

The two approaches are often regarded as alternatives, and their performances have been compared (Van Kuilenburg et al., 1982; Bregt et al., 1987). However, the information (soil map and point observations) may be complementary. Therefore, some research has been carried out to use some or all soil map delineations to stratify the study area followed by an interpolation from point observations (Stein et al., 1988; Voltz and Webster, 1990; Van Meirvenne and Hofman, 1991b). In this approach, the soil map supplies only information about the location of boundaries. Another approach is to merge the prediction methods completely. Winkler and Makridakis (1983) have discussed different strategies to combine several forecasting methods. They concluded that the weights assigned to different prediction methods should be related to the covariance matrix of the prediction errors. In soil science, to our knowledge the only attempt to combine different prediction methods in this way has been reported by Heuvelink and Bierkens (1992). They concluded that their method seems useful especially in situations where the number of point observations is small.

This paper aims to investigate the ability to obtain quantitative information from (i) the soil map, (ii) a geostatistical interpolation (both with and without stratification), and (iii) the combination method of Heuvelink and Bierkens (1992) in situations where the available information sources are limited.

THEORY

Soil map

On a choropleth soil map the spatial distribution of the soil variables is represented by polygons. Typically, each polygon is characterized by a representative class of a particular soil variable (e.g. soil texture class). To use the soil map as a quantitative predictor, a representative value is needed (e.g. % clay). If each mapping unit includes sufficient analytical observations then the (weighted) sample mean and sample variance can be calculated directly from the point observations. Otherwise, the soil surveyor has to estimate for each mapping unit a typical value, and the associated variance (σ_S^2), using his knowledge of the area.

Point observations

If only point observations are available then geostatistical interpolation (kriging) is suitable. However, if only few measurements have been made and large or abrupt variations are present then kriging might perform badly. A stratification into more homogeneous strata could account for an important part of the overall variance, but the available data are also subdivided. This might result in too few observations per stratum to characterize the variogram accurately. Voltz and Webster (1990) used a pooled within-stratum variogram for this reason. Their procedure assumed that the stratification resulted in units having the same within-class variance and the same structure of the spatial variation. If there are clear indications that the first of these two conditions is not met but the second is, then a standardized pooled within-stratum variogram is more appropriate:

$$\gamma_{rp}(\boldsymbol{h}) = \frac{1}{2\sum_{j=1}^{S} N_j(\boldsymbol{h})} \sum_{j=1}^{S} \sum_{i=1}^{N_j(\boldsymbol{h})} \frac{(Z_j(\boldsymbol{x}_i) - Z_j(\boldsymbol{x}_i + \boldsymbol{h}))^2}{\sigma_j^2} \qquad (1)$$

where $\gamma_{rp}(\boldsymbol{h})$ is the standardized pooled within-stratum semivariance at lag $\boldsymbol{h}$, S is the number of strata, $Z_j(\boldsymbol{x})$ are the point observations of variable Z situated inside stratum j, $N_j(\boldsymbol{h})$ are the number of pairs and σ_j^2 is the within-stratum variance of Z_j.

This standardized pooled variogram is subject only to the condition that its shape is the same for all strata. If the semivariance between points located within stratum j has to be calculated, then it is sufficient to multiply $\gamma_{rp}(\boldsymbol{h})$ by σ_j^2.

Combination method

If the soil map and kriging predictors of the same variable Z are available then the combined linear predictor of this variable, Z^*, is given by:

$$Z^* = w_S S + w_K K \qquad (2)$$

with S the soil map predictor and K the kriging predictor, each weighted by w_S and w_K respectively. Heuvelink and Bierkens (1992) have suggested to derive these weights from the prediction error variances as:

$$Z^* = \frac{(\sigma_K^2 - \rho_{KS}\sigma_K\sigma_S)S + (\sigma_S^2 - \rho_{KS}\sigma_K\sigma_S)K}{\sigma_K^2 + \sigma_S^2 - 2\rho_{KS}\sigma_K\sigma_S} \qquad (3)$$

with ρ_{KS} the correlation coefficient between the prediction errors of kriging and the soil map.

Equation (3) shows that the predictors K and S are weighted by the prediction variances. If one of the two is much less precise than the other one, then it will receive considerably less weight in the combined prediction.

Validation

In order to validate the performance of the different prediction methods two indices were used:

- The mean error (ME):

$$\mathrm{ME}=\frac{1}{n}\sum_{i=1}^{n}(Z_i-Z_i^*) \tag{4}$$

where n is the number of points at which prediction is attempted.

This index measures the bias of the prediction method. If ME is close to zero then there is no overall bias.

- The mean square error (MSE):

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}(Z_i-Z_i^*)^2 \tag{5}$$

The MSE should be as small as possible since it is a measure of the magnitude of the average prediction error.

MATERIALS AND METHODS

We tested the above methods in Bas-Zaïre where our aim was to predict soil texture, and in particular the percentage of sand from soil survey information. The study area is indicated in Fig. 1. It is the westernmost part of Zaire, situated roughly between Kinshasa in the east and the Atlantic Ocean in the west. It covers a total area of 60,300 km^2, or 2.5% of Zaire.

A reconnaissance soil survey was carried out by G. Baert under the bilateral development cooperation Belgium–Zaire, between 1988 and 1990. During 1991 the detailed analysis of the soil samples and the map drawing (scale 1/200,000) were finished.

A simplified choropleth soil texture map (scale 1/1,000,000) was created by the soil surveyor (Fig. 2). On this map the soil texture at a depth of 60 cm is given as classes according to the USDA texture triangle. Figure 2 also shows the locations of 151 sampled soil profiles.

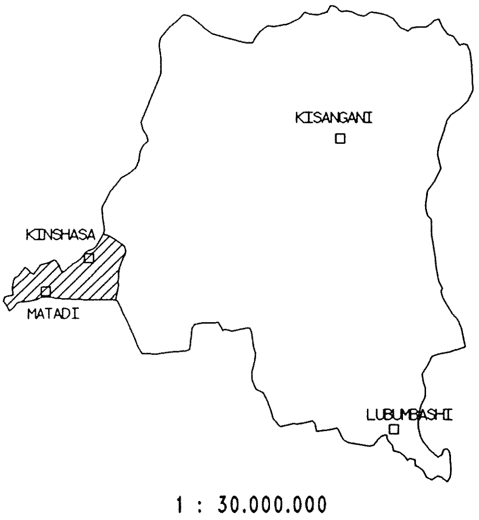

Fig. 1. Location of Bas-Zaïre within Zaire.

RESULTS AND DISCUSSION

Quantitative choropleth maps

Based on both the soil profile analyses and his knowledge of the region, the soil surveyor estimated for each polygon of the (1/1,000,000) soil texture map a typical value of the sand and clay content, plus their prediction variances.

Point observations and geostatistical analysis

The 151 sampling locations showed almost extreme differences in textural composition, e.g. the sand content ranged between 0.6 and 97.7%. Moreover, there were some important abrupt textural differences. Therefore a differentiation between the major soil textural regions was needed to reduce the overall variance. The choropleth soil texture map (Fig. 2) was used as a basis for the stratification. The polygons were grouped into 4 strata according to the soil texture classes:

- Stratum 1: Sand + Loamy sand
- Stratum 2: Sandy loam + Sandy clay loam
- Stratum 3: Clay loam + Silty clay loam
- Stratum 4: Clay.

Similar boundaries could have been drawn using a geological map because the soil texture at 60 cm was closely related to the geological substrate.

Table 1 gives statistics of the stratified sampling points. The stratification separates lithologically quite different regions, from the almost pure sandy

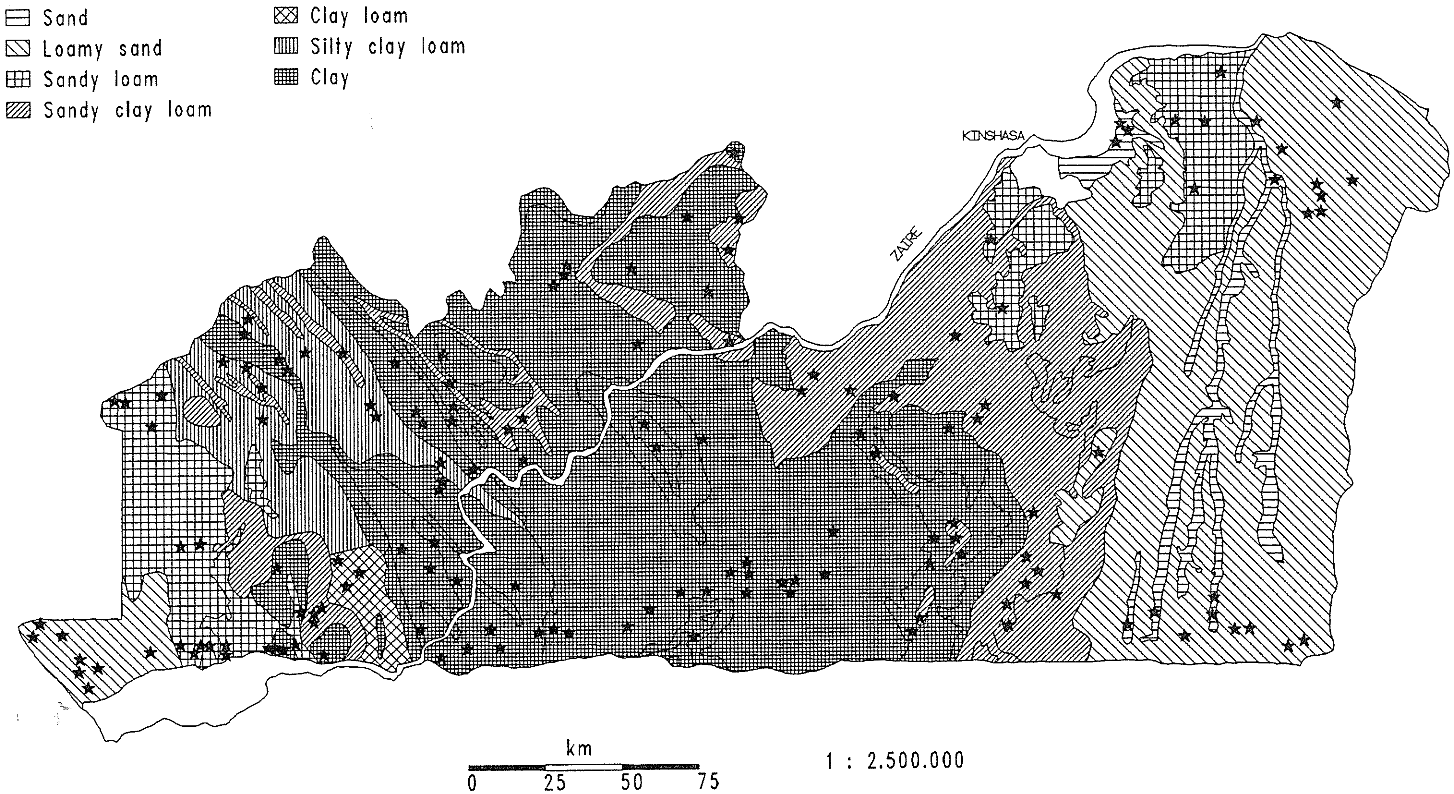

Fig. 2. Reconnaissance soil texture map of Bas-Zaïre with the 151 observation points shown as stars.

TABLE 1

Descriptive statistics of the sand content of the sampling points grouped into four strata

Stratum	n	m (%^{2})	s^2 (%)	CV (%)	Extremes (%)	g_1	g_2
1	30	88.7	32.8	6.5	74.0–97.7	−0.67	3.00
2	49	65.5	293.2	26.1	17.4–93.8	−0.50	2.82
3	10	26.2	139.8	45.2	8.5–38.3	−0.56	1.57
4	62	20.6	237.8	75.0	0.6–56.2	0.72*	2.35

*Significantly different from zero at $P=0.05$.
n=number of observations, m=mean, s^2=variance, CV=coefficient of variation, g_1=skewness, g_2=kurtosis.

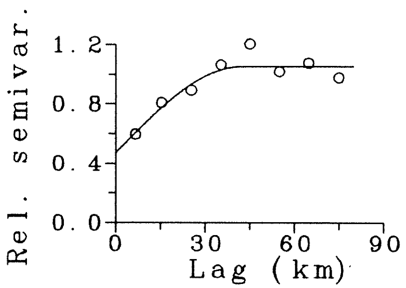

Fig. 3. Standardized pooled within-stratum variogram of the sand fraction.

Quaternary and Tertiary deposits in the east and the extreme western parts of Bas-Zaïre to the central heavy clayey region on Primary rocks. The values of the skewness and kurtosis gave no indications that the distributions depart strongly from a normal one ($g_1=0$ and $g_2=3$).

The numbers of measurements within the strata vary from 10 to 62 (Table 1). More seriously, the within-stratum variances of the measurements differ strongly (32.8%^{2} for stratum 1 and 293.2%^{2} for stratum 2). So we calculated the standardized pooled within-stratum variogram (eq. 1), shown in Fig. 3. The global variogram and, for comparative reasons, the pooled within-stratum variogram were also calculated (Fig. 4). The coefficients of the fitted spherical curves are given in Table 2.

These variograms allowed to krige texture globally without stratification and within strata using the standardized pooled within-stratum variogram corrected by the within-stratum variance.

Combined prediction

The prediction errors of the soil map and the kriging prediction were calculated for the 151 sampling points. The correlation coefficient between these

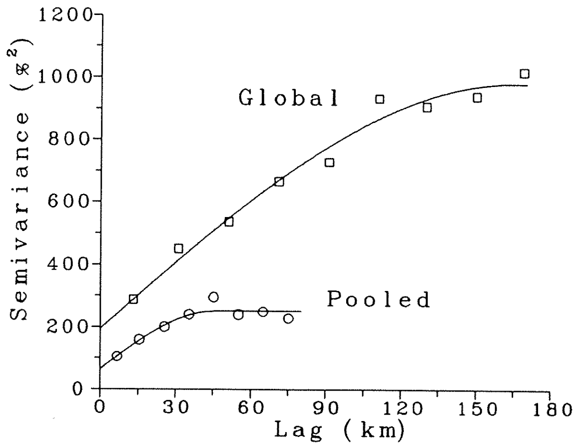

Fig. 4. Global and pooled within-stratum variograms of the sand fraction.

TABLE 2

Coefficients of the fitted spherical curves

Variogram	Nugget effect	Sill	Range (km)
Standardized pooled within-stratum	0.47	1.05	42
Pooled within-stratum	$65\%^2$	$250\%^2$	45
Global	$195\%^2$	$980\%^2$	165

two, ρ_{KS} was 0.75 for the sand fraction and 0.73 for the clay fraction. These values indicate that the two sources of information duplicate information to some extend.

Since the combination of the two prediction methods relies on the precision of their prediction variances, the latter were verified by calculating the standardized mean squared error (SMSE):

$$\mathrm{SMSE}=\frac{1}{n}\sum_{i=1}^{n}\frac{(Z_i-Z_i^*)^2}{\sigma^2} \tag{6}$$

with σ^2 the prediction variance (σ_K^2 for kriging or σ_S^2 for soil map predictions). If on average the actual observed prediction error is correctly estimated by the prediction method, then the SMSE shall be close to one. This verification index was calculated for the four strata and the two prediction methods. Figure 5 shows the result.

For kriging, the SMSE of the four strata were all close to one (0.87–1.36), but for the soil map much larger values were found (3.10–7.45). This indicated that the kriging prediction variances were on average correct, but the

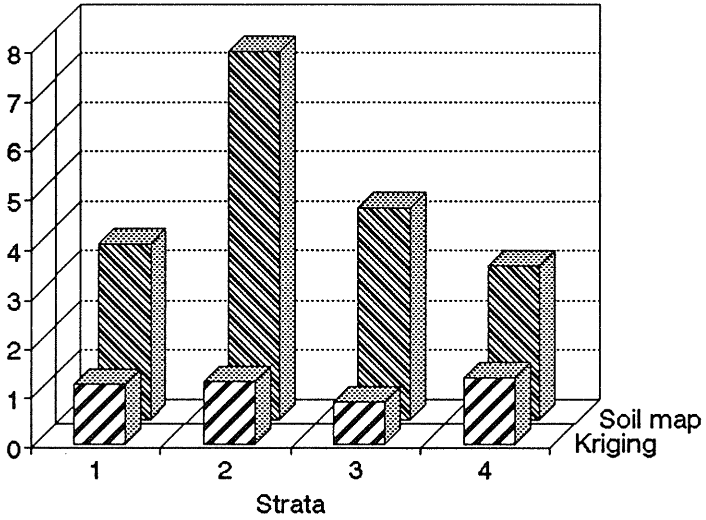

Fig. 5. SMSE of the sand fraction of the four strata and the predictions using the soil map and stratified kriging.

soil surveyor strongly overestimated the accuracy of the soil map. Consequently, the soil map predictions received, on average, between 3.10 to 7.45 times more weight than they should get. To account for this overweighting the soil map prediction variances were corrected by the values of the SMSE according to the stratum in which the polygons were located.

Cross-validation

Since we had no independent data, jack-knifing was used for cross-validation. The ME (eq. 4) and the MSE (eq. 5) of the sand and clay contents at the 151 points were calculated. Figures 6 and 7 give the results.

The ME of the soil map prediction was −2.4% for the sand fraction and 2.0% for the clay. The soil surveyor prediction on average was biased towards an underestimation of the sand content and an overestimation of the clay. Kriging (both the global and the stratified procedure) was unbiased: the absolute values of ME were all very small ($<0.29\%$). The combined procedure without correction of the soil map prediction variances produced again quite large ME. For the sand fraction the absolute value of the ME was even larger than for the soil map alone. However, after the correction of the soil map prediction variance, the combined method resulted in smaller absolute ME, especially for the clay fraction.

As mentioned above, the MSE is a measure of the average magnitude of the prediction error, and we want it to be as small as possible. Figure 7 shows that the MSE of the soil map prediction were relatively small (154$\%^2$ for the sand

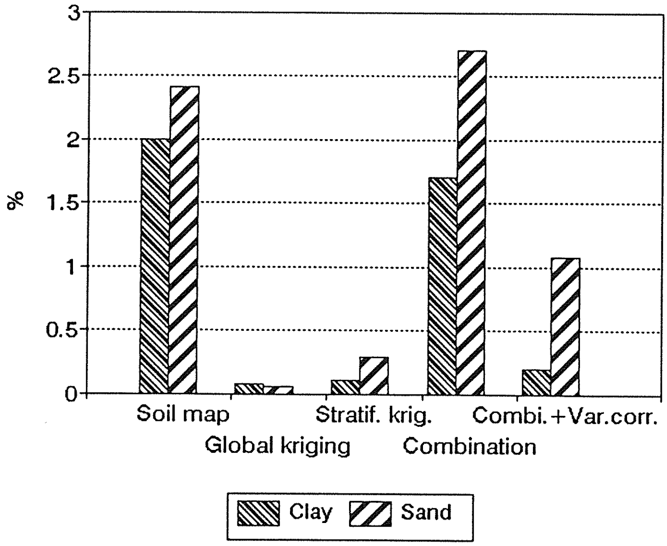

Fig. 6. Absolute values of the ME of the different prediction methods.

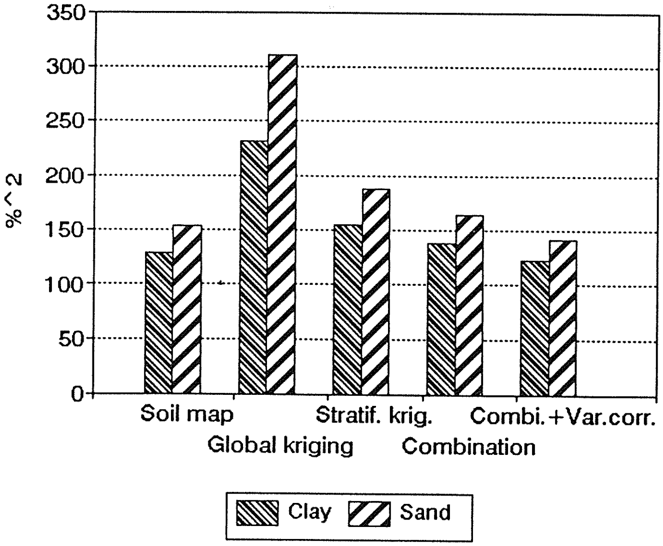

Fig. 7. MSE of the different prediction methods.

fraction) for the purpose intended: a reconnaissance survey. This is not surprising since the soil surveyor consulted the profile analyses when he made his predictions. As a result, the verification of the soil map is probably more optimistic than it would have been if independent data had been used. Global kriging performed much worse. The MSE were about twice as large as the soil

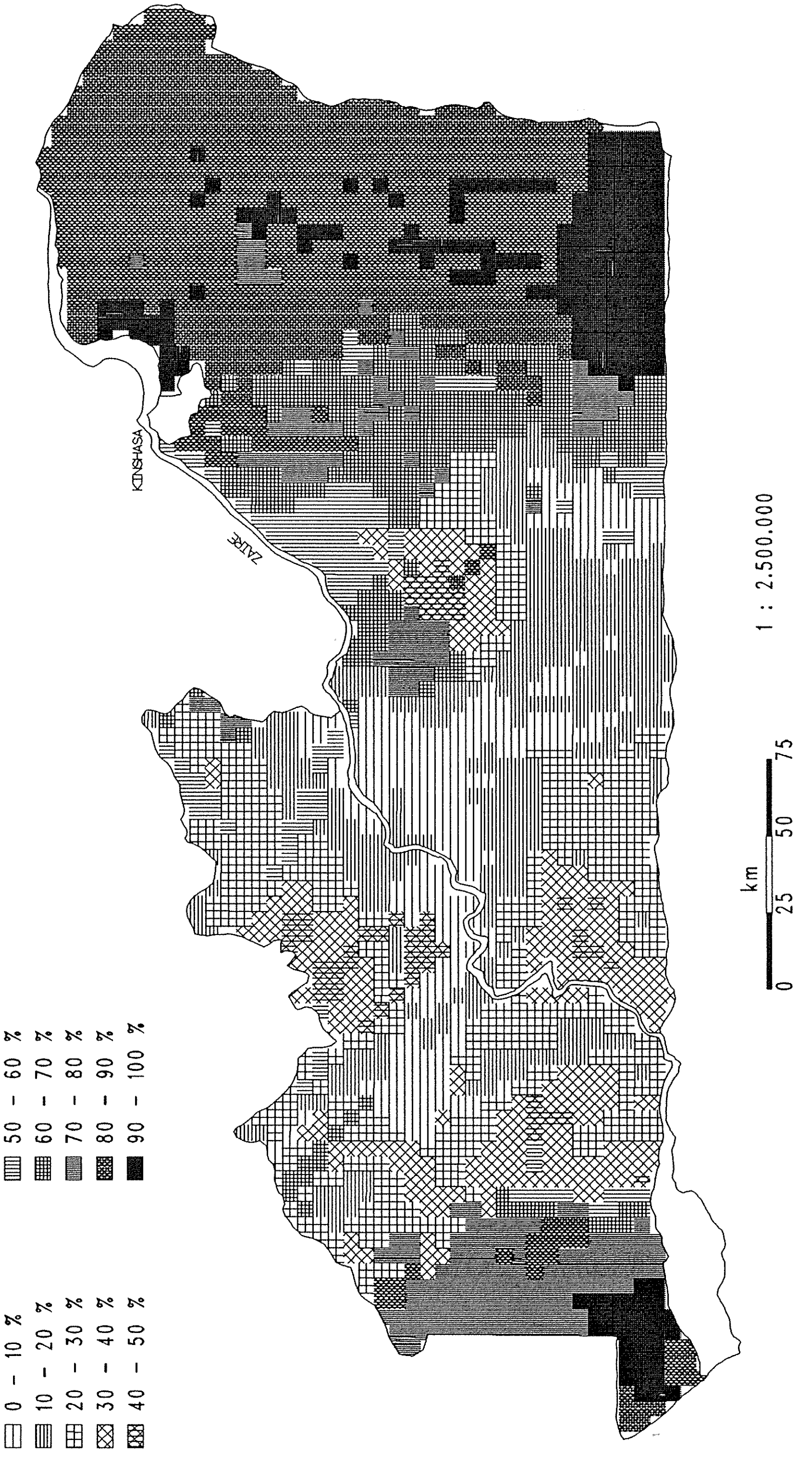

Fig. 8. Quantitative map of the sand content of Bas-Zaïre obtained by the combined prediction method.

map predictions. Stratified kriging resulted in a strong reduction of the MSE when compared to global kriging. This could indicate that the stratification represented to a large extend important changes in soil texture. However, the MSE were still somewhat larger than the values of the soil map. A further reduction was obtained by combining the soil map prediction with the original prediction variances with stratified kriging, but the MSE were still larger than for the soil map. Only after the correction of the soil map's prediction variances, resulting in a more equal weighting of both prediction sources, the MSE of both textural fractions became smaller than the values of the soil map ($142\%^2$ for the sand fraction).

Although the combined prediction resulted in only a very small reduction of the MSE, the overall improvement (accuracy and precision) was considered to be important enough to recommend this method for the mapping of the textural fractions.

Quantitative map of the sand fraction

The combination method predicted the textural fractions with an acceptable bias and on average most precisely, and so it was used to map the sand fraction. Since the survey was aimed as a reconnaissance study, we combined stratified kriging of 5 km × 5 km blocks with the soil map predictions. Figure 8 gives the result.

This map contains typical aspects of both the soil map and the kriging interpolations. Continuous changes inside areas indicated as one polygon on the soil map as well as abrupt changes are represented.

CONCLUSIONS

In general, the outcomes of reconnaissance soil surveys are not well suited for conversion into quantitative information for further analysis. Therefore, all available sources should be used to obtain an as correct as possible prediction of the variable of interest.

A cross-validation of the point observations showed that the combination method proposed by Heuvelink and Bierkens (1992) could produce, with an acceptable bias, the most precise predictions of the sand and clay content of Bas-Zaïre out of a quantified soil map and 151 point observations. However, this result was obtained only after a verification and correction of the soil surveyor's estimations of the soil map prediction variances and a stratification of the area combined with a standardized pooled within-stratum variogram. So, an investigation of available information is very desirable.

Serious underestimation of the prediction variances of soil map polygons by the soil surveyors were found, as reported by Heuvelink and Bierkens

(1992). Therefore, it is advised that soil surveyors quantify the within mapping unit variances of their maps.

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