GEOSTATISTICAL INTEGRATION OF HIGH-RESOLUTION REMOTE SENSING DATA IN SPATIAL ESTIMATION OF GRAIN SIZE

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ABSTRACT: Various geological thematic maps such as grain size or ground water level maps have been generated by interpolating sparsely sampled ground survey data. When there are sampled data at a limited number of locations, to use secondary information which is correlated to primary variable can help us to estimate the attribute values of the primary variable at unsampled locations. This paper applies two multivariate geostatistical algorithms to integrate remote sensing imagery with sparsely sampled ground survey data for spatial estimation of grain size: simple kriging with local means and kriging with an external drift. High-resolution IKONOS imagery which is well correlated with the grain size is used as secondary information. The algorithms are evaluated from a case study with grain size observations measured at 53 locations in the Baramarae beach of Anmyeondo, Korea. Cross validation based on a one-leave-out approach is used to compare the estimation performance of the two multivariate geostatistical algorithms with that of traditional ordinary kriging.

KEY WORDS: Kriging, Multivariate Geostatistics, Secondary Information

1. INTRODUCTION

Traditional geological thematic mapping tasks have used ground survey data which are typically sampled only at a limited number of locations due to some limitations such as high cost, inaccessibility, etc. Since most further analytical procedure requires a certain kind of map in which any attribute values of interest are exhaustively known, any interpolation algorithms such as inverse distance, TIN and Spline have been applied to obtain the map. Among several interpolation algorithms, geostatistical kriging has an advantage in considering the spatial correlation between neighbouring sample data (Goovaerts, 1997). If it is possible to obtain any additional information which is well correlated to the variable of interest and more densely sampled, sparsely sampled observation can be complemented by that information (Goovaerts, 2000). For example, DEM or weather radar data can be used for spatial estimation of rainfall and DEM for ground water level mapping (Raspa et al., 1997; Goovaerts, 2000; Chung and Lee, 1995).

In this paper, practical multivariate geostatistical algorithms are applied to spatial estimation of grain size by integrating remote sensing imagery with sparsely sampled grain size data. Two geostatistical algorithms applied in this paper are simple kriging with local means (SKLM) and kriging with an external drift (KED). High-resolution IKONOS imagery is used as secondary information. A case study from the Baramarae beach of Anmyeondo, Korea was carried out to illustrate the applicability of those algorithms. The performance of those multivariate geostatistical algorithms was evaluated and compared with traditional univariate geostatistical kriging by cross validation based a one-leave-out approach.

2. METHODOLOGY

2.1 Geostatistical kriging

Geostatsitics, which is developed by mining engineers in the 1960s to evaluate the recoverable reserves in mining deposits, provide statistical tools for analysis of space/time information (Goovaerts, 1997).

Geostatistical analysis is based on a random function model and considers attribute values as a certain realization of a random variable. Kriging is a generalized least-squares estimation algorithm by considering spatial correlation which is generally represented by variogram.

2.2 Multivariate kriging

One of main advantages of kriging is its ability to account for secondary information in spatial estimation problems. Among several multivariate kriging algorithms, SKLM and KED are applied in this paper. Though it can directly use the attribute values of secondary information in the estimation procedure, cokriging requires computation and modelling of direct and cross variograms. Thus, those two practical multivariate kriging algorithms, which do not require heavy computation cost but provide reasonably similar prediction capability, are applied in this paper.

The two multivariate kriging algorithms use the secondary information for deriving the local mean of primary variable considered. Detailed description of the algorithms can be referred to Goovaerts (1997).

SKLM replaces constant mean values of simple kriging by locally varying mean values. The varying mean values are derived from a calibration procedure of the secondary information with respect to the primary variable. In general, SKLM performs simple kriging of residual values and the estimates of the residual are added to the varying local mean values.

KED also derives the local mean values of the primary variable from the secondary information like SKLM. The main difference between KED and SKLM lies in the formulation of the local mean values. The regression coefficient values of KED are computed through the kriging system within each search neighbourhood (Goovaerts, 2000). In this approach, main assumption is that the relation between the primary variable and the secondary information should be linear.

2.3 Validation

To evaluate performance of kriging algorithms applied here, cross validation based on a one-leave-out approach is applied. First, a sampled point is temporally eliminated and kriging algorithms with the remaining samples are applied to estimate the value of the eliminated point. Then the difference between true and estimated values is compared and this procedure is repeated for all sampled points. Mean square error (MSE) was considered as quantitative measures of cross validation in this study.

3. CASE STUDY

3.1 Study Area and Data

A case study area is located in the Baramarae beach of Anmyeondo, Korea. Two data were used for spatial estimation of grain size in the study area. High-resolution IKONOS imagery acquired on February 26, 2001 was used as secondary information for grain size (Figure 1 (a)). By considering the image acquisition date and tide, ground survey was implemented on February 26, 2002. Sample data were acquired at a total 53 locations which are uniformly distributed in the study area (Figure 1 (b)) and then processed by traditional grain size analysis to obtain quantitative grain size information. Halmisom, Seomot and ocean areas were masked out by unsupervised classification for further analysis.

3.2 Results

First, the scatterplots of 4 multi-spectral bands and sampled data were computed to examine the magnitude of correlation. All 4 bands showed negative correlation and band 2 (green band) was the highest correlation value of -0.803. The negative correlation means that the larger the DN values of each band are, the smaller the grain size value will be. The IKONOS band 2 was used for KED

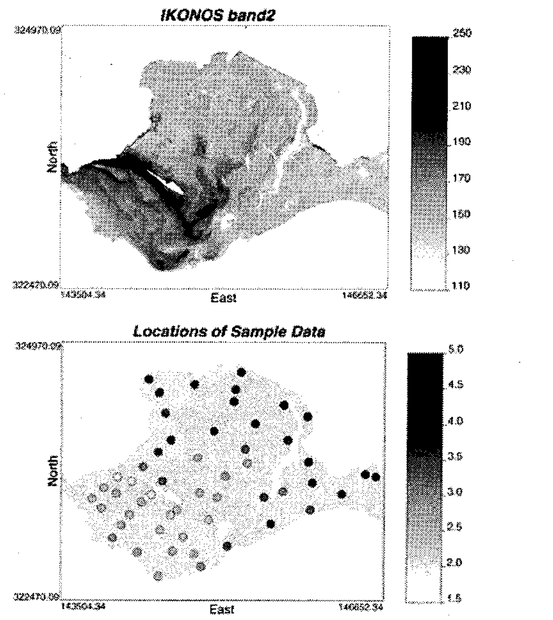

Figure 1. (a) IKONOS band 2 imagery, (b) Location map of sample data.

because only one information can be used as secondary information in KED. For SKLM, two band combination cases were considered: one case using the IKONOS band 2 like KED and the other case using all 4 bands. From the regression analysis for SKLM, the regression results using all 4 bands showed smaller residual standard errors (0.554) than those from band 2 (0.448).

As a comparison purpose, ordinary kriging and kriging with a trend (also called universal kriging) were applied as univariate kriging algorithms. From a varigram analysis, strong anisotropy was observed in NW-SW direction (not shown here). To reflect that trend in the kriging procedure, kriging with a trend was especially applied.

Figure 2 shows grain size distribution maps generated by various geostatistical algorithms. The maps generated by ordinary kriging and kriging with a trend show smoothing spatial patterns, which is a typical characteristic of the kriging algorithm. That is, small values are overestimated and large values are underestimated under the constraint of minimal variance errors. While, three multivariate geostatistical algorithms (one of KED and two of SKLM), which used the IKONOS imagery as the secondary information, reflect local details of the spatial variation of grain size with less smoothing effects.

The performances of various geostatistical algorithms were quantitatively assessed using cross validation and the results are given in Table 1. The univariate kriging algorithms (i.e. ordinary kriging and kriging with a trend) which do not consider the IKONOS imagery have larger mean square error values than the multivariate geostatistical algorithms. The relatively smaller prediction errors of kriging with a trend than those of ordinary kriging may be explained by the fact that kriging with a

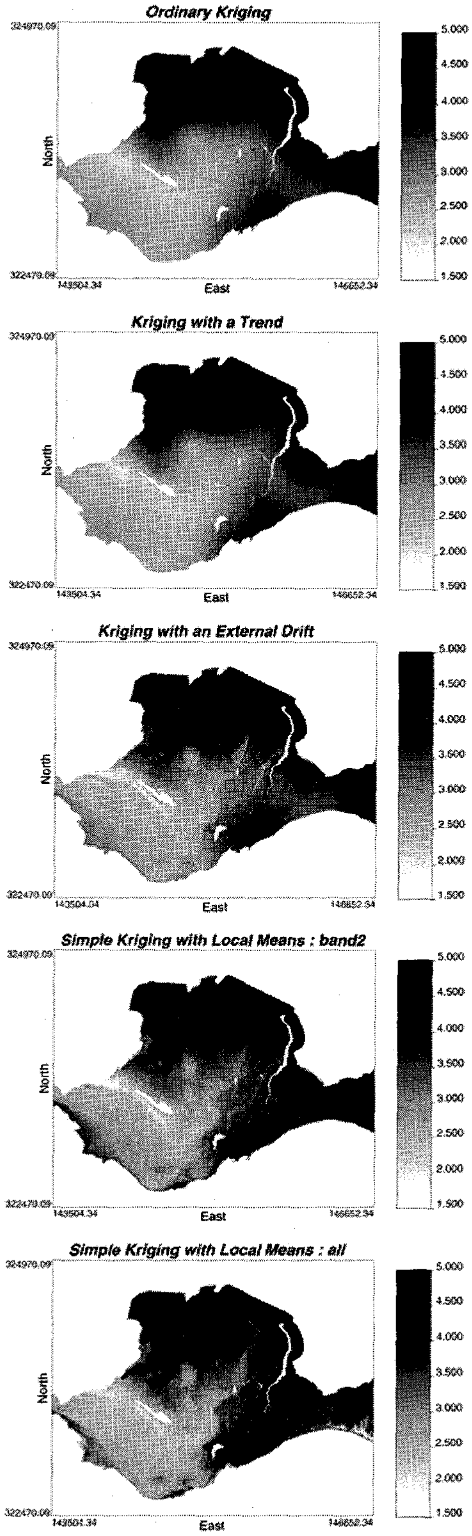

Figure 2. Grain size distribution maps generated by geostatistical algorithms.

trend could well reflect the strong anisotropy observed in the sampled data. Among multivariate geostatistical algorithms, SKLM with all IKONOS bands showed the best prediction capability than KED and SKLM with IKONOS band 2. From the regression analysis, the small

Table 1. Cross validation results

Algorithm	Mean Square Error (MSE)
Ordinary kriging	0.241
Kriging with a trend	0.233
KED	0.162
SKLM with IKONOS band 2	0.183
SKLM with all IKONOS bands	0.138

residual standard errors were observed in the regression results using all 4 bands. That result means that the linear relation between all bands and the grain size was stronger than that of band 2. This strong linear relation could be well reflected as local mean values in SKLM and better performance of SKLM with all bands could be obtained.

4. CONCLUSIONOS

The multivariate geostatistical algorithms, which can account for secondary information as well as spatial correlation between neighbouring sample data, were evaluated to estimate grain size values at unsampled locations. The case study results indicated that remote sensing imagery was well correlated to ground-based grain size observations and the multivariate geostatistical algorithm which could incorporate that secondary data into the kriging procedure produced the better prediction results than traditional univariate geostatistical kriging algorithms.

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