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The Effects of Spatial Patterns in Low Resolution Thematic Maps on Geostatistical Downscaling

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Abstract : This paper investigates the effects of spatial autocorrelation structures in low resolution data on downscaling without ground measurements or secondary data, as well as the potential of geostatistical downscaling. An advanced geostatistical downscaling scheme applied in this paper consists of two analytical steps: the estimation of the point-support spatial autocorrelation structure by variogram deconvolution and the application of area-to-point kriging. Point kriging of block data without variogram deconvolution is also applied for a comparison purpose. Experiments using two low resolution thematic maps derived from remote sensing data showing very different spatial patterns are carried out to discuss the objectives. From the experiments, it is demonstrated that the advanced geostatistical downscaling scheme can generate the downscaling results that well preserve overall patterns of original low resolution data and also satisfy the coherence property, regardless of spatial patterns in input low resolution data. Point kriging of block data can produce the downscaling result compatible to that by area-to-point kriging when the spatial continuity in block data is strong. If heterogeneous local variations are dominant in input block data, the treatment of the low resolution data as point data cannot generate the reliable downscaling result, and this simplification should not be applied to donwscaling.

Key Words : Scale, Downscaling, Kriging, Deconvolution

1. Introduction

A scale conversion or change of support problem has been regarded as one of main issues in spatial data analysis(Atkinson and Tate, 2000; Gotway and Young, 2002). The spatial data analysis including remote sensing data processing usually deals with various types of data with different spatial resolutions. For example, ground measurements provide high resolution point information, and regional or global information for various quantities can be provided by various remote sensing data. In spatial data modeling, the disparate data sets should be integrated not only within a unified framework, but also at a predefined target resolution.

For the integrated analysis of data sets with different spatial resolutions, the simplest and usual way is first to aggregate high resolution data to the coarsest resolution data, and then to analyze these upscaled low resolution data sets. This unspcaling or

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aggregation procedure, however, inevitably includes loss of information to be provided by the original high resolution data. Another way is to transform low resolution data to high resolution data, so called downscaling or super-resolution mapping. The simplest way of downscaling is to force the low resolution data to be the high resolution data through interpolation or simple assignment. In this approach, the low resolution data are implicitly treated as point data, and then interpolation methods are applied to their respective centroid points for downscaling.

In relation to downscaling, it should be noted that downscaling is regarded as an under-determined inverse problem(Boucher and Kyriakidis, 2005), in that there are multiple combinations of high resolution attribute values that can lead to the same aggregate values at a coarser resolution. This problem, also called the ecological inference problem(Young and Gotway, 2007), is illustrated in Fig. 1. In Fig. 1, two possible solutions of downscaling are displayed as an illustration purpose. In the second solution denoted as Downscaling case #2 in Fig. 1, the attribute values of Data 2 are the same as those in the first case, whereas the attribute value at each odd-numbered column of Data 1 is simply switched by that at the neighboring even-numbered column of the first solution(i.e. Downscaling case #1 in Fig. 1). The two solutions have the same mean and standard deviation values as well as the same aggregate values when averaged to the original coarse scale. Note the standard deviation values of the downscaled data sets are higher than those of the coarse scale data. From a bivariate analysis of Data 1 and Data 2, correlation coefficients at both the coarse resolution and the first donwscaling case are very similar, i.e., 0.97 and 0.96, respectively. However, the correlation coefficient

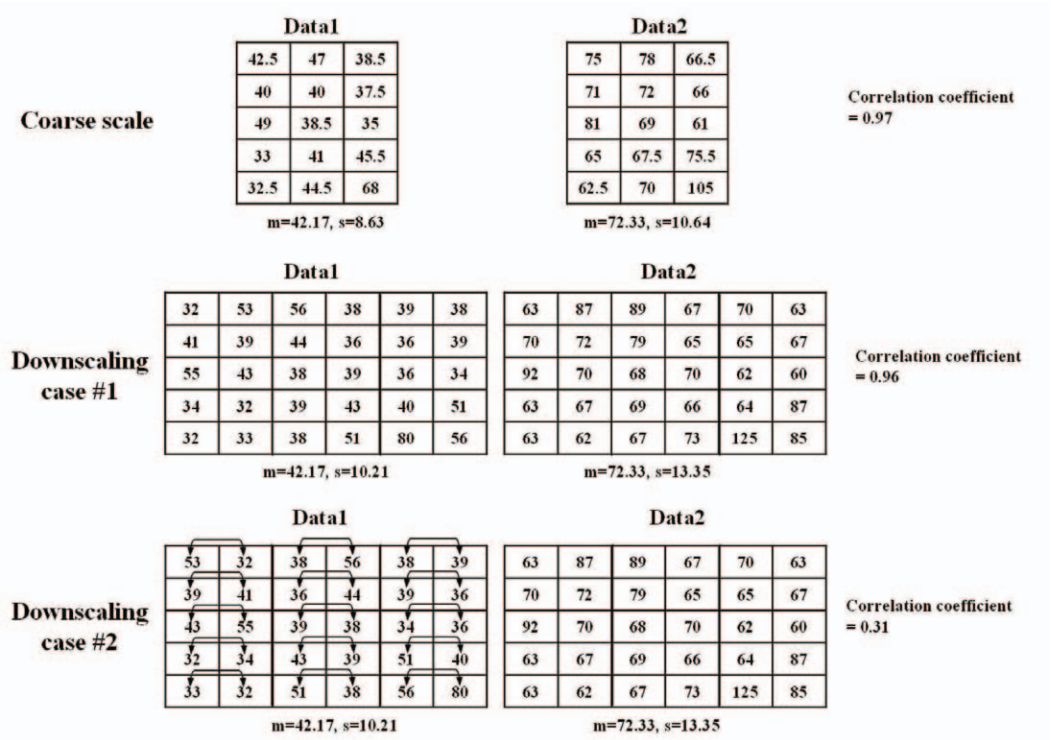


Fig. 1. Examples of downscaling showing the variation of statistical relationships after downscaling (modified from Kyriakidis(2008)).

value at the second donwscaling case is 0.31 and the linear relationship is greatly weakened, compared to the correlation coefficient value of 0.97 at the coarse resolution. From the illustration in Fig. 1, one can see that the statistical relationships between spatial data sets at a finer resolution may be different than those derived at the original coarse resolution. As a result, the traditional simple downscaling scheme, which cannot account for the spatial arrangement, may result in unrealistic modeling results.

Since the 2000s, several statistical downscaling schemes have been proposed and applied to many research fields such as hydrology, meteorology, and remote sensing(Harris and Foufoula-Georgiou, 2001; Tatem *et al*., 2001; Kaheil *et al*., 2008; Kim and Park, 2010; Hur *et al*., 2011, Jia *et al*., 2011). Besides these statistical approaches, geostatistics can provide a theoretical framework to account for the resolution difference between input data and target units(Journel and Huijbregts, 1978). Especially, a geostatistical framework for downscaling of areal data was proposed in Kyriakidis(2004) to predict point values from areal data. In his work, kriging of areal data to predict point values was referred to as area-to-point kriging. For remote sensing applications, Boucher and Kyriakidis(2005) proposed indicator kriging and simulation of land-cover fractions to generate high resolution land-cover maps. Their approaches were designed to predict categorical land-cover classes at a finer resolution. A practical issues is that they used the point-support variogram already defined for downscaling, which cannot be vailable in practice if there are no ground or field measurement data. Park(2010) integrated ground survey and remote sensing data for geostatistical downscaling. Since the ground survey data are available, the point-support variogram was directly estimated from them. From the availability aspect, however, it is not always the case.

The estimation of the point-support varigram from block data, which is necessary to compute kriging weight values, was discussed in Goovaerts(2008). He proposed a variogram deconvolution method, which is an iterative estimation algorithm that can be applied to both regular grid data and irregular geographic units. In variogram deconvolution, the spatial patterns or autocorrelation structures of input data affect the estimation of the point-support variogram at the target resolution. In the case of regular block data like remote sensing data, especially, the difference between the variogram from original low resolution data and the estimated point-support variogram may not be distinct unlike the case of irregular geographical units. If the difference is not large, to collapse low resolution block data into point data may be a simple but efficient downscaling scheme from a practical viewpoint. Otherwise, this crude simplification of the low resolution data may produce the unreliable downscaling result. These practical issues have not as yet been thoroughly investigated for downscaling of low resolution remote sensing data.

The objective of this paper is to investigate the impact of spatial patterns in input low resolution block data on the final downscaling results, when ground or field measurement data are not available. An advanced geostatistical downscaling scheme based on area-to-point kriging and variogram deconvolution is compared with the traditional simple downscaling scheme based on point kriging of block data. First, the point-support variogram estimated by variogram deconvolution is qualitatively compared with the variogram model from original low resolution data. Subsequently, the downscaling results by two kriging methods(area-to-point kriging vs. point kriging) are compared and discussed. Two experiments for downscaling of the Shuttle Radar Topography Mission(SRTM) DEM and MODIS leaf area index(LAI) products which show very different

spatial patterns are carried out for comparison purposes.

2. Geostatistical downscaling

In this section, the main geostatistical downscaling scheme adopted in this paper is briefly described, as synthesized from Kyriakidis(2004) and Goovaerts (2008).

Area-to-point kriging applied in this paper is a kriging algorithm that aims at predicting attribute values at a finer resolution from block or areal data available at a coarse resolution(Kyriakidis, 2004).

Suppose a study area of interest consists of K block data $\{z(\upsilon_k), k = 1, \cdots, K\}$, where $\upsilon_k = \upsilon(u_k)$ denotes the kth data with its centroid u_k. Throughout this paper, the block data mean the data obtained at a coarse resolution. Area-to-point ordinary kriging predicts the attribute value $z(u_p)$ at each discretizing point u_p within each block υ_k through a linear combination of neighboring block data as shown in equation (1):

$$z(u_p) = \sum_{k=1}^{K} \lambda_k(u_p)\, z(\upsilon_k) \tag{1}$$

where $\lambda_k(u_p)$ is a kriging weight assigned to the neighboring block data $z(\upsilon_k)$ at a prediction location.

Like a traditional ordinary kriging system, the kriging weight $\lambda_k(u_p)$ and the Lagrange multiplier $\mu(u_p)$ are computed by solving the following equation (2).

$$\begin{aligned} &\sum_{l=1}^{K} \lambda_k(u_p)\, \bar{C}(\upsilon_k, \upsilon_l) + \mu(u_k) = \bar{C}(\upsilon_k, u_p) \quad k = 1, \cdots, K \\ &\sum_{l=1}^{K} \lambda_k(u_p) = 1 \end{aligned} \tag{2}$$

where $\bar{C}(\upsilon_k, \upsilon_l)$ and $\bar{C}(\upsilon_k, u_p)$ are block-to-block covariance and block-to-point covariance, respectively.

The computation of the block-to-block and block-to-point covariances in equation (2) is critical to determine the kriging weights. In this study, these two covariances are calculated by averaging point covariances(Journel and Huijbregts, 1978; Goovaerts, 2008). Thus, one needs to know the point-support variogram at the target resolution. More specifically, the block-to-block covariance is computed by averaging the covariance values computed between any two points discretizing two blocks υ_k and υ_l. The block-to-point covariance is approximated by averaging the covariance values between the location u_p and a set of points discretizing the block υ_k.

When ground survey data are available, this point-support variogram can be estimated directly from them. In case that there are no ground data, however, it is impossible to estimate the point-support variogram, since there are only low resolution data(Goovaerts, 2008). Kaheil *et al*.(2008) used the variogram model estimated from the low resolution image to generate the image at the next finer resolution. As pointed out in Fig. 1, the spatial relationships or structures may be changed after downscaling.

To solve this practical issue, Goovaerts(2008) proposed an iterative deconvolution procedure for estimating the point-support variogram from block or areal data irrespective of their shapes. His approach was further refined and combined to area-to-point Poisson kriging for both the filtering of areal disease rate data and the fine resolution mapping of the areal data(Goovaerts, 2006, 2009). For variogram deconvolution, a regularized variogram, which is defined as the difference between the block-to-block variogram and the within-block variogam values(Journel and Huijbregts, 1978), is computed after defining an initial point-support variogram. Then, the regularized variogram model is compared with the variogram model of the block data. By inspecting the difference between those two models, the point-support variogram is modified to minimize the difference(Goovaerts, 2008). These procedure is

repeated until a stop criteria is satisfied.

An interesting property of area-to-point kriging is its ability of reproduction of the values of available block data, when upscaled, also called the coherence property(Kyriakidis, 2004). Unlike Kaheil *et al*.(2008) where a ratio bias remover was adopted as an additional processing step, the coherence property can be satisfied without further processing step if the prediction units are the same as a set of points discretizing the block data, and both the point and block data are used for the kriging kriging system in equations (1) and (2).

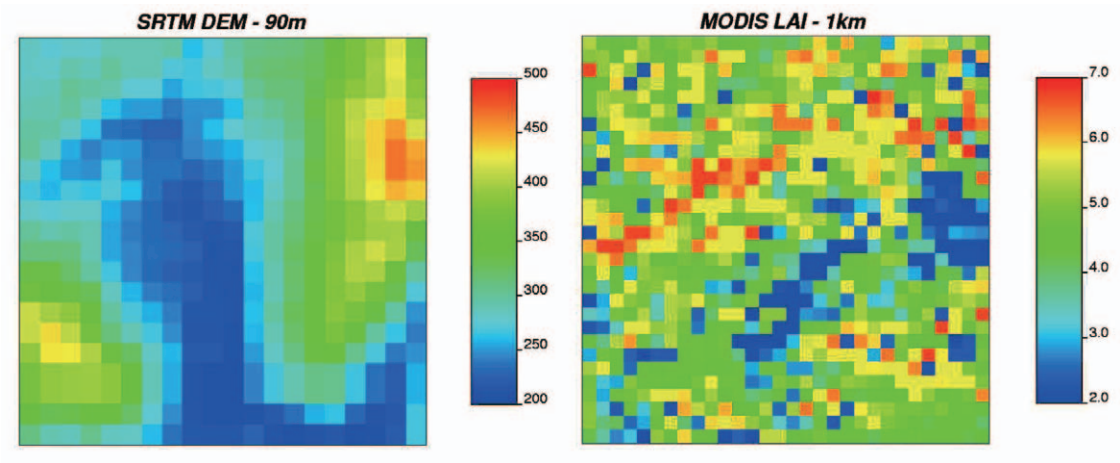
3. Experiment

1) Data

To illustrate the practical issues for geostatistical downscaling, experiments using two different data sets are carried out. The data sets include SRTM DEM data at the 90m resolution and MODIS LAI data at the 1km resolution(Fig. 2). These data sets consist of 20×20 and 30×30 pixels, respectively. The SRTM DEM data was the same one used in Park(2010). Note much more continuous patterns in the SRTM DEM data than the MODIS LAI data as shown in Fig. 2. The target fine resolution for the SRTM DEM is experimentally set to 15m, that of ASTER imagery. Each block of the MODIS LAI data is downscaled to the 250m resolution. The reference DEM used in Park(2010) is only available for accuracy assessment. Thus, the downscaling result of the SRTM DEM data will be validated using the reference data. For the LAI data, the coherence property and overall patterns of downscaling results are qualitatively checked and compared due to the lack of validation data.

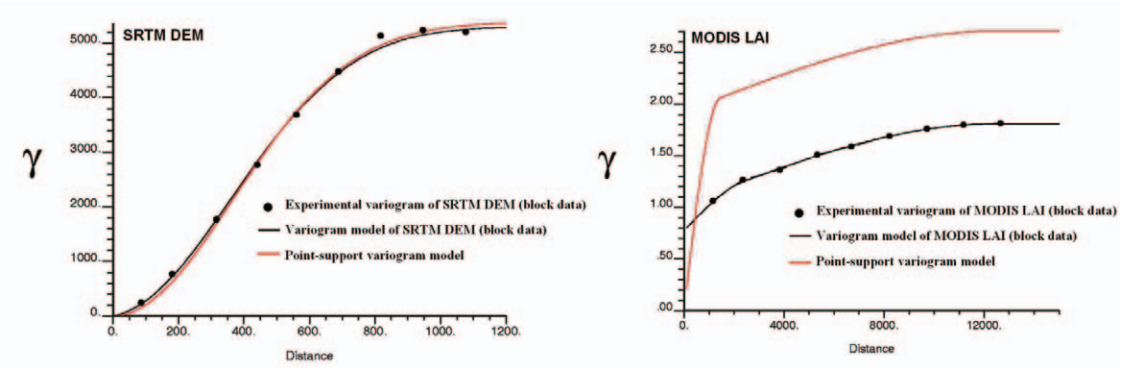
2) Point-support varigram estimation results

Prior to implementing area-to-point kriging, the point-support variogram was first estimated through variogram deconvolution. By considering the target resolution, each block or pixel of the two data sets was discretized by 36×36 points for the SRMT DEM and 16×16 points for the MODIS LAI. Variogram deconvolution was implemented using the



(a) (b)

Fig. 2. Data sets used in the experiments, (a) SRTM DEM, (b) MODIS LAI.



(a) (b)

Fig. 3. Variogram deconvolution results, (a) SRTM DEM, (b) MODIS LAI.

SpaceStat software(BioMedware, USA).

Fig. 3 shows the variogram deconvolution results for two data sets. The quadratic behaviors near the short range for the SRTM DEM were captured by using a Gaussian model. That is, the nearby attribute values of the SRTM DEM are very similar, and the high spatial continuity exists in the block data. In the case of the MODIS LAI, the variogram of the block data was modeled as two nested spherical models with a high relative nugget effect.

The distinctive difference between the two data sets is that the estimated point-support variogram for the SRTM DEM is very close to the variogram model of block data at the 1km resolution. This means that the block data can be collapsed into point data, and the variogram model from the block data can be approximated to the quasi-point support variogram model(Journel and Huijbregts, 1978). In this case, it is expected that the downscaling result by point kriging of the centroid values of blocks would be very similar to that by area-to-point kriging.

The point-support variogram model for the MODIS LAI has a higher sill value than the variogram of the block data, since point data tend to have a larger variance than the aggregated blocks(Goovaerts, 2008). This large difference between the point-support variogram and the variogram model from the block data for the MODIS LAI may result in much different downscaling results by two kriging algorithms.

From this comparison, it is observed that if block data show high continuous patterns, the difference between the estimated point-support variogram model and the variogram model of block data is not great. This result confirms that the effect of the block averages would be greatest for data which are spatially uncorrelated(Isaaks and Srivastava, 1989, p.465).

3) Downscaling results

After estimating the point-support variogram model, area-to-point kriging was conducted to downscale block data to the finer resolution. For the comparison purpose, point ordinary kriging of the values at the centroid points of blocks was also implemented to investigate the effects of the difference between the point-support and the block variograms on the final downscaling results.

The donwscaling results of the SRTM DEM data are shown in Fig. 4 (a) and (b). The area-to-point kriging result with the point-support variogram in Fig. 4 (a) reproduces overall patterns of the original

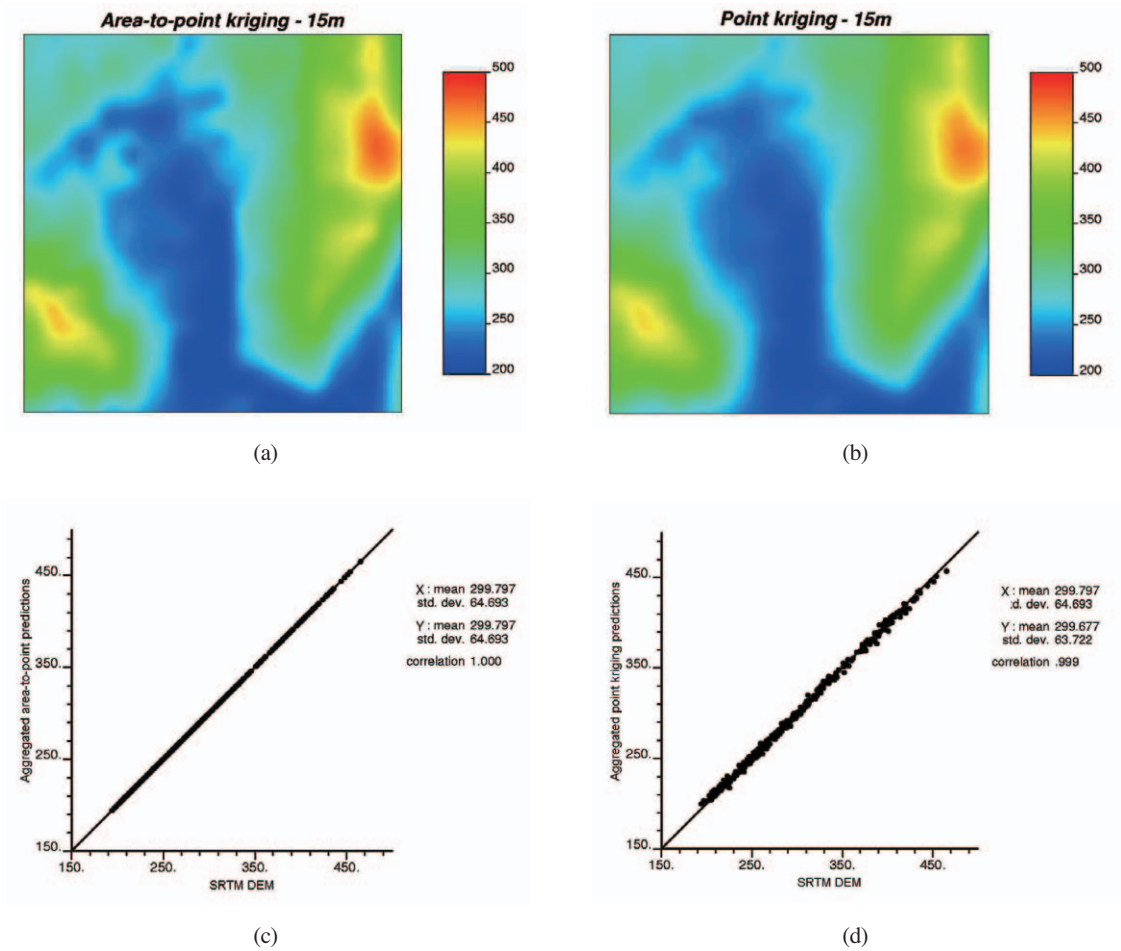


Fig. 4. Downscaling results of SRTM DEM data at the 15m resolution, (a) prediction by area-to-point kriging, (b) prediction by point kriging of block data. (c) scatterplot between the upscaled result of (a) and original block data, (d) scatterplot between the upscaled result of (b) and original block data.

block data in Fig. 2 (a), and also gives the smoothed variation of elevation values due to the use of Gaussian variogram model. Point kriging of block data shows more smoothing effects than area-to-point kriging as shown in Fig. 4 (b). However, their overall patterns are very similar and these are resulted from the fact that the point-support variogram model was very similar to that of the block data at the 1km resolution, as discussed in the previous subsection, To check out the coherence property, two downscaling results were upscaled by applying an average operator to the original 1km resolution. Fig. 4 (c) and (d) give the scatterplots between the upscaled predictions and the corresponding original block data. Area-to-point kriging perfectly satisfies the coherence property, and the point kriging also reasonably reproduces the values of the original block data. The mean error (ME) and mean absolute error (MAE) values were computed for accuracy assessment. The ME and MAE values for area-to-point kriging were -4.3m and 25.8m, respectively. Point kriging also showed the similar validation result; an ME value of -4.4m and an MAE value of 26.8m. These validation results are compatible to those in Park(2010). In the

case of the SRTM DEM data in which the high continuity exists, consequently, to collapse block data into their centroid point data can be the simplest solution for downscaling.

Fig. 5 (a) and (b) show the downscaling results of the MODIS LAI data. Unlike the SRTM DEM data, the two downscaling results are very different. The area-to-point kriging result well reflects overall patterns of original block data in Fig. 2 (b), and the local variations are also well preserved, whereas the point kriging result smooths out local details of the spatial variation of LAI values. High and low values at the fragmented blocks are underestimated and overestimated, respectively, and subsequently, their local patterns disappeared. Although smoothing effects are the typical characteristics of any kriging algorithms, the treatment of block data as point data by ignoring their spatial supports resulted in very strong smoothing effects in the case of the MODIS LAI data. As expected, the point kriging result fails to satisfy the coherence property by overestimation of low values and underestimation of high values(Fig. 5 (c)), whereas the area-to-point kriging result perfectly satisfies the coherence property as shown in Fig. 5 (d).

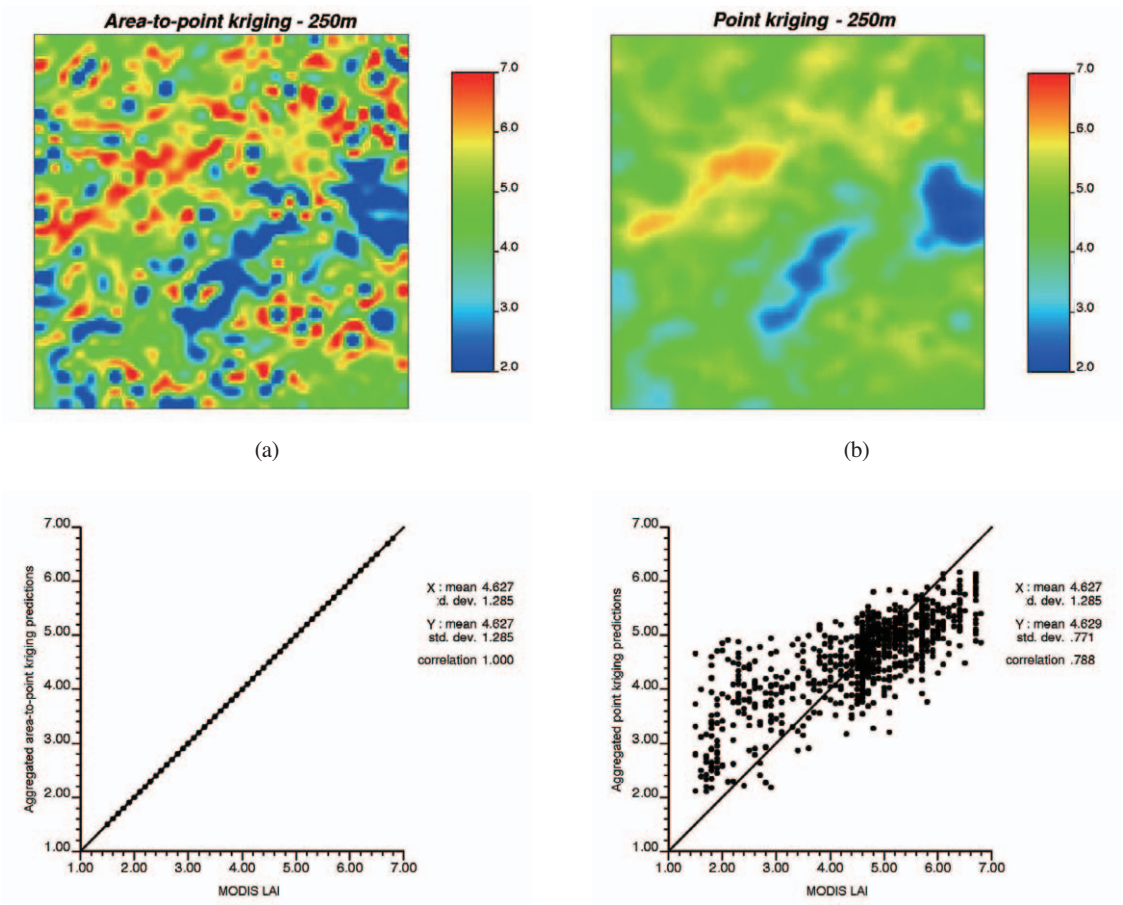


Fig. 5. Downscaling results of MODIS LAI data at the 15m resolution, (a) prediction by area-to-point kriging, (b) prediction by point kriging of block data. (c) scatterplot between the upscaled result of (a) and original block data, (d) scatterplot between the upscaled result of (b) and original block data.

The experiment using two distinctive data sets confirms that area-to-point kriging can generate high resolution data from low resolution block data by accounting for the support difference between prediction units and input data. Also, the estimation the point-support variogram is affected by the variogram model of original block data, and point kriging based on the treatment of block data as point data cannot be applied for downscaling, if local variation is dominant in the original block data.

4. Concluding Remarks

Since data sets obtained at the different resolutions are commonly used in spatial data analysis, scale conversion is often carried out for the consistent analysis. In this paper, the geostatistical downscaling scheme based on area-to-point kriging and variogram deconvolution has been tested for downscaling of low resolution thematic maps derived from remote sensing data without any additional data such as field measurement data or covariates related to the attribute of interest.

To investigate the impacts of spatial autocorrelation structures in original block data as well as the potential of geostatistical downscaling, the experiments using two data sets showing very different spatial patterns have been carried out. Major findings from the experiments are as follows:

1. Area-to-point kriging using the point-support variogram estimated by variogram deconvolution could generate the downscaled results that not only well preserved overall patterns of the original block data, but also perfectly reproduced the values of block data, when upscaled to the original resolution. Regardless of the patterns of input block data, it is expected that area-to-point kriging, which can account explicitly for the support differences, would be an effective downscaling method.

2. If input block data had the strong continuity or long range of autocorrelation(e.g. the SRTM DEM data in this experiment), the point-support variogram model was very similar to that of block data, and thus, the application of traditional point kriging to centroid points after treating block data as point data could generate the downscaling result similar to that by area-to-point kriging.

3. If there were heterogeneous patterns in input block data(e.g. the MODIS LAI data in this experiment), sill and range values of the point-support variogram model was quite different from those of the block variogram model. As a result, the downscaling result by point kriging failed to reproduce variations of block data and showed much strong smoothing effects. Thus, the simple application of interpolation methods to downscaling by simplification of block data as point data cannot generate reliable downscaling results under the above condition.

Multiple secondary data obtained at a finer resolution can improve the quality of downscaling, although this issue is not covered in this paper. For example, elevation at the finer resolution can be useful information for downscaling of precipitation data from low resolution remote sensing data. Area-to-point kriging can be extended to incorporate multivariate variables, like area-to-point residual kriging with multiple regression models presented by Liu *et al*.(2008).

Another research issue is to extend the kriging-based downscaling approach to a stochastic simulation framework. As discussed in Introduction, downscaling should be understood as an under-determined inverse problem. Area-to-point kriging applied in this paper provides the best solution in the least-squares sense. However, there exist multiple alternatives realizations that all reasonably satisfy the

constraints of area-to-point kriging. Unlike only one solution from kriging, the multiple realizations can be used for spatial uncertainty measures and uncertainty propagation problems. Thus, the extension of kriging to stochastic simulation should be investigated for downscaling problems.

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References

Atkinson, P.M. and N.J. Tate, 2000. Spatial scale problems and geostatistical solutions: a review, *Professional Geographe*r, 52(4): 607-623.

Boucher, A. and P.C. Kyriakidis, 2005. Super-resolution land-cover mapping with indicator geostatistics, *Remote Sensing of Environment*, 104(3): 264-282.

Goovaerts, P., 2006. Geostatistical analysis of disease data: accounting for spatial support and population density in the isopleth mapping of cancer mortality risk using area-to-point Poisson kriging, *International Journal of Health Geographics*, 5(52):doi:10.1186/1476-072X-5-52.

Goovaerts, P., 2008. Kriging and semivariogram deconvolution in the presence of irregular geographical units, *Mathematical Geosciences*, 40(1): 101-128.

Goovaerts, P., 2009. Medical geography: a promising field of application for geostatistics, *Mathematical Geosciences*, 41(3): 243-264.

Gotway, C.A. and L.J. Young, 2002. Combining incompatible spatial data, *Journal of the American Statistical Association*, 97(458): 632-648.

Harris, D. and E. Foufoula-Georgiou, 2001. Subgrid variability and stochastic downscaling of modeled clouds: effects in radiative transfer computations for rainfall retrieval, *Journal of Geophysical Research*, 106(D10): 10349-10362.

Hur, Y., M. Choi, and H.W. Kim, 2011. Mapping soil moisture at high resolution using fusion downscaling method with AMSR-E & MODIS imagery, *Proceedings of the KSRS Spring Conference 2011*, Kyungjoo, Mar. 24-25, pp. 124-127 (in Korean).

Isaaks, E.H. and R.M. Srivastava, 1989. *An Introduction to Applied Geostatistics*, Oxford University Press.

Jia, S., W. Zhu, A. Lu, and T. Yan, 2011. A statistical spatial downscaling algorithm of TRMM percipitation based on NDVI and DEM in the Qaidam Basin of China, *Remote Sensing of Environment*, 115(12):3069-3079.

Journel, A.G. and C.J. Huijbregts, 1978. *Mining Geostatistics*, Academic Press.

Kaheil, Y.H., M.K. Gill, M. McKee, L.A. Bastida, and E. Rosero, 2008. Downscaling and assimilation of surface soil moisture using ground truth measurements, *IEEE Transactions on Geoscience and Remote Sensing*, 46(5): 1375-1384.

Kim, G.-S. and H.-G. Park, 2010. Estimation of drought index using ART algorithm and satellite data, *Journal of the Korean Association of Geographic Information Studies*, 13(1): 128-141 (in Korean).

Kyriakidis, P.C., 2004. A geostatistical framework for area-to-point spatial interpolation, *Geographical Analysis*, 36(3): 259-289.

Kyriakidis, P.C., 2008. *Lecture Notes on Analytical Methods in Geography*, University of California Santa Barbara.

Liu, X.H., P.C. Kyriakidis, and M.F. Goodchild, 2008. Population-density estimation using regression and area-to-point residual kriging, *International Journal of Geographical Information Science*, 22(4): 431-447.

Park, N.-W., 2010. Downscaling of thematic maps based on remote sensing data using multi-scale geostatistics, *Korean Journal of Remote Sensing*, 26(1): 29-38 (in Korean).

Tatem, A.J., H.G. Lewis, P.M. Atkinson, and M.S. Nixon, 2001. Super-resolution target identification from remotely sensed images using a Hopfield neural network, *IEEE Transactions on Geoscience and Remote Sensing*, 39(4): 781-796.

Young, L.J. and C.A. Gotway, 2007. Linking spatial data from different sources: the effects of change of support, *Stochastic Environmental Research and Risk Assessment*, 21(5): 589-600.