Assessment of Land Surface Complexity In Relation To Information Capacity and the Fractal Dimension in Different Landform Regions Using Landsat Data

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Abstract. Remote sensing images are highly structured, and contiguous pixels of space domain have strong correlations that contain abundant information on land surface structure features and land surface electromagnetic radiation features. The information capacity model, which is a quality evaluation model based on a multi-dimensional histogram, includes local correlations within different pixels. Thus, the information capacity can illustrate land surface structural information more objectively and effectively than other single-pixel calculation models. Our results reveal that the information capacity value correlates well with the meaningful grey level of remote sensing imagery. This high correlation is related to the complexity of terrestrial surface landscapes. Therefore, information capacity, as applied to geoscience, is introduced in this study to demonstrate the spatial differentiation of information capacity of different landform regions. Generally, the information capacity of a mountain is large and is followed in decreasing order by those of the hills and the plains. Moreover, the correlation between information capacity and the fractal dimension is analysed. Based on the results of this study, it can be concluded that the level of correlation for information capacity and the fractal dimension is high, and the correlation coefficient for the basic landform areas and the loess landform areas is 0.874 and 0.825, respectively. Finally, this paper proposes that information capacity be used as a new reference index for geoscientific analysis in quantitative research on the characteristics of land surface complexity.

1. Introduction

Remote sensing technology can continuously provide a variety of land surface feature information in different spatial and temporal scales. Multispectral remote sensing data, which are used to extract surface environment parameter indices, such as the vegetation index [1] and the vegetation fraction [2], are particularly useful in providing land surface feature information. These parameters can accurately evaluate real-time land surface processes through remote sensing technology applications. Although remote sensing data contain potential information on land surface features, this technology still requires human manipulation to extract land surface information.

As a concept in the field of image processing, information capacity is a quantitative unit of pixel density information. Generally, the basic characteristics of information capacity can be summarised as follows [3]: (1) the information capacity corresponds to the image quality: the greater the image quality, the greater the information capacity value; (2) the information capacity value is closely related

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to the grey level of the image: the higher the grey level, the greater the information capacity value; and (3) the information capacity is related to the complexity of land surface features reflected in the images. Currently, research on information capacity mainly focuses on evaluating image quality with computer image processing, such as the quality assessment of thermal images [4] and evaluation of the China-Brazil earth resources satellite (CBERS) images [5].

The information in remote sensing imagery is recorded by pixels, which have different spectral response characteristics and represent different land cover types and surface topography. Characteristics of the local area where the pixels are located are included in the calculation of information capacity. Thus, information capacity can objectively and effectively express land surface structural information. In this study, information capacity is introduced to the applied geographical field and is used to demonstrate the spatial differentiation of information capacity of different landform regions.

2. Information Capacity and the Fractal Dimension

2.1. Information Capacity

The calculation of information capacity is mainly based on three definitions. First, a k-dimensional histogram is defined as follows: for an M × N digital image $\{x(i,j) | i \in [1,m], j \in [1,n]\}$, the frequency set $\{Num(G_1, G_2 \ldots G_k) | G_1, G_2 \ldots G_k \in \Omega\}$, which represents the pixel number, is statistically calculated. If a pixel grey value of this image is G_1 and relevant $k-1$ pixel grey values are $G_2 \ldots G_k$, respectively, the frequency set is termed a k-dimensional histogram. Second, a k-dimensional logarithmic peak normalised histogram is defined as follows: if the frequency set is normalised with the maximum frequency, the normalised frequency set $\{Norm(G_1, G_2 \ldots G_k)\}$ can be obtained and is termed a k-dimensional normalised histogram. If the frequency set is normalised with the logarithm of the frequency peak, the normalised frequency set $\{Norm_{\log}(G_1, G_2 \ldots G_k)\}$ can be obtained and is termed a k-dimensional logarithmic peak normalised histogram such that

$$\{Norm_{Log}(G_1, G_2, ..., G_k)\} = \frac{Log[1 + Num(G_1, G_2, ..., G_k)]}{Log[1 + Max(Num(G_1, G_2, ..., G_k))]} \quad (1)$$

Finally, information capacity is obtained by the following definition: generally, the cumulative sum of a k-dimensional logarithmic peak normalised histogram within the constraint domain $\omega \subseteq \Omega$ is defined as the information capacity. The cumulative sum of the histogram is logarithmically transformed, as expressed by the following formula,

$$C_{\inf o} = Log_2[1 + \sum_{\omega} Norm_{Log}(G_1, G_2, ..., G_k)] \quad (2)$$

where $C_{\inf o}$ represents information capacity (in bits), and the cumulative constraint domain ω represents a measure of the histogram definition domain.

2.2. Fractal Dimension

For irregular and fragmented structures, fractal geometry [6] has been successfully used to illustrate natural scenes, such as mountains, islands, rivers, plants, and landscapes, and is particularly well suited for describing rough surfaces [7-8]. The fractal dimension is a quantitative parameter used to characterise fractals, which can describe the irregularity and self-similarity of objects. In remote sensing data applications, the fractal dimension can quantitatively describe the complexity of land surface features. To estimate the fractal dimension, the image is usually regarded as a curved surface with grey pixel values. The fractal dimension is then equal to the fractal dimension normal vector of the spatial surface if the grey values are used to represent the third dimension [9-11]. Therefore, the image fractal dimension is closely related to the complexity of the land surface. The surface integration values of remote sensing spatial surface imagery are calculated to solve the fractal

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dimension, which is shown in Equation 3. In general, the fractal dimension of a smooth and less-variable grey surface is close to 2.0, while the fractal dimension of an extremely complex surface is close to 3.0.

$$D = 2 - \frac{N\sum_{i=1}^{N}\lg r_i \lg A(r)_i - \sum_{i=1}^{N}\lg r_i \sum_{i=1}^{N}\lg A(r)_i}{N\sum_{i=1}^{N}(\lg r_i)^2 - (\sum_{i=1}^{N}\lg r_i)^2} \tag{3}$$

where D represents the fractal dimension; r represents the transformation scale; A(r) represents the curved surface area of an image measured with the scale of r; N represents the number of scale transformations; and i represents ordinal numbers that range from 0 to N.

3. Study Areas and Data

In China, landforms are complex and diverse, and surface morphology is variable. Based on the surface morphology landform classification system, the Qinba mountain region, Shandong hilly region, North China plain region and loess landform region were selected for this study. Enhanced Thematic Mapper Plus (ETM+) images, taken in 2003, were selected for analysis in this study. The orbital map of the ETM + satellite is shown in Figure 1.

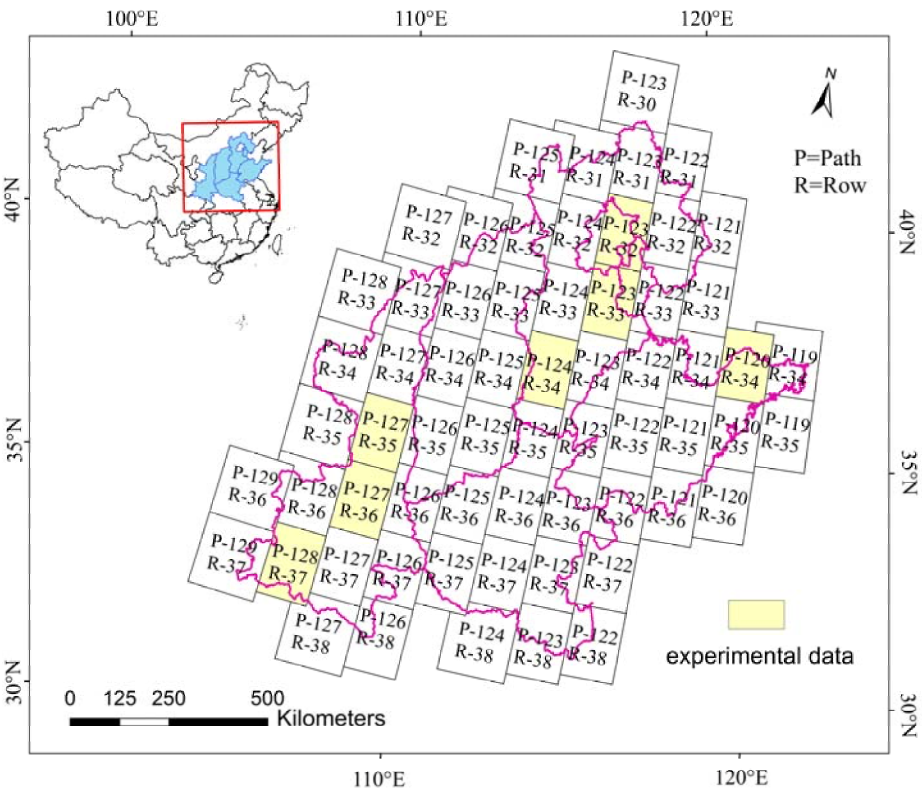

Figure 1. ETM + Orbital Map of Experimental Areas.

4. Experiment Results

4.1. Information Capacity of different landform regions

4.4.1. Plain Areas. The ground surface of plain areas is relatively flat and broad, and the slope of plain areas is small. The main types of land cover are settlements and arable lands, and there are no obvious shadows appearing in the remote sensing imagery. These sample areas are located in the North China Plain, and relevant statistics on information capacity and fractal dimension are shown in Table 1.

Table 1 reveals that the information capacity value of the plain sample areas is between 9.8 and 10.3, and the fractal dimension value ranges from 2.4 to 2.5. These sample areas are located in the less-undulating plain, where surface structures are relatively simple. Thus, the information capacity is mainly affected by the surface complexity of the different types of land cover.

4.4.2. Hilly Areas. The degree of surface fluctuation of hilly areas varies with the fluctuations from plain areas to mountain areas. Surface structures of hilly areas are more complex, and a large area of vegetation land cover types includes woodland or arable land. These hilly sample areas are located in Shandong, and the relevant information capacity and fractal dimension values are shown in Table 2. Table 2 reveals that the information capacity value of hilly sample areas ranges from 10.4 to 11.6, which is greater than that of the plain areas. The fraction dimension value of the hilly sample areas ranges from 2.5 to 2.7, which is much greater than that of the plain areas.

Table 1. Information Capacity and the Fractal Dimension in the North China Plain.

Sample Area	Value of Information Capacity	Fractal Dimension
Jinzhou	9.86	2.40
Wei County	9.99	2.41
Shenzhou	10.12	2.43
Hejian	10.21	2.44
Shuiqing	10.35	2.47
Xushui	10.32	2.52

Table 2. Information Capacity and the Fractal Dimension of the Hilly Areas in Shandong.

Sample Area	Value of Information Capacity	Fractal Dimension
Wulian	11.57	2.66
Yiyuan	11.52	2.62
Rizhao	11.48	2.61
Jiaozhou	11.19	2.58
Penglai	10.41	2.52

4.4.3. Mountain Areas: The degree of surface fluctuation in mountain areas is greater than that of hilly areas. The types of land cover in mountain areas are more diverse, and the vegetation land cover type consists mainly of woodlands. The sample areas are located in the Qinba Mountain area, and the relevant information capacity and fractal dimension values are shown in Table 3. Table 3 reveals that the information capacity value in the mountain areas ranges from 11.4 and 12.2. The information capacity value here is the greatest among the plain, hilly and mountain areas. The fractal dimension value varies between 2.6 and 2.7, which means that the mountain areas also have the greatest fraction dimension value among the studied areas.

4.4.4. Loess Areas: The landform types in loess areas mainly consist of plateaus, ridges and mounds. Loess plateaus often suffer from soil erosion and are surrounded by ditches or valleys. The tops of loess plateaus are flat, while the edges are uneven and have obvious slopes. The surfaces of loess ridges in the study areas tilt to varying degrees. The tops of wide ridges are rounded, while the tops of narrow ridges are angular. Loess mounds are dome-shaped or rounded, and the slopes are steeper than those of loess ridges. The texture structures of loess mounds image appear to be more fragmentary than those of loess ridges, where many small and round objects are piled up haphazardly. The sample loess areas are located in the Loess Plateau of the North Shaanxi Province. The information capacity and fractal dimension values of the loess areas are shown in Table 4. Table 4 reveals that the information capacity value in the loess areas ranges from 9.7 to 11.0. The maximum information capacity value occurs in the loess mound areas, and the minimum value occurs in the loess plateau areas. The fractal dimension value varies between 2.5 and 2.8, and the trend of change in the fractal dimension values is similar to that of the information capacity values. In contrast to the basic landform areas described above (plain, hilly and mountain areas), the grey level of remote sensing images of loess ridge areas lies between those of plain areas and hilly areas. The information capacity value of the loess mound areas is higher than that of the loess ridge areas. For the loess mound and loess ridge areas, the landscape complexity of the land covers is almost the same; there is little difference in the grey levels of the remote sensing images, and the texture structures are similar.

Table 3. Information Capacity and the Fractal Dimension of Qinba Mountain Areas.

Sample Area	Value of Information Capacity	Fractal Dimension
Ankang	11.99	2.76
Ningqiang	12.00	2.69
Zhenba	12.16	2.73
Mian County	12.22	2.75
Chenggu	11.78	2.64
Yang County	11.57	2.69
Ziyang	11.77	2.75
Zhen'an	11.49	2.64

Table 4. Information Capacity and the Fractal Dimension of Loess Areas.

Landform	Sample Area	Value of Information Capacity	Fractal Dimension
Loess plateau	Bing County	9.76	2.55
	Luochuan	9.80	2.56
	Huangling	9.83	2.57
Loess ridge	Ganquan	10.47	2.73
	Yanchang	10.60	2.76
	Zichang	10.66	2.75
Loess mound	Yanchuan	10.84	2.79
	Zizhou	10.95	2.80
	Qingjian	10.95	2.82

4.2. Correlation Analysis between Information Capacity and The Fractal Dimension

To verify the validity of information capacity in the characterisation of land surface complexity, correlation analysis was applied, using fractal dimension as a reference factor, to explore the correlation between information capacity and the fractal dimension. The scatter diagrams of the basic landform areas and the loess sample areas are shown in Figure 2 and Figure 3, respectively. The scattered points are all in the vicinity of the fitted straight line, and relevant correlation coefficients are 0.874 and 0.8253 for the basic landform areas and the loess areas, respectively. The scatter diagrams illustrate that there is a strong correlation between information capacity and the fractal dimension in all sample areas.

5. Conclusions

Information capacity has been examined in a geoscientific analysis of remote sensing imagery information. Based on a quantitative analysis of information capacity, the relationships between information capacity and surface landscape complexity have been studied in several basic landform areas and typical loess landform areas. The main results reveal that there is a strong correlation between information capacity and the fractal dimension. In principle, information capacity based on a multi-dimensional histogram is an expression of spatial form entropy in a broad sense, reflecting the quantity and proportionality of geographic area system elements, and the fractal dimension of a curved surface image can be used to describe the complexity and structural features of remote sensing images, reflecting the quantity and proportionality of geographic area system control variables. In this sense, information capacity and the fractal dimension are two aspects of the same issue.

The estimated information capacity value, which is based on the quantification of image grey levels, not only includes quantitative information on landform complexity but also contains quantitative information on land cover complexity. Therefore, information capacity can be a quantitative index that reflects the complexity of land surface landscapes. In summary, information capacity can be regarded as a new reference index for quantitative evaluation of remote sensing information and for geoscientific applications.

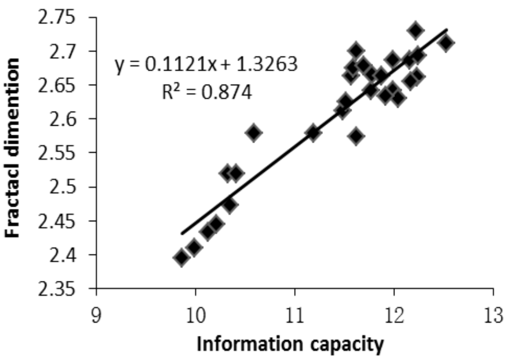

Figure 2. Correlation of Information Capacity and the Fractal Dimension in Basic Landform Areas.

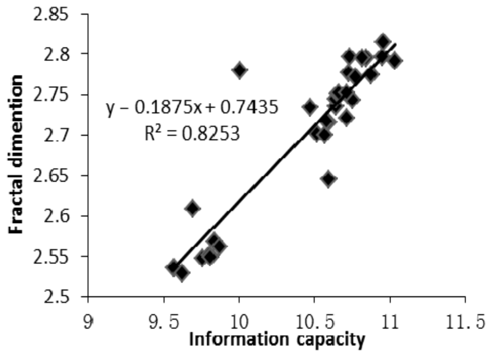

Figure 3. Correlation of Information Capacity and the Fractal Dimension in Loess Landform Areas.

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