QUALITY AND RELIABILITY IN REPRESENTATIONS OF SOIL PROPERTY VARIATIONS

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ABSTRACT

Soil maps portray variations in the physical and chemical properties of soil using a mapping unit model. According to this model, soil properties are homogeneous within mapping units and change abruptly at mapping unit boundaries. This model masks within-unit variations in soil properties and accentuates discontinuities between adjacent mapping units.

The purpose of this study is to explore the reliability with which spatial variations in soil properties are represented on digital soil maps. The approach involves kriging of soil property data collected at point locations and comparison of the resulting interpolated surfaces against the values predicted by the traditional soil map. The study area is Bear Brook Watershed in eastern Maine. Available data include a detailed, Level I soil survey, and independent estimates of depth to bedrock derived from a seismic survey.

Results suggest that the quality of the interpolated surface can vary significantly with changes in the number of points used in interpolation. Single measures of quality, such as the mean squared error, may alone be insufficient to assess the reliability of an interpolated surface. Excessive smoothing of surfaces can be offset by merging the interpolated surface with information from the soil map. In the present study, however, the resulting hybrid surfaces have relatively low reliability, due to apparent systematic bias in depth estimates derived from the soil map.

INTRODUCTION

In an environment in which federal agencies will be asked to document the quality of their products to be in compliance with the new Content Standards for Digital Geospatial Metadata (FGDC 1994), methods of quality reporting for geographical databases need to be addressed. Currently soil survey reports give little or no information on the quality of soil maps (Heuvelink and Bierkins 1992). The quality of the map is also difficult to assess in hindsight as field information has been massaged into a cartographic product for which quality assessment is nearly impossible.

Soil maps are made by various survey methods but most include variations on the following steps: definition of classes of soil profiles; observation of soil profiles in the study area; delineation and naming of areas corresponding to the named soil classes. Soil classification is based on several definitive soil properties. Once classified, prototype classes form the basis for predicting individual properties. The soil surveyor identifies locations in the field for test profiles and describes the vertical variation of the soil by distinguishing different soil horizons. Lateral variations are delineated as soil unit boundaries on aerial photo-based field sheets.

This approach yields maps which display classes of soils as discrete units with sharp boundaries. This representation has several advantages from a production perspective but several disadvantages for map users. Soil classification is a useful abstraction method for condensing and describing the continuum of the soil surface. However, soil properties can exhibit significant amounts of internal variability and often do not show sharp discontinuities associated with mapping unit boundaries (Burrough 1986).

Users of soil information are often interested in the individual soil properties or suitability ratings of a soil class rather than the class per se. Hence they are more likely to be directly interested in the reliability of the spatial distribution of the property of interest rather than the reliability of the soil classes. Soil scientists have investigated different methods to test the quality of soil maps and recommended survey methods for improving quality (Marsman and de Gruijter 1986). The quality of soil maps has typically been assessed by validating the classification methods. This approach however does not address the reliability of the spatial distribution of any individual property.

This paper looks at an alternate form for representing soil information. The emphasis is on generating spatial representations of individual soil properties as opposed to discrete soil classes. The advantage lies in the ability to derive reliability estimates for the spatial representation of individual soil properties. Improvements in computing power and geostatistical tools make such an approach feasible.

The purpose of this study is to explore the quality with which patterns of spatial variation in soil properties are represented on digital soil maps. The study area is Bear Brook Watershed in eastern Maine. Available data include a detailed, Level I soil survey, and independent estimates of depth to bedrock derived from a seismic survey. Depth to bedrock data at sampled locations are used to derive a smooth statistical surface based on kriging. The resulting surface is then compared against the values predicted by the traditional soil map.

Ordinary kriging assumes that soil properties vary smoothly over space, rather than being constrained by the boundaries of mapping units. Because the distribution of soil properties may also contain a discontinuous component, methods for incorporating information about discontinuous variation into the interpolation procedure are also considered. Visualization techniques are presented that facilitate comparison of the interpolated surfaces and their mapping unit-based counterparts.

BACKGROUND

Empirical studies indicate that even at relatively large map scales it is generally not feasible to delineate mapping units within which soil properties are strictly homogeneous (Beckett and Burrough 1971). The degree of internal variability depends on mapping unit size, which is constrained by such factors as map scale and purpose. Maps of larger scale can depict variation at higher frequencies but this necessarily entails a reduction in map simplicity and interpretability. Internal variation in soil mapping units is thus normally viewed as an inevitable consequence of soil mapping procedures.

One solution to this problem is to allow soil properties to vary continuously over space rather than forcing these properties to honor the locations of mapping unit boundaries. This can be achieved through interpolation of soil property values at a set of regularly-spaced grid locations. Grid estimates are weighted combinations of the values at neighboring sampled points. Interpolation can be achieved using a variety of methods, including trend surface analysis, kriging and cubic splines (Lam 1981, Laslett et al. 1987). Interpolated surfaces tend to be smoother than traditional soil maps and are generally more representative of values at sampled point locations (Voltz and Webster 1990).

The interpolation method that has met with the most success to date is kriging. Kriging yields unbiased, minimum-variance estimates and provides an estimate of the interpolation error variance at each grid location (Burgess and Webster 1980). Kriging models spatial variation as a composite of systematic and random components. This distinction is somewhat scale-dependent, since random variation at one scale may be resolvable at another. Normally, kriging assumes that the variable of interest belongs to a random field with constant mean (stationarity) and a semivariance that depends only on distance between sample locations (isotropy). Under these conditions the interpolation error has a mean of zero and a variance that depends on the location of sample points.

Various authors have demonstrated the potential of kriging for interpolating soil property data (Oliver and Webster 1986, Bregt, Bouma and Jellinek 1987, Bregt and Beemster 1989). In general, properties are represented with higher accuracy on surfaces derived from kriging than on traditional soil maps. Soil property values derived from soil maps are reasonably good predictors of mean soil property values within mapping units. However, due to their reliance on the mapping unit model, soil maps are unable to capture much of the spatial variation in soil properties. This variation often occurs at a relatively high spatial frequency and makes it difficult to predict soil property values at specific locations

One limitation of kriging is that it can cause excessive smoothing, thus eliminating any discontinuities that do exist in soil property distributions. Several studies have experimented with methods for incorporating information about such discontinuities into the kriging model (Heuvelink and Bierkens 1992, Van Meirvenne et al. 1994). The most common method of combining estimates is to use a weighted sum of the kriged value and the value derived from soil map. Weights can be selected to reflect the error variances of the two sets of values, with the contribution of each source inversely proportional to its error variance. Results suggest that the combination of data from kriging and soil maps can increase accuracy relative to estimates derived from either kriging or soil maps alone.

METHODS

Our study area is Bear Brook Watershed in eastern Maine. Data for this area includes a detailed, Level I soil survey, and independent estimates of depth to bedrock data. Depth values were measured for 47 point locations in the watershed by the Center for Earth and Environmental Science, State University of New York at Plattsburgh (Bogucki and Greundling, no date). Depth values were obtained using seismic refraction techniques. The accuracy of these estimates is reported to be on the order of ± 0.3 m.

Only that area of the watershed within the minimum bounding rectangle defined by the 47 point locations is used in the analysis. The mapping units from the soil survey are shown in Figure 1. Point locations are also shown in this figure.

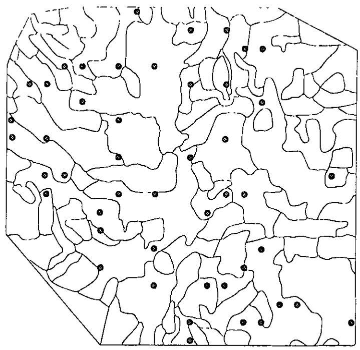


Figure 1. Soil mapping units and point locations for seismic data.

Table 1 contains summary depth statistics for soil mapping units and point locations. Note that for the soil data, depth to bedrock is given as a range of values for each mapping unit.

Component	n	Mean	Std.Dev.	Min.	Max.
Minimum depth (soil map)	104	0.706	0.540	0.0	1.524
Maximum depth (soil map)	104	1.067	0.358	0.0	1.524
Point data	47	2.606	0.975	0.0	5.200

Table 1. Descriptive statistics for depth to bedrock (in meters).

The seismic depth data at the 47 sampled points are used to derive interpolated surfaces using kriging. Since there are too few points to allow for separate calibration and validation subsets, cross-validation techniques based on jack-knifing are used to assess the quality of the interpolated surface. Two measures of quality are used. The first, mean error (ME), is a measure of bias in interpolation,

$$ME = \frac{1}{n} \sum_{i=1}^{n} e_i \tag{1}$$

The second index is the mean squared error (MSE),

$$MSE = \frac{1}{n} \sum_{i=1}^{n} e_i^2 \tag{2}$$

In the equations, n is the number of sampled points and e_i is the difference between the seismic depth value and the kriged value for point i.

Kriging can be performed using various neighborhood sizes. The neighborhood size affects the number of points used to interpolate the value at a given grid point location. It is generally held that as the influence of points decreases with distance, only a small neighborhood is required to obtain an accurate estimate at a given grid location (Burgess and Webster 1980). In this study various neighborhood sizes between 5 and 45 sample points are examined.

Comparison of the soil map depth estimates to the point data is also achieved using the ME and MSE statistics. In this case, e_i is the difference between the seismic depth value for point i and the soil map depth value for the mapping unit within which point i is located. For comparison of the soil map depth estimates to the kriged data, e_i is the difference between the kriged value at point i and the soil map depth value for the mapping unit within which point i is located.

Methods for incorporating information about discontinuities in the distribution of depth to bedrock data are also considered. The approach adopted here is to produce a hybrid surface as a weighted combination of the soil map depth values and the values derived from the kriged surface. Other authors have suggested using weights based on the interpolation error variance (Heuvelink and Bierkens 1992). However, there is no estimate of error variance available for the soil data in the present study. For this reason, our approach is to examine various combinations of weights that favor either the kriged data or the soil map. The quality of these results is assessed with cross-validation procedures based on the ME and MSE indices.

RESULTS

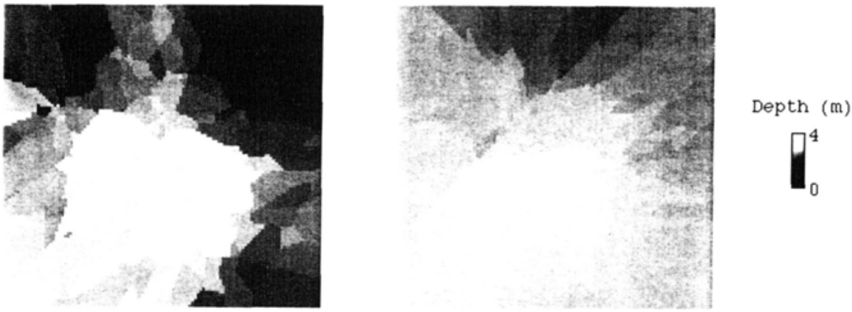
Neighborhood Size

Kriging can be performed using different neighborhood sizes. Our analysis examines neighborhoods of between 5 and 45 points Results are presented in Table 2. In all cases a linear variogram model (with sill) is used, as this provides the closest fit with observed data. The parameters of the model are as follows: a = 390.0 m, c_0 = 0.67 m, c = 0.043 m.

Number of points	ME (m)	MSE (m^2)
5	0.069	1.721
10	0.058	1.569
20	-0.097	1.118
30	0.053	1.006
40	-0.029	0.659
45	-0.139	0.782

Table 2. Cross-validation results for surfaces derived from kriging.

The table indicates that as neighborhood size increases, bias (ME) fluctuates. However, MSE declines consistently as the neighborhood size increases (with the exception of the largest neighborhood of 45 points). On the basis of these results, one might conclude that a larger neighborhood produces a more accurate surface. This is true from the standpoint of the MSE index. However, larger neighborhoods also tend to produce surfaces with unrealistically high degrees of smoothness. This effect is seen in Figure 2, which shows two kriged surfaces, one based on a neighborhood size of 5 points and one based on a neighborhood size of 20 points. While the second of these has a lower MSE, it is also extremely smooth. At the largest neighborhood sizes, the kriged surface is nearly flat.



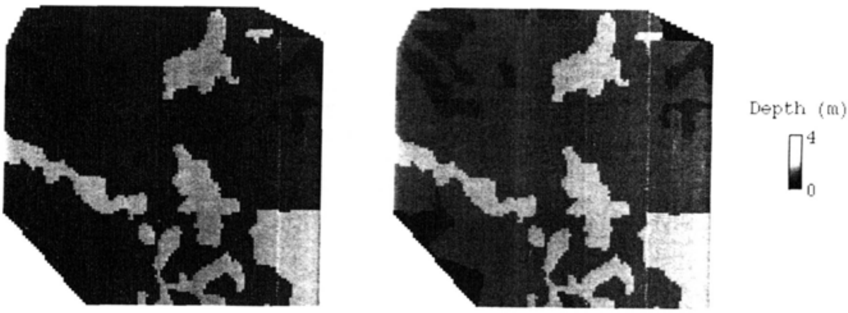
(a) (b)

Figure 2. Examples of surfaces derived by kriging.
(a) Linear model, 5 points. **(b)** Linear model, 20 points.

This result suggests that there is a need to base the selection of an appropriate neighborhood size on criteria other than MSE. One suggestion is to select a surface with an acceptable level of accuracy that has the same overall semivariogram as the original data. For the depth to bedrock data, this criterion suggests a neighborhood size of about 5 cells. (This neighborhood size is used in the remainder of the study.)

Soil Data Quality

Figure 3 shows the depth to bedrock values derived from the soil map.



(a) (b)

Figure 3. Soil map depth to bedrock values.
(a) Minimum depth. **(b)** Maximum depth.

Table 3 compares depth estimates from the soil map and seismic data. Results indicate a consistent bias in soil map data. If bias were absent, a positive ME value would be observed for minimum depth (i.e., seismic value > minimum) and a negative ME value would be observed for maximum depth (i.e., seismic value < maximum).

Component	ME (m)	MSE (m^2)
Minimum depth	1.886	4.633
Maximum depth	1.486	3.173

Table 3. Deviations between soil map depth estimates and seismic data.

Table 4 compares soil map depth estimates to kriged data. Results are similar to those for soil data and kriged estimates (Table 3).

Component	ME (m)	MSE (m^2)
Minimum depth	1.919	3.992
Maximum depth	1.519	2.505

Table 4. Deviations between soil map depth estimates and kriged surface.

Combined Estimation

Kriged surfaces have low error but are relatively smooth compared to the soil map. Information on discontinuities can be incorporated into the interpolation procedure by producing a hybrid surface as a weighted combination of the soil depth values and the depth value from the kriged surface. Table 5 shows the cross-validation results for various combinations of weights. The table indicates that accuracy decreases as the soil map is weighted more heavily. This is due to the apparent bias in depth estimates from soil maps (Tables 3 and 4).

Relative weights		ME	MSE
Soil map	Kriging	(m)	(m^2)
0.25	0.75	0.637	1.814
0.50	0.50	1.230	2.756
0.75	0.25	1.826	4.429

Table 5. Cross-validation results for hybrid surfaces.

Figure 4 shows the hybrid surface derived using equal weights for the soil map and kriged surface (using a linear semivariogram model with a neighborhood size of 5 points). The surface shares some of the characteristics of the smoother kriged surfaces and the soil map.

Visualization

Figure 5 shows a pair of difference maps computed for the depth data derived from soil maps and the hybrid surface in Figure 4. Figure 5a shows overestimation in soil data (i.e., locations where the soil map minimum depth value is greater than the interpolated value on the kriged surface). Figure 5b shows underestimation in soil data (i.e., locations where the soil map maximum depth value is less than the kriged surface). The degree of over- or under-estimation is shown in shades of gray.

Underestimation appears to be higher in prevalence and degree than overestimation. This results from the general tendency for the soil map to underestimate depth values relative to the seismic data (Tables 3 and 4). Areas of underestimation are associated with the fact that the hybrid surface is smoother than the soil map. Thus errors tends to occur where the soil map deviates away from the smoother interpolated surface.

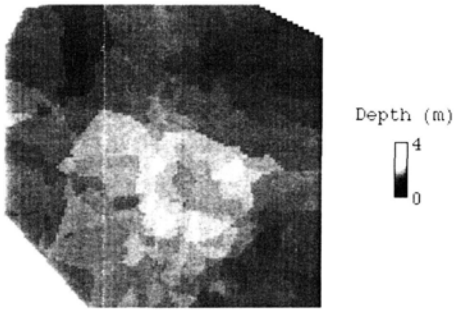


Figure 4. Hybrid surface.

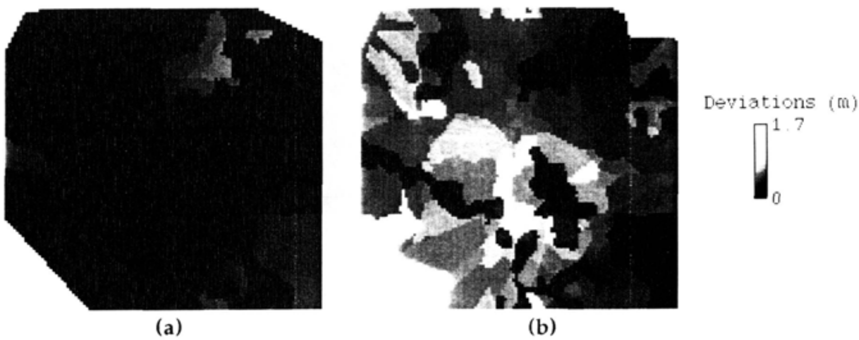


Figure 5 Differences between soil map and hybrid surface.
(a) Overestimation in soil map. **(b)** Underestimation in soil map.

CONCLUSIONS

The quality of the surfaces derived from kriging is dependent on neighborhood size. As neighborhood size increases (i.e., a larger number of points is used in interpolation) the MSE declines fairly consistently, indicating an improvement in interpolation accuracy. The ME index, indicative of bias, fluctuates without a definite pattern. A larger neighborhood is also associated with increased smoothing of the interpolated surface. This suggests that there is a need to look at criteria other than MSE when evaluating the quality of interpolation. One suggestion is to use the interpolated surface that yields approximately the same semivariogram as the original point data values, such that the original spatial pattern is preserved.

Results also show consistent bias (under-estimation) in soil depth values relative to seismic data. This suggests a systematic difference in the way in which depth is measured in the soil map and by seismic techniques. This type of systematic error may not be typical of all soil properties. Merging of soil and kriged data yields hybrid surfaces that are less smooth than the original kriged surfaces. In this study, the quality of these surfaces is lower than that of the kriged surfaces due to systematic differences in soil and seismic data. Quality declines as the relative weight of soil data is increased.

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