The Influence of DEM Resolution on the Extraction of Terrain Texture

HUANG XiaoLi
Key laboratory of Virtual Geographic Environment, Ministry of Education
Nanjing Normal University
Nanjing, China
Xiaoli_yanyee@vip.163.com

Liu Kai
Key laboratory of Virtual Geographic Environment, Ministry of Education
Nanjing Normal University
Nanjing, China
lklkymym@163.com

Abstract—**Terrain texture is the important basis to distinguish different landform. Terrain texture analysis based on DEM has become one of the important parts of digital terrain analysis. However, the scale effect of DEM data on the terrain texture extraction has been mostly ignored in recent researches. In this paper, 6 sample areas from different landform types of Shaanxi Province were selected to make scale-effect analysis on the terrain texture by Gray level co-occurrence matrix (GLCM) model. The result shows that the parameters of slope data and hill-shading data are insensitive with the change of data resolution. Angular Second Moment (ASM) and Contrast (CON) have the strongest ability to distinguish different types of landforms.ASM is suitable for recognizing the detail terrain texture and CON is suitable for recognizing wide-range terrain texture in contrast. Our results could deepen the understanding of DEM based terrain texture and the scale effect of some other texture models will be investigated in the further study.**

I. INTRODUCTION

Terrain texture is an important type of natural texture. The existing literatures mainly focus on the terrain texture from Remote sensing data, which have been widely used for improving the methods in features extraction and land type classification. Recently, the terrain texture derived from DEM has drawn more attention, due to its purity in representing terrain surface morphology and its derivability in terrain analysis. Shruthi et al. [1] thought texture measure based on flow direction could be applied for gully identification. Tao et al. [2] proposed an improved 3D Lacunarity model based on DEM for quantifying spatial structure characteristics of terrain surface. Liu et al. [3] used the GLCM model to quantize the terrain texture from DEM in different area, and then made the landform recognition using BP neural network. It is obvious that, the terrain texture from DEM could be regarded as an important index on macro scale analysis, which overcomes the shortcomings of common pixel-based index. Furthermore, the texture analysis shows the special potential in recognition of geomorphic signatures and landform classification.

It should be noted that digital elevation model (DEM) and terrain analysis based on DEM is scale-dependent. Scale effect is a basic problem in DEM based terrain analysis and application, such as DEM error investigation, land surface parameters extraction and hydrological modeling [4-8]. However, litter research has focused on the scale effect in terrain texture analysis, in which the influence of DEM resolution could not be neglected.

The aim of this paper is to investigate the scale effect of the terrain texture extraction from DEM. In this paper, 6 parameters of gray level co-occurrence matrix model were chosen as the quantitative indices, meanwhile DEM data from 6 sample areas representing different landform types were regarded as the study data.

II. Materials and Methods

Materials

6 sample areas, with 25m cell size of DEM data representing different landform types of Shaanxi Province, China, were selected as the test area to investigate the scale effect of terrain texture extraction. The DEM data was resampled to different cell sizes ranging from 25m to 325 m with an interval of 50m using the method of bilinear interpolation in ArcGIS. The experiment datasets contain the DEM and its derivatives (slope, hill-shading and roughness). The existing research proved that the derivations parameters from DEM could also be applied for terrain analysis, hence, the datasets in this study contain not only the DEM but also its three kinds of derivations i.e., slope, hill-shading and roughness. Figure 1 shows the test datasets.

In: Geomorphometry for Geosciences, Jasiewicz J., Zwoliński Zb., Mitasova H., Hengl T. (eds), 2015. Adam Mickiewicz University in Poznań - Institute of Geoecology and Geoinformation, International Society for Geomorphometry, Poznań

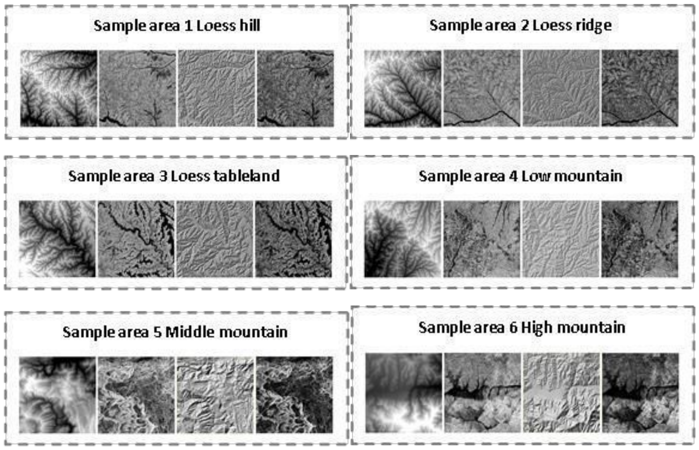


Fig.1 The test datasets of different landform types

Methods

The GLCM (Gray-level co-occurrence matrix) is a common technique in statistical image analysis that is used to estimate image properties related to second-order statistics. GLCM considers the relation between two neighboring pixels in one offset, as the second order texture, where the first pixel is called reference and the second one the neighbor pixel. GLCM is the two dimensional matrix of joint probabilities $P_{d,\theta}(i, j)$ between pairs of pixels, separated by a distance d in a given direction θ. Haralick defined 14 statistical features from gray-level co-occurrence matrix for texture classification [9] In this paper, we choose the most commonly used 6 statistical features as indices. They are Angular Second Moment (ASM), Contrast (CON), Variances (VAR), Inverse Difference Moment (IDM), Entropy (ENT) and Difference Variance (DFV). Meanwhile, according to previous researches[10], 5-pixels is chosen as the analytic distance of GLCM model, and use mean values of 4 different directions of NE, SE, SW and NW as the values of statistical features.

III. RESULTS

(1) When considering single sample area, the change rates of texture parameters with variation of the resolution are calculated. The result shows that overall mean of parameters of slope data and hill-shading data are the 2 smallest among the 4 parameters. That means slope data and hill-shading data are more insensitive with change of data resolution relatively. Table 1 shows the results.

Tab.1 Rates of texture parameters with the variation of the resolution

DEM	ASM	CON	VAR	IDM	ENT	DOV	**Overall mean**
S1	0.220	1.185	0.001	0.079	0.135	0.268	
S2	0.143	0.441	0.002	0.057	0.063	0.153	
S3	0.100	0.314	0.003	0.047	0.043	0.106	
S4	0.109	0.256	0.028	0.042	0.042	0.085	
S5	0.062	0.194	0.008	0.037	0.023	0.066	
S6	0.023	0.150	0.004	0.028	0.015	0.058	
Average	**0.109**	**0.423**	**0.008**	**0.048**	**0.053**	**0.123**	**0.128**
Slope	ASM	CON	VAR	IDM	ENT	DOV	**Overall mean**
S1	0.149	0.172	0.044	0.055	0.033	0.073	
S2	0.187	0.227	0.084	0.057	0.063	0.110	
S3	0.086	0.115	0.0004	0.038	0.027	0.050	
S4	0.013	0.010	0.033	0.005	0.003	0.012	
S5	0.029	0.039	0.016	0.014	0.008	0.020	
S6	0.062	0.039	0.035	0.004	0.016	0.041	
Average	**0.088**	**0.100**	**0.036**	**0.029**	**0.025**	**0.051**	**0.055**
Hill-shading	ASM	CON	VAR	IDM	ENT	DOV	**Overall mean**
S1	0.105	0.014	0.024	0.057	0.035	0.079	
S2	0.237	0.176	0.015	0.040	0.059	0.150	
S3	0.193	0.162	0.013	0.037	0.054	0.131	
S4	0.053	0.055	0.020	0.004	0.022	0.049	
S5	0.107	0.075	0.007	0.023	0.029	0.075	
S6	0.004	0.005	0.006	0.002	0.001	0.003	
Average	**0.116**	**0.081**	**0.014**	**0.027**	**0.033**	**0.081**	**0.060**
Roughness	ASM	CON	VAR	IDM	ENT	DOV	**Overall mean**
S1	0.318	0.408	0.287	0.056	0.249	0.151	
S2	0.373	0.746	0.480	0.096	0.331	0.201	
S3	0.109	0.240	0.125	0.037	0.078	0.087	
S4	0.019	0.031	0.009	0.002	0.0006	0.010	
S5	0.013	0.087	0.032	0.009	0.0206	0.037	
S6	0.059	0.030	0.045	0.009	0.022	0.018	
Average	**0.148**	**0.257**	**0.163**	**0.035**	**0.117**	**0.084**	**0.134**

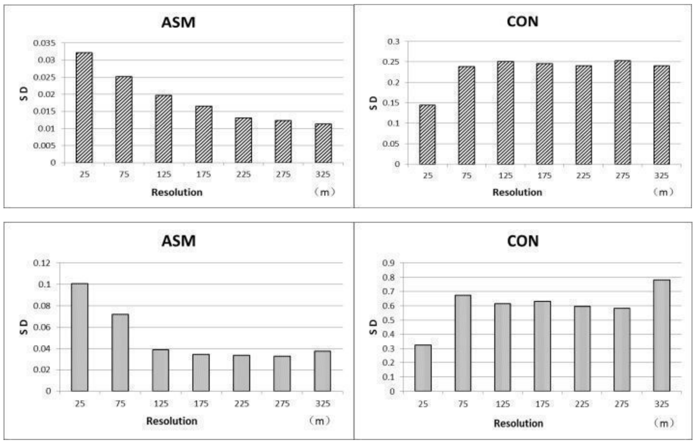
(2) While considering different types of sample areas, according to above statistics, we use variation coefficient as the index to measure original DEM data and roughness data's ability of recognition of different types of landform. The result shows the variation coefficients of ASM and CON are the 2 biggest among the 6 parameters. Table 2 shows the results.

Tab.2 Variation coefficients of texture parameters with the variation of resolution.

DEM	ASM	CON	VAR	IDM	ENT	DOV
25	0.249	0.485	0.183	0.077	0.079	0.231
75	0.268	0.414	0.202	0.094	0.066	0.185
125	0.240	0.337	0.205	0.086	0.052	0.148
175	0.216	0.281	0.206	0.076	0.046	0.124
225	0.182	0.242	0.205	0.068	0.039	0.110
275	0.182	0.226	0.209	0.065	0.038	0.109
325	0.171	0.199	0.208	0.060	0.032	0.099
Average	**0.216**	**0.312**	**0.203**	**0.075**	**0.050**	**0.144**
Roughness	ASM	CON	VAR	IDM	ENT	DOV
25	0.431	0.464	0.274	0.103	0.220	0.234
75	0.483	0.514	0.328	0.148	0.205	0.308
125	0.401	0.328	0.561	0.123	0.142	0.255
175	0.302	0.369	0.244	0.115	0.114	0.213
225	0.310	0.327	0.233	0.115	0.108	0.211
275	0.300	0.315	0.231	0.111	0.102	0.191

Average	**0.366**	**0.391**	**0.312**	**0.120**	**0.147**	**0.234**

(3)Additional, we calculated the standard deviations of ASM and CON with change of data resolution. The result shows below (Figure.2)



(The above 2 pictures are results of DEM; the under 2 pictures are the results of roughness)

Fig.2 Standard deviations of ASM and CON with change of data resolution

IV. CONCLUSIONS

(1) The result shows that parameters of slope data and hill-shading data are the most insensitive with change of data resolution. That means the texture characteristics of these two kinds of data are enhanced compared with original DEM data to some extent, therefore strengthen the structural features of the image and make them relatively not easily affected by the change of resolution.

(2) The value of variation coefficient of ASM and contrast are the biggest among the six parameters in the model, showing that ASM and contrast have the strongest ability to distinguish different types of landforms.

(3) ASM has relatively high scale-dependent and its distinguish ability declines dramatically with the change of data resolution (the values of standard deviation change from 0.032 to 0.011 and 0.101 to 0.038), which means ASM is suitable for recognizing the detail terrain texture. On the contrary, the ability of CON to distinguish landforms experienced an increase trend from 25 m to 325 m resolution (the values of standard deviation change from 0.145 to 0.241 and 0.325 to 0.783), and it has relatively low scale-dependent indicating its better adaptability in coarse resolution.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (41171320, 41401440) and the Foundation of Graduate Innovation Plan of Jiangsu Province (KYLX_0701). The authors express their great thanks to everyone who have helped in the writing of this article.

REFERENCES

[1]Shruthi, R.B.V., Kerle, N., Jetten, V. Object-based gully feature extraction using high resolution imagery. *Geomorphology*. 2011(134), 260–268.

[2]Tao, Y., Tang, G., J. Strobl, et al. Detecting spatial pattern characteristics of terrain texture based on 3D Lacunarity Model. *Chinese Geographical Science*, 2012, 22(1):88-96.

[3]Kai Liu, Guoan Tang, Shen Jiang. Research on the classification of terrain texture from DEMs based on BP neural network[C], *Geomorphometry 2013*, Nanjing, 2013.

[4]Jun L. Spatial-scaling Effect of DEM on the Simulation of Spatial Distribution of Temperature in Mountain Area[J]. *Journal of Mountain Science*, 2012.

[5]TANG Guo'an ,LIU Xuejun, FANG Liang, et al. A review on the scale issue in DEMs and digital terrain analysis[J].*Geomatics and Information Science of Wuhan University*. 2006, 31(12): 1059-1066.

[6]LIU Xue-jun,LU Hua-xing,REN Zheng.et al. Scale issues in digital terrain analysis and terrain modeling[J].*Geographical Research*. 2007,26(3): 433-442.

[7]Chow, T. Edwin, and Michael E. Hodgson. Effects of lidar post-spacing and DEM resolution to mean slope estimation. *International Journal of Geographical Information Science* 23.10 (2009): 1277-1295.

[8]Barrios, M., and F. Francés. Spatial scale effect on the upper soil effective parameters of a distributed hydrological model. *Hydrological Processes* 26.7 (2012): 1022-1033.

[9]Haralick R M. Statistical and structural approaches to texture[J].*Proceedings of the IEEE*.1979,67(5):786-804.

[10]Ulaby F T, Kouyate F, Brisco B, et al. Textural infornation in SAR images[J]. *IEEE Transactions on Geoscience and Remote Sensing*, 1986, 24(2): 235-245.