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Quantitative Evaluation of Spatial Interpolation Models Based on a Data-Independent Method

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1. Introduction

Spatial interpolation, i.e. the procedure of estimating the value of properties at unsampled sites within areas covered by existing observations (Algarni & Hassan, 2001), appears various models using local/global, exact/approximate and deterministic/geostatistical methods. As being an essential tool for estimating spatial continuous data which plays a significant role in planning, risk assessment and decision making, interpolation methods have been applied to various disciplines concerned with the Earth's surface, such as cartography (Declercq, 1996), geography (Weng, 2002), hydrology (Lin & Chen, 2004), climatology (Attorre et al, 2007), ecology (Stefanoni & Ponce, 2006), agriculture and pedology (Wang et al, 2005; Robinson & Metternicht, 2006), landscape architecture (Fencik & Vajsablova, 2006) and so on.

Since spatial interpolation is based on statistics, there are inevitably a certain assumptions and optimizations. As a result, errors introduced by spatial interpolation and their propagation in analysis models will certainly influence the quality of any decision-making supported by spatial data. This has been one of the hot issues of geographical information science in recent years (David et al, 2004; Shi, W. Z, et al, 2005; Weng, 2006). There are many factors affecting the performance of spatial interpolation methods. The errors are mainly generated from sample data density (Stahl et al., 2006), sample spatial distribution (Collins and Bolstad, 1996), data variance (Schloeder et al., 2001), grid size or resolution (Hengl, 2007), surface types (Zimmerman et al., 1999) and interpolation algorithms (Weng, 2006). However, there are no consistent findings about how these factors affect the performance of the spatial interpolators (Li & Heap, 2011). Therefore, it is difficult to select an appropriate interpolation method for a given input dataset.

With the increasing applications of spatial interpolation methods, there is a growing concern about their accuracies and evaluation measures (Hartkamp et al., 1999). The previous studies have greatly focused on individual evaluation methods of spatial interpolation (Weber & Englund, 1992 & 1994; Erxleben et al, 2002; Chaplot, 2006; Weng, 2006; Erdogan, 2009; Bater & Coops, 2009). It is necessary to explore comprehensive evaluation methods of interpolation accuracy. Two fundamental issues related to assessment measures of interpolation are addressed here as follows.

1. Comparison results: most commonly used methods for evaluation of spatial interpolation models compare the measured data with the interpolated data. However, it is no doubt that measured data are always unsatisfactory. This leads to unknown errors inherent in measured data (Zhou & Liu, 2002). The results may not always keep consistent and even get some controversial conclusions. For example, Laslett et al. (1987), Jarvis & Stuart (2001) and Erdogan (2009) thought Thin Plate Spline interpolation model can give better interpolated results, while Bater & Coops (2009) argued that Nature Neighbour Interpolation is with more accurate interpolated value. Meanwhile, some researchers (Hosseini et al., 1993; Gotway et al., 1996; Zimmerman et al. 1999; Erxleben et al., 2002; Vicente-Serrano et al., 2003; Attorre et al., 2007; Piazza et al., 2011) found that Kriging is the best one among all the existing interpolation models. Another phenomenon should be mentioned is that the frequency of interpolation methods compared varies considerably among methods and different studies have compared a suite of different methods, which makes it difficult to draw general conclusions.
2. Assessment indices: there are two typical assessment indices, i.e. statistical measures and spatial accuracy measures. The statistical measures such as Root Mean Squared Error (RMSE), Standard Deviation (SD) and Mean Error (ME) are most frequently used (Weber & Englund, 1994; Weng, 2002; Vicente-Serrano et al., 2003; Hu et al., 2004; Weng, 2006; Tewolde, 2010), whereas incapable of describing the spatial pattern of errors. Then the morphological accuracy measures such as accuracy surface and spatial autocorrelation (Weng, 2002; Weng, 2006; Tewolde, 2010) are employed. However, in order to obtain full evaluation of the interpolations, following problems should be further addressed: (1) most of the evaluations are still concentrated on the statistical measures, while the spatial accuracy ones are likely to be ignored relatively; (2) the maintenance of integrity of an interpolated surface has attracted little attention and a suitable quantitative index is still lack; (3) without consideration of the robustness of interpolation algorithms to data errors.

To overcome the above-mentioned problems, the author (2002, 2003 & 2004) developed a quantitative, data-independent method to evaluate algorithms in Digital Terrain Analysis. With this method, six slope/aspect algorithms and five flow routing algorithms were evaluated properly. Here we hope to employ this method to comprehensively evaluate spatial interpolation models and identify a set of accuracy measures.

2. Unified interpolation models

So far, more than ten spatial interpolation models have been developed in different fields. Here eight commonly used interpolation algorithms are examined and discussed, e.g. Inverse Distance Weighted (IDW), Kriging, Minimum Curvature (MC), Natural Neighbor Interpolation (NNI), Modified Shepard's Method (MSM), Local Polynomial (LP), Triangulation with Linear Interpolation (TLI) and Thin Plate Spline (TPS). According to the range of interpolation, these interpolations can be classified as global interpolation, block interpolation and point-by-point interpolation. While in view of mathematical mechanism, they can also be grouped into deterministic algorithms and geostatistical algorithms.

Although there are various spatial interpolation algorithms with diverse functions, they share the same essential factors, i.e. on the basis of describing the relationships between data points, and computing the values of unmeasured points through different function combinations of sample points. In another word, the relationships depict the spatial

correlations between the known points, while the combined functions are the performance of interpolations in mathematics, both of which constitute the commonality of interpolation functions in mathematics and physics. Therefore, they can be unified as one general interpolation model, just as follows:

$$Z_p = w_1Z_1 + w_2Z_2 + \dots + w_nZ_n + m = WZ + m \tag{1}$$

where Z_p is the estimated value of an interpolated point $P(x_p, y_p)$, Z_i denotes a sample point with w_i indicating its corresponding weight, m presents a constant, and n is the total number of sample points.

In this united model shown as Formula 1, any interpolation function can be regarded as a linear combination of sample points, with the difference of rules for weight allocation. In other words, the determination of the weight vector W is essential and critical for interpolations. For example, IDW determines its weight according to the distance between sample points directly, while NNI employs Thiessen polygons and Kriging uses semivariable functions instead. As for the moving curved surface fitting interpolation, though, the weight function is not obvious, surface-fit functions are employed to allocate weights, implying the spatial relationships of data points. The united interpolation models of the eight interpolation algorithms discussed in this study have been separately listed in Tab. 1.

It has been proved in Tab. 1 that in spite of various interpolation algorithms and models, they have the same intrinsic interpolation mechanism, and any common interpolation method can be transformed into a united model. From the mathematical mechanism, any spatial interpolation is actually a process of assigning weights to sample points, and

Interpolation models	Interpolation functions	Weight vector(W)	Constant (m)	Parameter Specification
IDW, Inverse Distance Weighted	$Z_p = \sum_{i=1}^n w_i Z_i$	$w_i = \frac{d_i^{-k}}{\sum_{i=1}^n d_i^{-k}}$	0	d_i : the distance between P_0 and P_i ; k : a power parameter
Kriging	$Z_p = \sum_{i=1}^n w_i [z_i - m] + m$	w_i	$m(1 - \sum_{i=1}^n w_i)$	d_i : the distance between P_0 and P_i ;
MC, Minimum Curvature	$Z_p = \sum_{i=1}^n w_i R(d_i) + T(x, y)$	w_i	$T(x, y)$	$R(d_i)$: the principal curvature function; $T(x, y)$: a 'trend' function

Interpolation models	Interpolation functions	Weight vector(W)	Constant (m)	Parameter Specification
NNI, Nature Neighbor Interpolation	$Z_p = \sum_{i=1}^n \frac{a_i}{a} z_{p_i}$	$w_i = \frac{a_i}{a}$	0	a_i : area of Thiessen polygon(P_i); a : the total areas of all Thiessen polygons
MSM, Modified Shepard's Method	$Z_p = \sum_{i=1}^n w_i Q_i$	$w_i = \frac{d_i^{-k}}{\sum_{i=1}^n d_i^{-k}}$	0	Q_i : a quadratic polynomial at the interpolated point P_i ; d_i : the distance between P_0 and P_i ; k : a power parameter
LP, Local Polynomial	$Z_p = A[P^T P]^{-1} P^T Z$	$W = A[P^T P]^{-1} P^T$	0	A : position vector of unknown point; P : position vector of known points
TLI, Triangulation with Linear Interpolation	$Z_p = AP^{-1}Z$	$W = AP^{-1}$	0	A : position vector of unknown point; P : position vector of known points
TPS, Thin Plate Spline	$Z_p = \sum_{i=1}^n w_i (\sigma \cdot d_i) \ln(\sigma \cdot d_i) + w_{n+1}$	w_i	w_{n+1}	d_i : the distance between P_0 and P_i ; σ : the optimal parameter

* In this study, the power parameter k of IDW function is set as 2, as well as MSM; the quadratic polynomial is applied in LP interpolation.

Table 1. Unified interpolation models of common spatial interpolation algorithms

different interpolation models have different patterns of weight allocation. While concerning the meaning of geography, the essence of interpolations lies in the spatial correlations between unmeasured points and sample points, reflected during the course of weight allocation. Both sides of mathematics and geography mentioned here can not only give a hypostatic explanation for the spatial interpolation physical mechanism, but can also provide certain guidance for further analysis and evaluation of spatial interpolation models.

3. Methods and procedures

In order to achieve the objectives proposed above, a data-independent experiment has been carried out, which allowed us to quantitatively analyze and evaluate different spatial interpolation models. Fig. 1 shows the flowchart of the whole process employed for our experiment. More specific procedures are illustrated as follows: (1) Constructing a mathematical surface with a known-formula; (2) Discretizing the mathematical surface and then randomly sample N points from those discrete ones; (3) Adding errors with varying levels to the randomly sampling points, so that we can get discrete points with the same distribution but varying error-levels; (4) Making interpolated operations separately on the sampling points without errors and the ones with varying error-levels, using the eight interpolation models mentioned above; (5) Analyzing and evaluating the results acquired from different interpolation algorithms according to different evaluation indices.

It is noted that all of the eight interpolation algorithms applied in this study are fulfilled by Surfer 8.0, a powerful contouring, gridding and 3D surface mapping package. Another aspect should be indicated is about the parameter-setting during interpolation. The parameters here mainly consist of three kinds: (1) a search neighborhood including its search radius and the number of sampling points, which should be set for the local interpolation methods such as LP, IDW, MSM and TPS; (2) the maximum residual and the maximum number of cycles when gridding with MC method; (3) variogram models like linear, gaussian and logarithmic models for Kriging interpolator. Except variogram models used in Kriging interpolation, the parameters in the others interpolation methods are control parameters and can be set as default of Surfer 8.0, for they have no effect on weight allocation. While for Kriging, the choice of variogram models has a close connection with weight allocation and may affect the results of interpolation. Through repeated tests and validations, the linear model is selected in this study.

3.1 Design of mathematical surfaces

In this study, we took the similar approach as reported by Zhou and Liu (2002, 2003 & 2004) by employing pre-defined standard surfaces for testing and comparing selected algorithms. As a result, the 'true' attribute value of any point on the standard surfaces which are pre-defined by known mathematical formulas can be acquired without errors. Our focus is on the difference between the values calculated by interpolation methods and the 'true' values to compare these interpolation algorithms objectively. According to the complexity of the surfaces, three surfaces have been selected for test, namely a simple surface, a more complex surface and a Gauss synthetic surface, which are defined by the equations below:

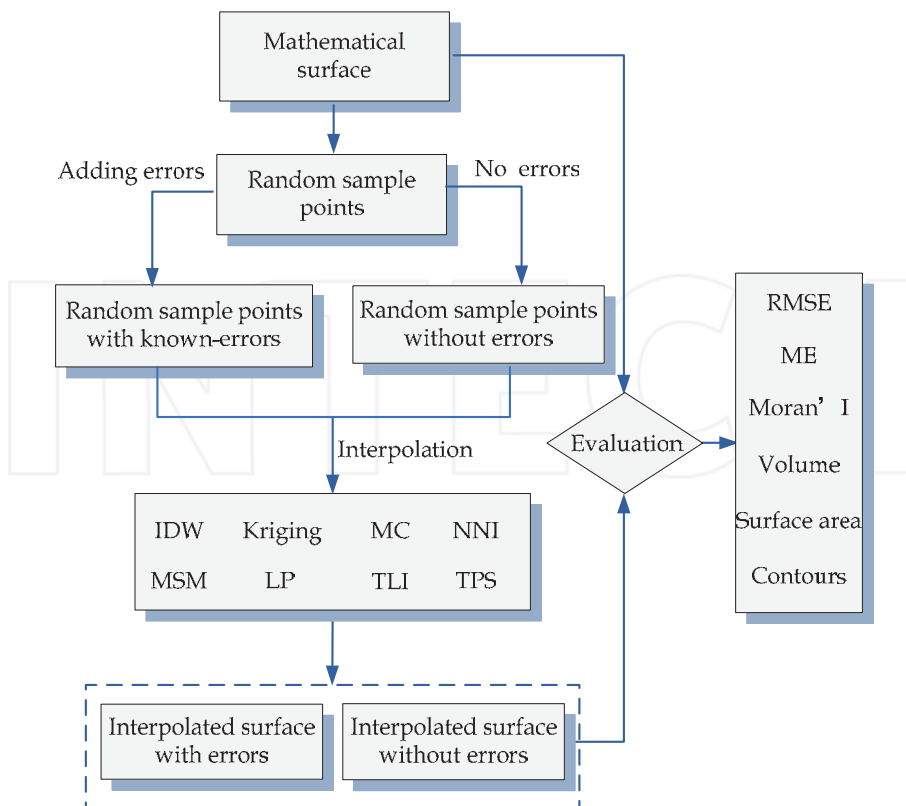


Fig. 1. Flowchart of the scheme to analyze and evaluate the spatial interpolation models

$$\text{Surface1} : \setminus f(x,y) = 30 \times \sin\left(\frac{x}{60}\right) \times \cos\left(\frac{y}{100}\right) + y \times \frac{20}{100} \setminus (50 \leq x \leq 150; 0 \leq y \leq 100) \quad (2)$$

$$\text{Surface2} : \setminus f(x,y) = \left(\sin\left(\frac{x}{y}\right) - \sin\left(\frac{x \times y}{800}\right)\right) \times 10 + 100 \setminus (-100 \leq x \leq 0; 10 \leq y \leq 110) \quad (3)$$

$$\text{Surface3} : \setminus f(x,y) = 3(1-x^2)e^{-x^2-(y+1)^2} - 10(0.2x-x^3-y^5)e^{-x^2-y^2} - \frac{1}{3e^{-(x+1)^2-y^2}} \quad (4)$$

($-50 \leq x \leq 50; -50 \leq y \leq 50$)

Then the three selected surfaces are separately scattered into discrete points, from which one thousand points were randomly sampled. All of the three simulated mathematical surfaces are showed in Tab. 2, as well as the distribution of their randomly sample points. After that, add different errors with the same mean 0 but varying Root Mean Square Errors (RMSE), which are in turn 0.5, 1, 1.5, 2, 4, 6, 8, 10, to these sample points, making their errors with the same distribution but different levels of values.

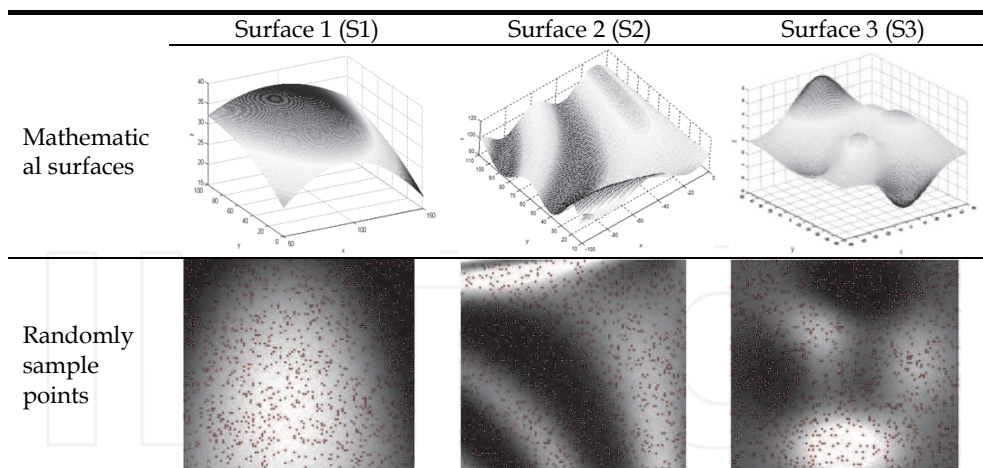


Table 2. Mathematical surfaces and distribution of randomly sample points

3.2 Design of evaluation indices

The interpolation result can be regarded as an original surface recovered by sample points. It has two implications, i.e. one is to reflect the closeness between the original surface and the recovered one on the value, and the other one is to recover the structural features of the original surface. It means that the interpolated surface should as far as possible keep the characteristics of the original surface both on statistics and structures, which should be considered for the accuracy assessment of the interpolation results as well.

The evaluation indices about statistical features mainly include RMSE (Root Mean Square Error), ME (Mean Error) and spatial autocorrelation. In this study, RMSE and ME are selected to describe the quality of the interpolation functions. For following the first law of geography (Tobler, 1970), the original surface itself has a strong spatial autocorrelation, so as to the whole interpolated surface. As a result, the surface acquired by interpolations should keep the spatial autocorrelation measured by Moran'I here, or else leading to a meaningless result with an almost randomly interpolated surface. What's more, another two spatial indices, volume and surface area are chosen to reflect the maintenance of overall performance after interpolation. The volume stands for the room above a datum plane and under an original surface or an interpolated surface whose area is measured by surface area. Structural characteristic is the other important evaluation method. It can be regarded as the skeleton of a surface, determining its geometric shape and basic trend, on which the interpolated surface should be in accord with the original one. For the integrity of the structural characteristic, so far there is lack of a suitable quantitative index. In this study, a method of contour-matching has been applied to compare and analyze different interpolations qualitatively, by means of overlaying the contours generated from an interpolated surface and the original one. If these overlaid contours match generally without great deviation or distortion, it can be induced that the structural characteristic of the surface has been kept well after being interpolated, or the structural characteristic will be lost leading to a fault result.

4. Results and discussion

4.1 RMSE and ME

As the RMSE statistics of the interpolated results from the three surfaces shown in Tab. 3, it is not difficult to identify that all of the three interpolated surfaces present similar variation tendency as a whole. The RMSEs of the interpolated surfaces keep pace with the increasing errors of the original surface, leading to a decreasing interpolated accuracy.

	S1			S2			S3		
	0	1	10	0	1	10	0	1	10
IDW	0.13	0.46	1.38	1.14	1.19	1.72	0.25	0.50	1.30
Kriging	0.02	0.65	2.13	0.11	0.65	1.99	0.01	0.67	1.98
MC	0.07	0.83	2.79	0.29	0.90	2.53	0.06	0.88	2.51
NNI	0.03	0.62	2.02	0.27	0.67	1.91	0.05	0.64	1.88
MSM	0.02	1.07	3.62	0.29	1.07	3.22	0.01	1.11	3.28
LP	0.22	0.25	0.43	2.51	2.49	2.50	0.56	0.58	0.69
TLI	0.03	0.70	2.31	0.26	0.76	2.17	0.05	0.72	2.14
TPS	0.02	0.84	2.86	0.07	0.87	2.58	0.01	0.90	2.56

* 1) 0, 1, 10 are the RMSE added to the original sample points; 2) For the interpolation methods of NNI and TLI cannot deal with the boundary problem well, therefore their boundary values which are replaced with the maximum have been excluded when calculated in statistics.

Table 3. RMSE statistics of the interpolated results from the three surfaces

As shown in Tab.3, Fig. 2 and Fig. 3, when sample points have no errors, the RMSEs of the interpolated results for different methods have an decreasing sequence as LP > IDW, MC > NNI, TLI > Kriging, MSM, TPS. However, the interpolated results vary with the augment of data errors. When the RMSE of sample points increases to 10, the RMSE of the surface interpolated by MSM achieves the maximum, with the minimum gained by LP and the sequence of RMSE for different interpolations changes to MSM > TPS, MC > TLI, Kriging, NNI > IDW > LP. The results show that if the original data has a better quality, the methods of TPS, MSM and Kriging can get a high precision for the interpolated results, while the quality of the original data becomes poorly, the result of LP turns to be relatively reliable.

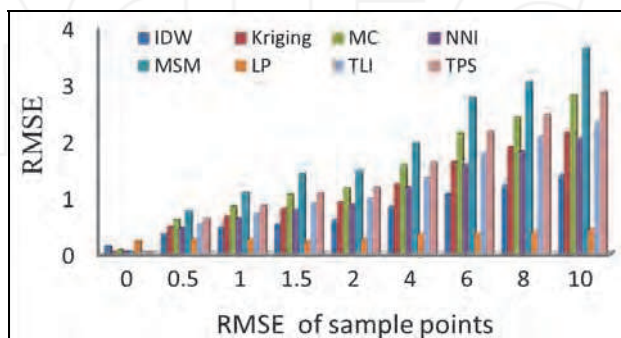


Fig. 2. RMSE statistics of interpolated results from S1

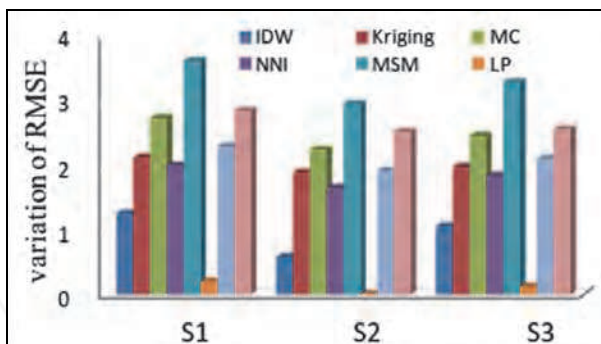


Fig. 3. Changes in RMSEs of the three surfaces before and after adding errors

Actually, it is not difficult to explain the results. When sample points have no errors or small errors, these sample points themselves can portray the characteristics of the original surface in a relatively accurate degree. Using semi-variogram, the geostatistical method of Kriging recovers the spatial correlation of the original surface exactly, while TPS and MSM are means of finding a proper way to allocate weights to sample points according to the distance between known points and interpolated points. With the increasing of sample data errors, the surface generated by sample points starts to deviate from the original surface, meaning the sample surface can no longer describe the characteristics of the original surface completely. No matter Kriging or TPS, the surfaces they want to depict or recover are just sample surfaces. For LP, although not all of the sample points are strictly passed through, this interpolated method can make a certain restraint on the original data errors, showing a role of peak-clipping and valley-filling for the interpolation. Furthermore, the restraining effect can also reflect the variation tendency of the surfaces created by sample points, bringing about a higher interpolated precision. The interpolated results for the three surfaces with different complexity levels have been showed by Fig. 3. On the whole, the changing tendencies of these three surfaces present a roughly consistent pace, that is to say the largest change of RMSE before and after adding errors belongs to MSM with the minimum belonging to LP, and an ascending order between the two extremes are as follows: TPS, MC, TLI, NNI and IDW. It has been further proved that the interpolated method of LP is less vulnerable to data errors appearing a superior resistance to errors, while MSM is extremely sensitive to data errors showing a worst error-resistance.

4.2 Moran'I index

The Moran'I statistics of S1 with no data-errors and higher data-errors acquired from different interpolation methods have been compared in Fig. 4 and Fig. 5. For the data without errors, the Moran'I of Kriging 0.9980 reaches the topmost showing the best spatial correlation, then followed by LP, TPS and IDW with a better spatial correlation, and the lowest Moran'I belongs to MC whose spatial correlation is the worst (refer to Fig. 4). However, with the increasing of the sample data errors, the Moran'I of LP, 0.9977, changes to the highest with the optimal spatial correlation and by contrast, MSM turns to the lowest as shown by Fig. 5. The other two surfaces present a similar variation regularity or tendency for the entire, although there are a few differences among individual interpolation methods. In order to further interpret the impact caused by the increasing data-errors on spatial

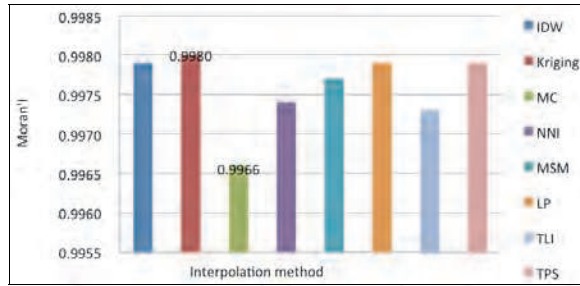


Fig. 4. Moran'I statistics of S1 (RMSE = 0)

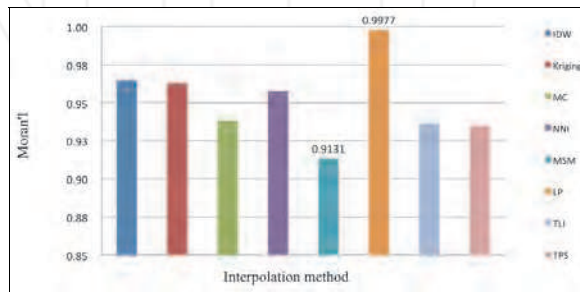


Fig. 5. Moran'I statistics of S1 (RMSE = 10)

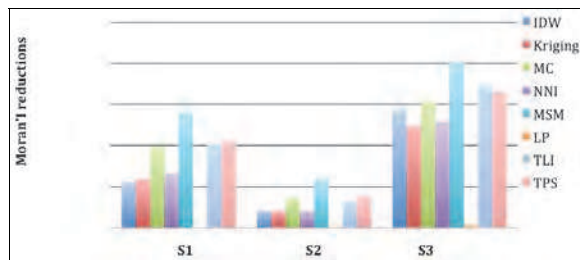


Fig. 6. Comparisons of Moran'I reductions among three surfaces

correlation, Fig. 6 reveals the overall variations of the three surfaces. Though Moran'I reductions of the three surfaces have a few differences, they share the same changing tendency. No matter what surface it is, the Moran'I reductions caused by interpolation LP is the smallest with its spatial correlation kept best, while MSM loses most. And the increasing sequence between LP and MSM is listed as follows: IDW, Kriging, NNI < MC, TLI, TPS, which is nearly in accordance with the statistical results of RMSE and ME given in Section 4.1.

4.3 Volume and surface area

To further analyze the maintenance of overall performance after interpolation, the absolute differences between the 'true' volume and volumes calculated by surfaces interpolated by different models have been compared, except NNI and TLI for their boundary effect. Still taking the first surface for example, the absolute volume difference showed in Fig. 7 stands

for the difference of the 'true' volume and the volume between an interpolated surface and the datum plane whose elevation is 0. All of the results are calculated by Surfer 8.0.

As shown in Fig. 7, when the original data has no error, the absolute volume differences of MSM, TPS and Kriging are smaller, and by comparison, LP, MC and IDW are relatively larger, with the minimum belonging to MSM and the maximum belonging to LP. However, their relationships make changes after adding a certain errors, similar as the variation of RMSE in Section 4.1. Aside from LP, the absolute volume differences of other interpolation methods are increased with mounting errors, keeping a consistent sequence of LP < IDW < Kriging < TPS < MC < MSM. Beyond doubt, the above analysis results are approximately accordant with the results of RMSE, ME and Moran'I. Moreover, judging from the variation tendency, MSM changes greatest with LP changing least, which has demonstrated the powerful robustness of LP to data errors again. Similar conclusions as volume index can be got from Fig. 8, which presents the absolute differences of the 'true' surface area and different interpolated surfaces areas.

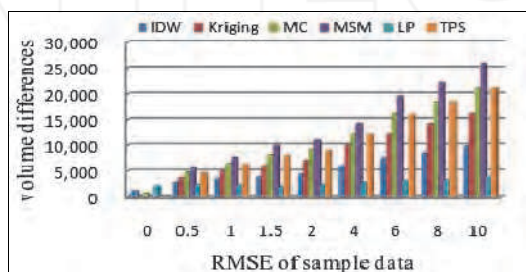


Fig. 7. Absolute volume differences of S1

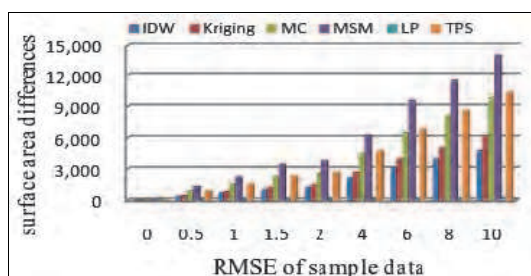


Fig. 8. Absolute surface area differences of S1

4.4 Contour matching

Comparison between the contours of the original surface and those of the interpolated surfaces will be discussed in this section. Fig. 9 takes the second surface for instance to present the comparisons when the original data is without errors. As shown in Fig. 9, the contours generated by Kriging, MSM and TPS perform preferably smooth, matching with contours of the original surface well. For NNI and TLI, the inside shapes of the contours maintain well with smooth lines, however, some abnormalities like figure losses appear on the boundary, further verifying their boundary effect mentioned above. Though the shapes of contours produced by LP keep well too, it is easy to notice that their positions shift on the

whole. On the contrary, the contours of IDW and MC display evident deformation and distortion, especially an obvious bull's eye effect appears for IDW. By contrast, contours of MSM which shares a similar interpolation theory as IDW maintain a better shape without the bull's eye effect, for its improvement in the weight function. As a result, it has been proved again that weight allocation and its corresponding spatial relationship between interpolated points and known points are the ultimate causes for the results of different interpolation methods.

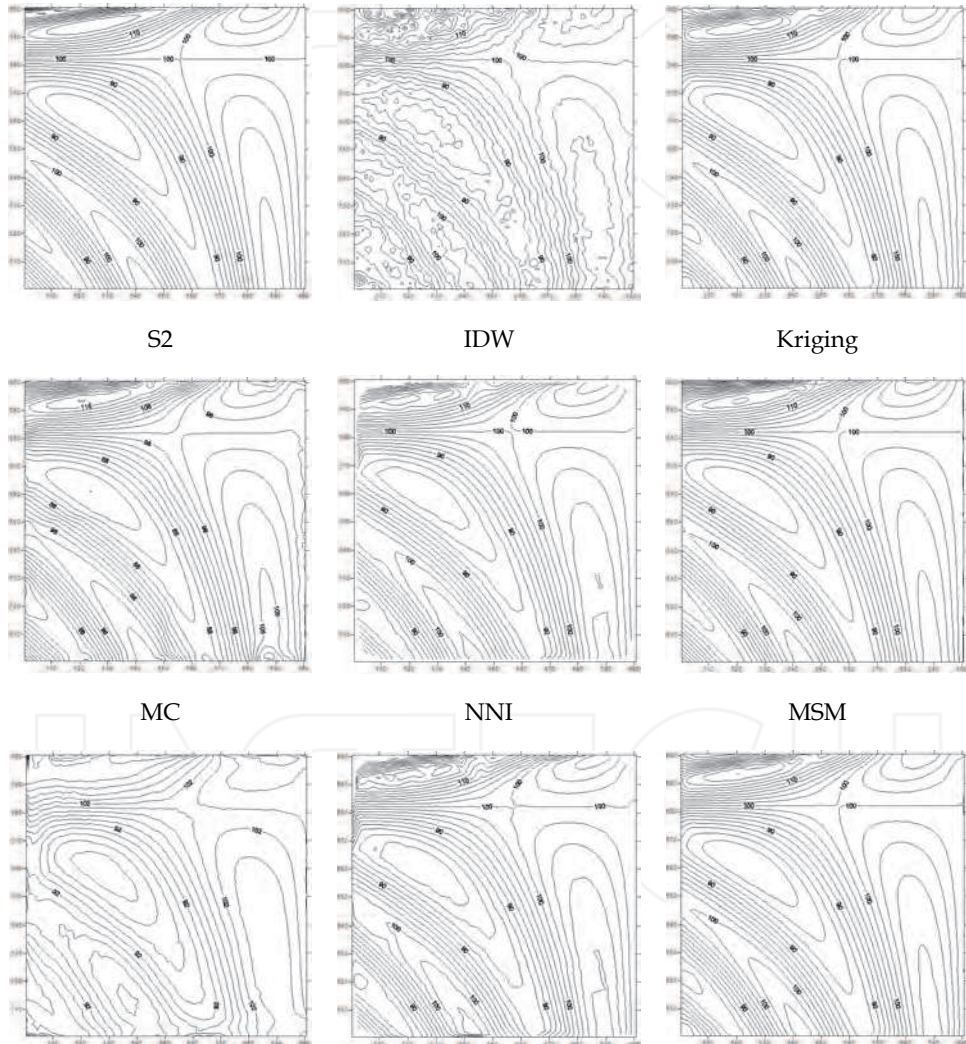


Fig. 9. Contour comparison among different interpolated surfaces from non-error original data (cell size = 1m)

When RMSE of sample points rises to 8, the contours produced by the same eight interpolation methods have been showed in Fig. 10, most of them deforming or distorting drastically except LP. More specifically, the shape or distribution of the deformed contours can be divided into two cases: as for IDW, Kriging, MC, MSM and TPS, the bull's eye effect appears in the regions with high errors, and for TLI and NNI, their contours display as roughly fold-lines with an uneven intensity. Compared with other methods, the contours of LP, though, are not that smooth as the original ones, their shape and distribution are both kept relatively intact, showing a powerful robustness to errors.

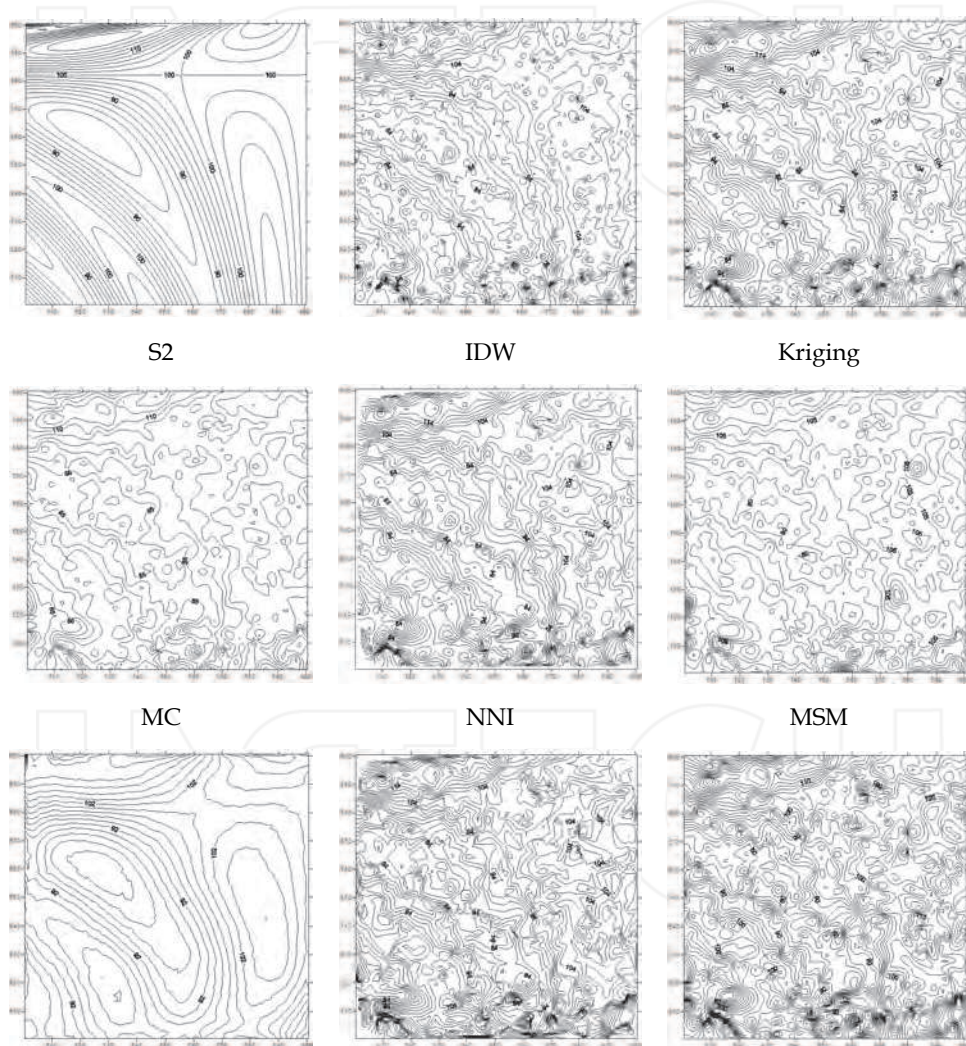


Fig. 10. Contour comparison among different interpolated surfaces when RMSE of original data is 8 (cell size = 1m)

4.5 Comprehensive evaluation

Combing the various evaluation indices discussed above, Tab. 4 gives a comprehensive evaluation for various interpolation models. The levels of interpolation accuracy are defined as: lowest, lower, high, higher and highest, while the levels of robustness to errors are set as: weakest, weaker, strong, stronger and strongest. When the original data has no errors, the interpolation accuracy of TPS is the highest, followed by MSM, and MC is the lowest. After higher errors being added to the original data, the interpolation accuracy of TPS changes from the highest to the lowest, while the precision of LP alters from lower to the highest. As a result, the strongest robustness to errors is LP, and the weakest is MSM by contrast. As for MC, regardless of the original data with errors or not, its interpolation accuracy always keeps lower.

Models	Accuracy with non-error data	Accuracy with error data	Robustness
IDW	lower	higher	stronger
Kriging	high	higher	strong
MC	lowest	lower	weaker
NNI	high	high	stronger
MSM	higher	lowest	weakest
LP	lower	highest	strongest
TLI	high	lower	weaker
TPS	highest	lower	weaker

Table 4. Comprehensive Evaluation for interpolation models

5. Conclusions

From the mechanism of spatial interpolation, weight allocation and its corresponding spatial relationship between interpolated points and known points, this article proposes an evaluation and analysis approach of spatial interpolation in GIS based on data-independent method, with the construction of mathematical surfaces without errors to objectively reflect the precision of different interpolation algorithms and with the addition of varying degree-errors to examine their robustness to errors. Based on our study, following conclusions can be given: (1) when the quality of original data is relatively well, TPS and Kriging can acquire more reliable results; (2) when the quality of original data becomes worse, for its resistance to data errors, LP can maintain a preferable interpolated precision, showing a powerful robustness to errors; (3) the validity of weight function and its corresponding spatial relationship are the kernel for design and analysis of weight function; (4) a kind of data

smooth process or data precision improvement method can be an effective way to advance the interpolated accuracy.

In order to further quantitatively depict the differences of morphological characteristics between original surfaces and interpolated surfaces, further studies will be focused on developing a visually quantitative index, such as an area enclosed between homologous contours (two level contours separately derived from an original surface and an interpolated surface). The real-world tests will also be conducted to compare with the findings by the theoretical analysis and a set of high-accuracy data should be needed for test.

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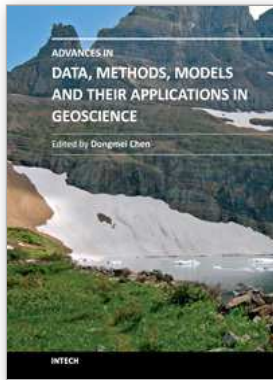
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With growing attention on global environmental and climate change, geoscience has experienced rapid change and development in the last three decades. Many new data, methods and modeling techniques have been developed and applied in various aspects of geoscience. The chapters collected in this book present an excellent profile of the current state of various data, analysis methods and modeling techniques, and demonstrate their applications from hydrology, geology and paleogeomorphology, to geophysics, environmental and climate change. The wide range methods and techniques covered in the book include information systems and technology, global position system (GPS), digital sediment core image analysis, fuzzy set theory for hydrology, spatial interpolation, spectral analysis of geophysical data, GIS-based hydrological models, high resolution geological models, 3D sedimentology, change detection from remote sensing, etc. Besides two comprehensive review articles, most chapters focus on in-depth studies of a particular method or technique.

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