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Research paper

Connotations of pixel-based scale effect in remote sensing and the modified fractal-based analysis method

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ABSTRACT

Scale problems are a major source of concern in the field of remote sensing. Since the remote sensing is a complex technology system, there is a lack of enough cognition on the connotation of scale and scale effect in remote sensing. Thus, this paper first introduces the connotations of pixel-based scale and summarizes the general understanding of pixel-based scale effect. Pixel-based scale effect analysis is essentially important for choosing the appropriate remote sensing data and the proper processing parameters. Fractal dimension is a useful measurement to analysis pixel-based scale. However in traditional fractal dimension calculation, the impact of spatial resolution is not considered, which leads that the scale effect change with spatial resolution can't be clearly reflected. Therefore, this paper proposes to use spatial resolution as the modified scale parameter of two fractal methods to further analyze the pixel-based scale effect. To verify the results of two modified methods (MFBM (Modified Windowed Fractal Brownian Motion Based on the Surface Area) and MDBM (Modified Windowed Double Blanket Method)); the existing scale effect analysis method (information entropy method) is used to evaluate. And six sub-regions of building areas and farmland areas were cut out from QuickBird images to be used as the experimental data. The results of the experiment show that both the fractal dimension and information entropy present the same trend with the decrease of spatial resolution, and some inflection points appear at the same feature scales. Further analysis shows that these feature scales (corresponding to the inflection points) are related to the actual sizes of the geo-object, which results in fewer mixed pixels in the image, and these inflection points are significantly indicative of the observed features. Therefore, the experiment results indicate that the modified fractal methods are effective to reflect the pixel-based scale effect existing in remote sensing data and it is helpful to analyze the observation scale from different aspects. This research will ultimately benefit for remote sensing data selection and application.

1. Introduction

The scale effect is widely considered to be of the primary challenges in earth observation. Geo-research mainly uses remote sensing images that have a large span in spatial and temporal resolution. A homogeneous phenomenon on a given spatial scale maybe become another heterogeneous phenomenon on another spatial scale (Ming et al., 2013), which means that the spatial pattern or phenomena is scale-dependent (Sun and Jane, 2013). Therefore, the scale of study (defined in terms of spatial resolution) has a certain impact to both the modeling of certain processes/phenomena (for example, the effect of land surface temperature and the spatial resolution of imagery to the study of temperature diurnal variation) and the representation of spatial features (landcover objects, buildings etc).

In this field of interpretation of the relationship between scale effect and spatial resoultion in the remote sensing imagery, the following research efforts summarize the most significant achievements. Strahler et al. (1986) built a framework for distinguishing between the scene, which is real and exists on the ground; Woodcock and Strahler (1987) proposed the idea for selecting the optimal spatial resolution by using average Local Variance; Cracknell (1998) discussed the question of pixel size or instantaneous field-of-view (IFOV) both from the simple geometrical point of view and from a more physical point of view. Ming et al., (2008, 2011, 2013) used the Modified Average Local Variance (MALV) method based on constant ground area (variable window size and variable resolution) to study the optimal spatial resolution of

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different features on remote sensing images; The above studies are almost based on geo-statistics methods and utilize geometry to analyze the linear features (Su et al., 2014) of remote sensing images. However, both linear and non-linear features (Shokoohi et al., 2013) are prominent in remote sensing images. The statistic values of spatial features in image are a function of the scale. Within a certain range, the linear features (some statistic values of feature in remote sensing image are a linear function of the spatial resolution) increase and the nonlinear features (the statistic values of features in remote sensing image are not a linear function of the spatial resolution) decrease with decreasing scale. Beyond this range, the linear features decrease and the nonlinear features increase with decreasing scale (Ming et al., 2008). Because geo-statistical methods are mainly used to analyze linear features, the capability of scale feature description of nonlinear structures based on geo-statistics is limited. The fractal theory originated from chaos theory (Foroutan-pour et al., 1999), and it mainly uses fractal dimensions to analyze the spatial patterns' nonlinear features in remote sensing images. It is important to use the fractal theory to analyze the scale effect for remote sensing from different aspects.

There are several existing methods for fractal dimension computing: including Brown motion (Hermann et al., 2015) and box dimension (Chen et al., 2004). However, the applicable range of each method is different in practical use and the current fractal dimension computing methods do not take the spatial resolution into account when analyzing the scale effect of remote sensing images (Zhou and Lam, 2009; Ju and Lam, 2009), which results that the scale effect change with spatial resolution can't be clearly reflected.

This paper performs an in-depth analysis of the connotation of the pixel-based scale effect and proposes to use the spatial resolution as the modified scale parameter to calculate the fractal dimensions. Based on the modified fractal dimensions, the relationship among fractal dimension, spatial resolution, and the size of geo-object in remote sensing image can be further analyzed, so that it is possible to choose some feature scales to best characterize the specific objects or phenomena of interest. Existing information entropy (Emerson et al., 2005) is used to evaluate the validity of modified methods.

2. Connotations of pixel-based scale effects in remote sensing

2.1. General meanings of scale in geosciences

Scale is a widely used term that mainly refers to the extent or degree of detail of the study in the field of general scientific research (Goodchild and Quattrochi, 1997). Scale has different connotations in different areas of geography. It is understood as the mapping scale in the field of cartography, the grain size of the study (i.e., the plaque size of the study) in the field of ecology, and the maximum time interval to ensure the homogeneity of environmental parameters in the field of environment (Bierkens et al., 2000), and it is understood as spatial resolution or the minimum size of object that a sensor can distinguish in the field of remote sensing (Wu and Li, 2009). The concept of scale summarized by Lam and Quattrochi is relatively comprehensive, which can be extended to other research fields of geography. They defined four types of scale related to the spatial phenomena (Lam and Quattrochi, 1992): mapping scale (i.e., the scale of the map); observation scale or geography scale (i.e., the expansion of the study spatial region); measurement scale or resolution (i.e., the smallest distinguishable parts in spatial data set, such as the pixel size of remote sensing image); and operation scale (i.e., the range of spatial environment that occurred the geography phenomena).

2.2. Pixel-based scale in remote sensing

Based on the general meanings of scale in geosciences proposed by Lam and Quattrochi (1992) and Ming et al. (2011) generalize the three level of connotation of spatial scale of remote sensing image, and they are pixel-based scale, object based scale (Bian, 2007; Blaschke, 2010) and pattern-based scale. Of these three connotations of spatial scale, the former belongs to the level of image data, and the middle one belongs to the level of image processing, however the last one belongs to the level of image understanding.

From the view of remote sensing imaging, pixel-based scale refers to spatial resolution. The essence of pixel-based scale is observation scale determined by the different capability of satellite sensor. Remote sensing data with different spatial resolution carries different information that are presented at different scales.

2.3. Pixel-based scale effects in remote sensing

So far, the scale effect has not been given a complete academic definition. In landscape ecology, scale effect refers to the variations of landscape features with the change of scales (Rietkerk et al., 2002) when the small scale landscape patterns are re-combined to form the large scale landscape patterns through scaling. In remote sensing, the pixel-based scale refers to spatial resolution. Pixel-based scale effects are mainly caused by the existence of mixed pixels, which lead to differences between different calculated results (for example, the average local variance or classification accuracy) with the change of scale. As shown in Fig. 1, pixel-based scale effect in remote sensing can be understood from the following two perspectives.

First, from the point of view of remote sensing, landscape scale effect results in variations of landscape features, which leads to mixed pixels. This type of scale aggregation makes some statistical features in image (e.g., local variance and fractal dimension) present a change in the trend with the changing of scale, and this trend, to a certain extent, reflects internal homogeneity or heterogeneity among categories. At the same time, pixel classification accuracies also present a change in trend with changing of scale, and these changes in trends are theoretically the embodiment of pixel-based scale effects (Zhou et al., 2014).

Secondly, from the point of view of the data products in remote sensing, pixel-based scale effect means that under the same set of conditions (i.e., the same area, same time, similar spectral, similar imaging conditions, and the same inversion model), the inversed surface parameters, which are used to measure the physical truth-value of the geo-surface, differ at different scales. This phenomenon is known as the scale effect of remote sensing products (Liu, 2014).

3. Data and method

3.1. Study area

Six pieces of an experimental image (3(a, b, c) for building area and 3(a, b, c) for farmland area) with 0.6 m spatial resolution and 1000×1000 size are a subset from panchromatic QuickBird images in Beijing. The data points are first resampled to 1 m, and then each image is gradually degraded at a gap of 1 m (with standard deviation stretch), consequently the series of experimental images with different spatial resolution (from 1 m to 10 m) are prepared (Fig. 2). The nearest neighbor method is used in resampling procedure because it does not produce new pixel values and also not change the values of pixels.

3.2. Traditional fractal dimension calculation methods for remote sensing image pixels

3.2.1. Windowed Fractal Brownian Motion Based on the Surface Area Method (FBM)

Among the dimension calculation methods based on the fractal theory, the fractal Brownian motion method is widely used in a substantial number of studies. The related model expression is as follows:

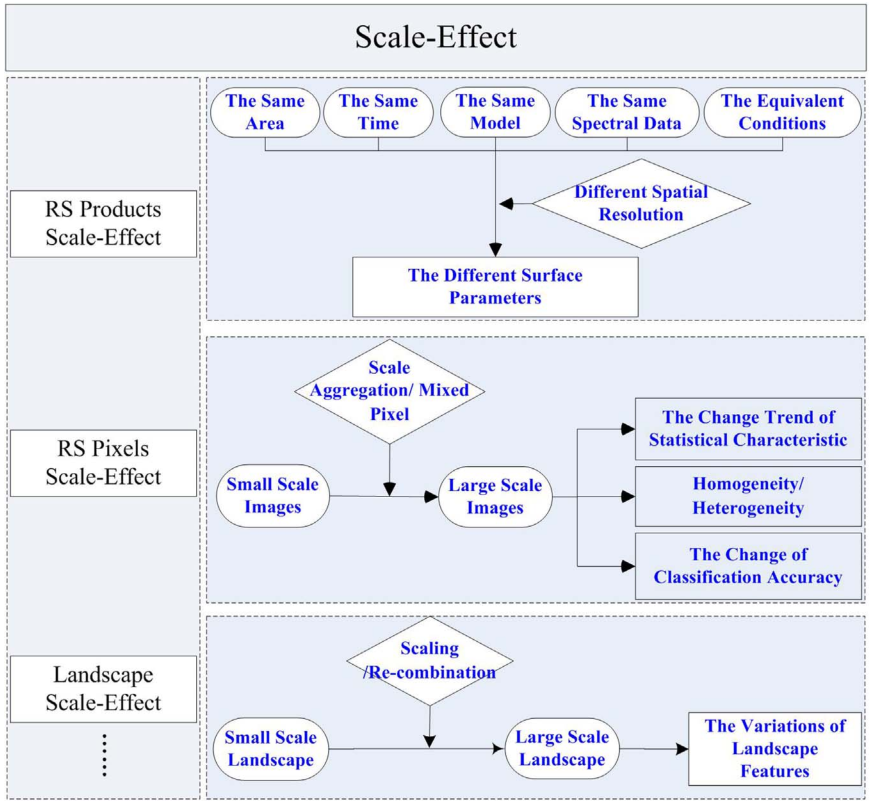

Fig. 1. The conceptual framework for scale effect in remote sensing.

$$\lg A(r) = (2 - D)lgr + lgK \tag{1}$$

By the principle of linear regression, the following equation can be written:

$$D = 2 - \frac{M\sum_{i=1}^{M} \lg r_i{*} \lg A(r) - \sum_{i=1}^{M} \lg r \sum_{i=1}^{M} \lg A(r)}{M\sum_{i=1}^{M} (lgr_i)^2 - (\sum_{i=1}^{M} \lg r_i)^2} \tag{2}$$

where r is the scale, $A(r)$ is the space curved surface area when the scale is r, D is the fractal dimension, and K is a constant.

Eq. (2) shows that the surface areas of images in several different scales are required for the fractal dimension calculation. A digital image is composed of neat rows of pixels and can be observed as a step in which each pixel constitutes a cube step. The height of the steps is the pixel gray value (Fig. 3). When the spatial quantization scale is r, the attribution of every pixel in the surface area $A(r)$ is the sum of the area of the horizontal plane of the post on top of A_H and the side-vertical surface areas A_{V1} and A_{V2}. Four side-vertical surfaces are present in one pixel, whereas every side-vertical surface is shared with adjacent pixels. To avoid repeated calculations, we only calculate the front and left vertical surfaces (see Fig. 4). In Fig. 4, $A_H = r \times r$, where A_{V1} and A_{V2} are the product of the difference between the adjacent pixel

Fig. 3. Sketch of the remote sensing cube.

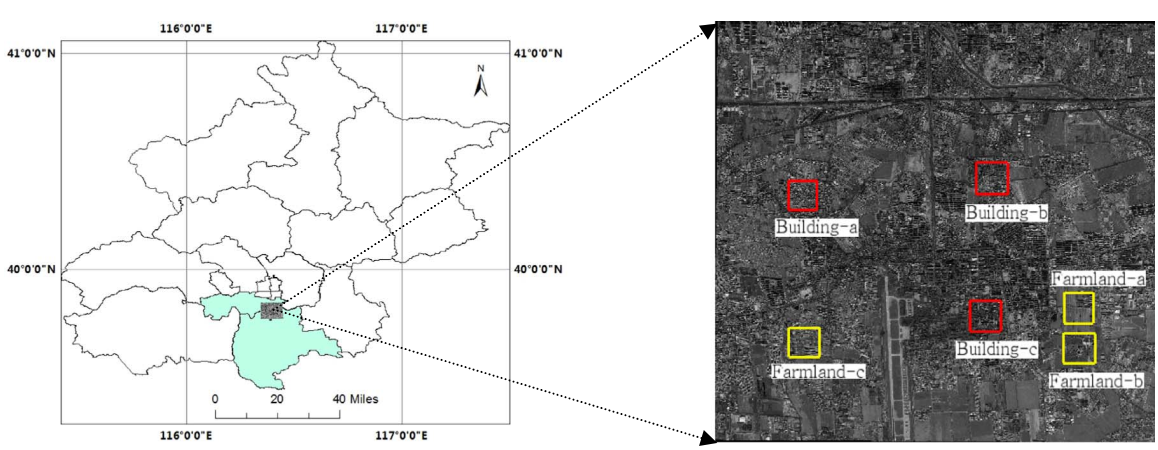

Fig. 2. To the left is a map of Beijing, in which the colored regions are the Daxing and Fengtai districts, where the six study areas located. To the right is the resampled QuickBird panchromatic image with 1 m spatial resolution, from which the six pieces of experimental images are cut.

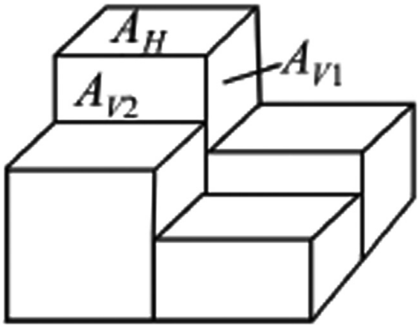

Fig. 4. Sketch of the surface calculation.

gray value and the scale. A set of the pixels in the image is $M \times N$; therefore, the space curved surface area $A(r)$ can be calculated by Eq. (3):

$$A(r) = \sum_{i=1}^{M}\sum_{j=1}^{N} A_H(i, j) + \sum_{i=1}^{M-1}\sum_{j=1}^{N} A_H(i, j) + \sum_{i=1}^{M}\sum_{j=1}^{N-1} A_H(i, j)$$
$$= M*N*r^2 + r*\sum_{i=1}^{M-1}\sum_{j=1}^{N} |f(i, j) - f(i+1, j)| + r * \sum_{i=1}^{M}\sum_{j=1}^{N-1} |f(i, j) - f(i, j+1)| \tag{3}$$

Where $f(i, j)$ indicates the gray value of a digital image when the scale is r(i = 1, 2⋯M; $j = 1, 2\cdots N$).

3.2.2. Windowed Double Blanket Method (DBM)

The double blanket method calculates the fractal dimension by enclosing the volume formed by the gray image surface similar to the box method. The related model expression is as follows:

If the image is $f(i, j)$, then the gray function $f(i, j)$ can be treated as a surface in 3D space (X, Y, I), in which $I = f(X, Y)$ is the gray value of pixels in image (x, y). According to the fractal method, we can assume that this surface can be used to display fractal characteristics on a certain scale. To calculate the fractal dimensions of this surface, the surface is wrapped into two "carpets" in a certain scale on the top and bottom of this surface. The surface areas of the carpets changes with the scale (Fig. 5). Initially, the two carpets overlapped with the image surface:

$$f(i, j) = u_0(i, j) = d_0(i, j) \tag{4}$$

Where $u_0(i, j)$, $d_0(i, j)$ are the top and bottom carpet values, respectively, of the image in (i, j) when the scale is 0. When the scale is ε=1, 2... the two carpet values are as follows:

$$\begin{cases} u_\varepsilon(i, j) = max(u_{\varepsilon-1}(i, j) + r, max(u_{\varepsilon-1}(m, n))) \\ d_\varepsilon(i, j) = min(d_{\varepsilon-1}(i, j) - r, min(d_{\varepsilon-1}(m, n))) \end{cases} \tag{5}$$

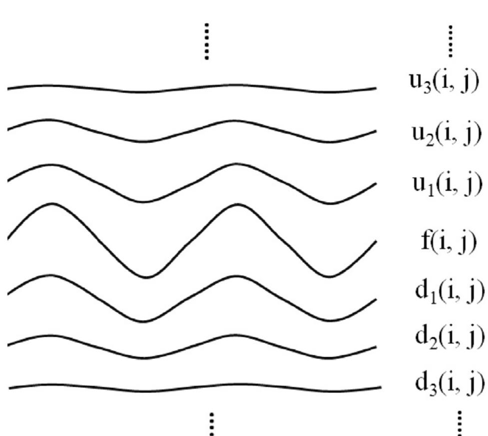

Fig. 5. Sketch of the double blanket method.

where (m, n) is the four adjacent points; the volume of the two wrapped carpets is as determined by Eq. (6):

$$V_\varepsilon = \sum_{i,j} (u_\varepsilon(i, j) - d_\varepsilon(i, j)) \tag{6}$$

The surface area is as follows:

$$A(\varepsilon) = V_\varepsilon/(2*\varepsilon) \tag{7}$$

The fractal estimation of the local gray surface can be calculated as follows:

$$A(\varepsilon) = F\varepsilon^{2-D} \tag{8}$$

After taking the logarithm, the equation can be rewritten as follows:

$$\lg A(\varepsilon) = (2 - D)lg\varepsilon + lgF \tag{9}$$

The above experimental data series are used to calculate the fractal dimensions. The results of the experiment are shown in Fig. 6(a) and (b):

3.2.3. Discussions of FBM and DBM calculation results

Theoretically, there should be peaks on the fractal dimension graphs. Actually, shown as in Fig. 6, they do not decline, as the theory suggests, but gently rise as the spatial resolution declines. The causes of this phenomenon include the following two aspects:

(1) From the aspect of image, the image used in this study is the high-resolution images with fine internal structures. When the same windows size (such as 16×16) were used to calculate the fractal dimensions, the features outside neighboring the window boundary may appear in this window with declining spatial resolution. At this time, the complexity of image in the window increases, which results in the increasing trends of fractal dimensions but not declining trends.
(2) By analyzing the above two methods, it is found that the key to calculate fractal dimension is to calculate the surface area of the image. There is a very important scale parameter r in calculating the surface area, which the specific meaning is not very clear, and it is always expressed as the number of pixels in previous research (Ju and Lam, 2009). In calculating the fractal dimensions of remote sensing images at different scales, if the values of the scale parameter r are just the numbers of pixels, and the numbers of pixels are a group of the same values at different scales (such as 2×2, 4×4……) , there are very slight changes of the surface areas, and these surface areas cannot completely highlight the specific details of the change in regional features (such as original feature size) at different scales. Therefore, this paper proposes to use spatial resolution as the modified scale parameter to calculate the fractal dimension for further analyzing the pixel-based scale effect.

3.3. Modified Fractal Dimension Calculation Methods for Remote Sensing Image Pixels

As analyzed above, it is important to consider the factor of spatial resolution in pixel-based scale effect analysis. Therefore, this paper proposes the modified scale parameter r in fractal dimension calculation and redefines the expression r as follows:$r = R*r_i$, where R is the spatial resolution, and r_i is the numbers of pixels in calculating the unit surface (e.g., 1×1, 2×2……$r_i \times r_i$). Modifications to existing fractal methods are listed as follows:

3.3.1. Modified Windowed Fractal Brownian Motion Based on the Surface Area (MFBM)

The equation for calculating the horizontal plane area $A_H = r_i*r_i$ is modified to $A_H = R*r_i*R*r_i$, and the two side areas A_{v1}、A_{v2} also are modified similar to Eq. (10), in which the scale coefficients are modified to $R*r_i$. Therefore, Eq. (3), that is used to calculate surface area of

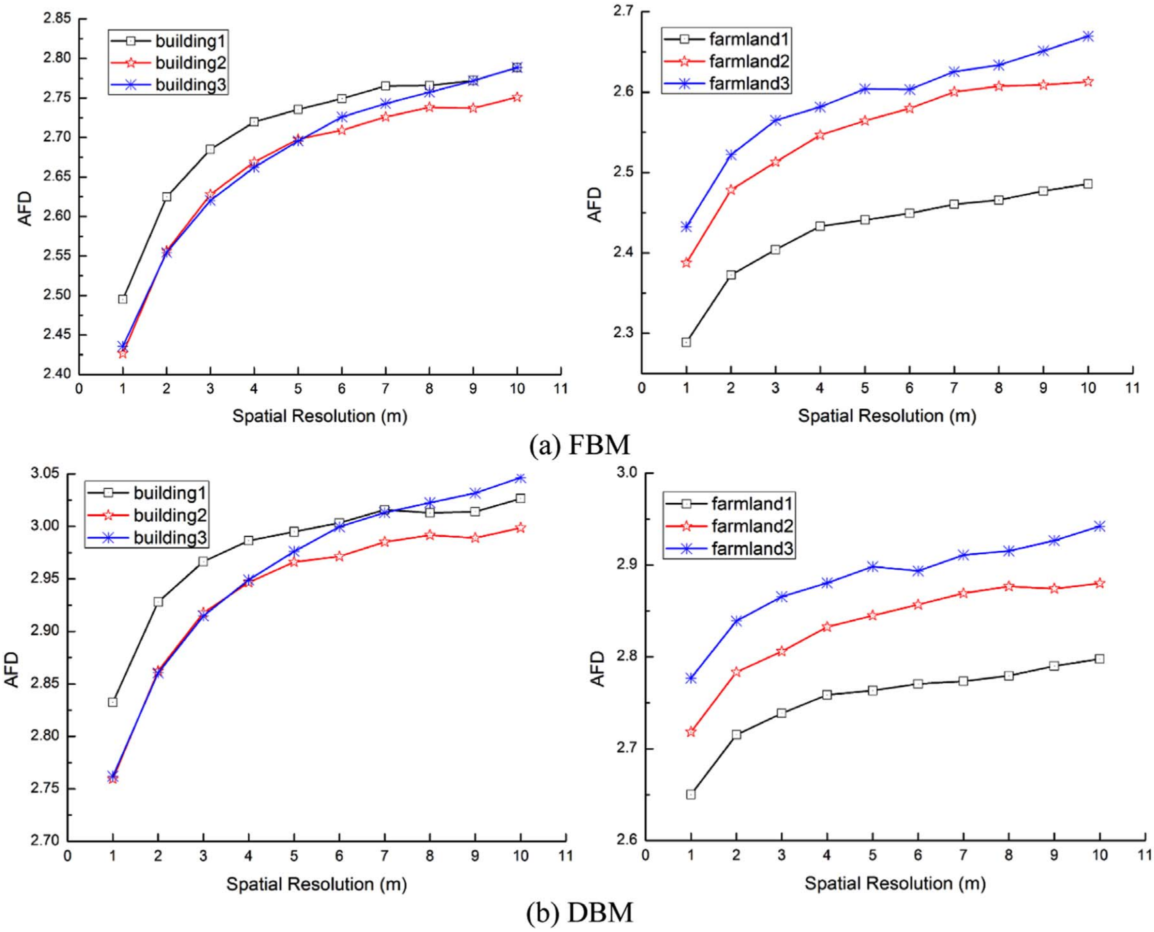

Fig. 6. Traditional fractal dimension statistics.

image, is further modified as follows:

$$A(r)=\sum_{i=1}^{M}\sum_{j=1}^{N}A_H(i,j)+\sum_{i=1}^{M-1}\sum_{j=1}^{N}A_H(i,j)+\sum_{i=1}^{M}\sum_{j=1}^{N-1}A_H(i,j)$$
$$=M*N*R^2*r_i^2+R*r_i*\sum_{i=1}^{M-1}\sum_{j=1}^{N}|f(i,j)-f(i+1,j)|+R*r_i*\sum_{i=1}^{M}\sum_{j=1}^{N-1}|f(i,j)-f(i,j+1)| \tag{10}$$

3.3.2. Modified Windowed Double Blanket Method (MDBM)

Eq. (5), which is used to calculate the two blanket values of image, is further modified as follows:

$$\begin{cases} u_{r_i}(i,j)=max(u_{r_i-1}(i,j)+R*r_i,\ max(u_{r_i-1}(m,n))) \\ d_{r_i}(i,j)=min(d_{r_i-1}(i,j)-R*r_i,\ min(d_{r_i-1}(m,n))) \end{cases} \tag{11}$$

4. Results

4.1. Experimental results obtained by the modified fractal method

The experimental data mentioned above were used to calculate the modified fractal dimensions. The results are shown in Fig. 7 and are analyzed as follows.

(1) As shown in Fig. 7(a) and (b), whether for MFBM or for MDBM, the same trends occur with the curves of the two modified fractal changing with the spatial resolutions from scale ranges of 1–10 m. That is, within a certain spatial scale, with the decrease of the spatial resolution, average fractal dimensions generally increase a first and then decrease.

This is because within a certain scale range, the nonlinear features of remote sensing image first enhance then weaken, and linear features first weaken then enhance with the decrease of scale (Ming et al., 2008). However, fractal dimensions can reflect nonlinear features of remote sensing images, and it is an index to measure the complexity of features. When the image complexity is reduced, the fractal dimension is also reduced. Therefore, the experimental results of fractal dimension are basically reliable.

(2) The statistical results of the fractal dimension calculated by MFBM and MDBM differ from each other. From the sensitivity to the change of spatial resolution, the former can produce more inflections reflecting details of geo-object than the latter, and the latter is more capable of clearly showing the suitable scale range for features than the former. In general, the trends of the curves by using MFBM and MDBM are basically the same, and there are also inflection points at a certain range of scale.

The fractal dimension calculation methods are different in different applications, and the feature type to which the algorithm is suitable is also different. As analyzed in the literature (Pentland, 1984), this is because the definition of similar fractal dimension algorithms may have very different properties. Even if a “good” data set was used in the experiment, the fractal dimensions calculated by these similar fractal dimension algorithms will not be exactly the same even for the same objects.

(3) Fig. 7 shows that there are inflection points at different spatial resolution on the fractal dimension curves for building areas and farmland areas. For the former, the inflection points mainly appear at spatial resolutions of 3 m, 4 m, and 7 m. However, for the latter, the inflection points appear at spatial resolutions of 2 m, 3 m, and

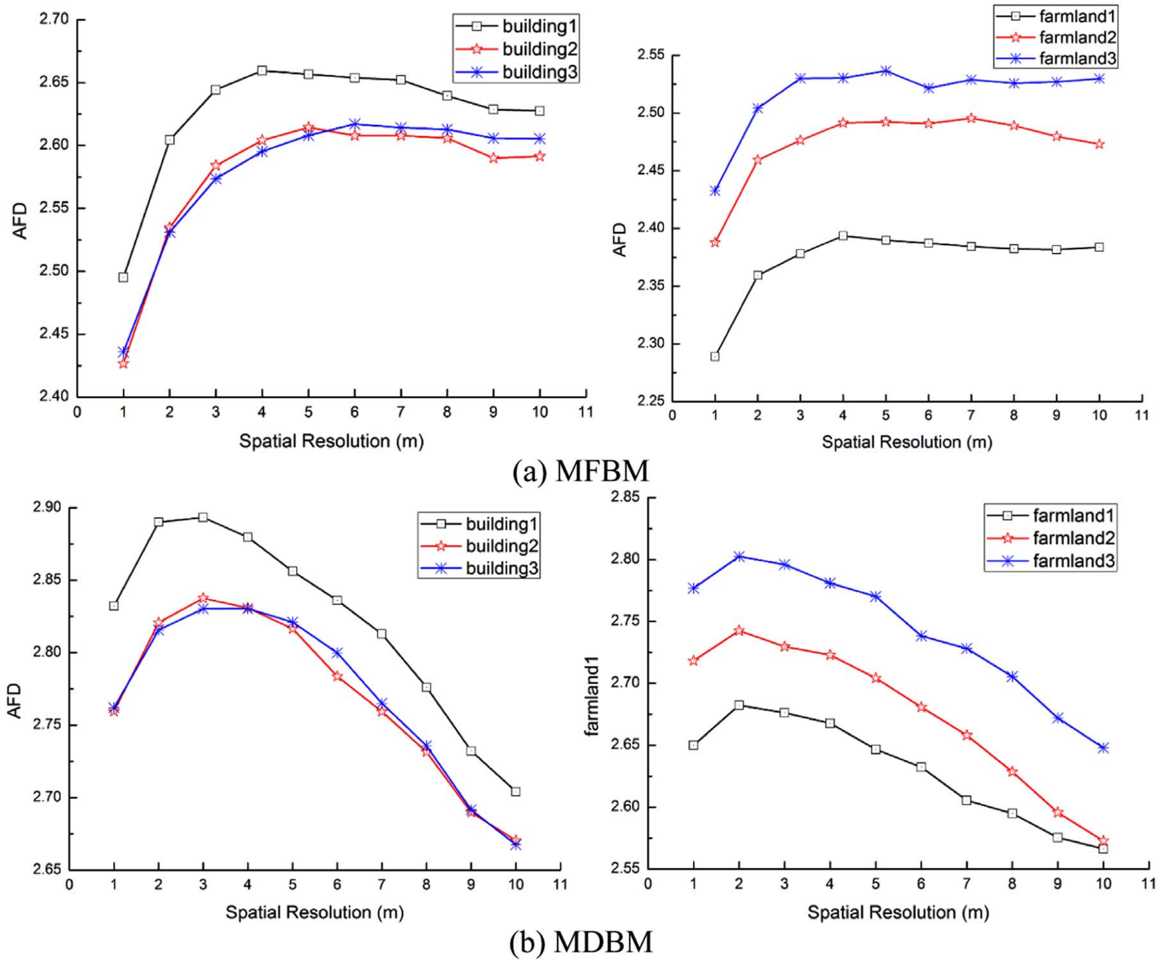

Fig. 7. Modified fractal dimension statistics.

5 m. These scales corresponding to the inflection points are called the feature scales (the optimal observation scale). The greater the fractal dimension of the feature scales is, the more suitable the scale is for studying the regional landscape structure. This scale is called the optimal observation scale. Therefore, the optimal observation scale for studying the building is 4 m, and the suitable range for studying the city landscape is 2–5 m. Similarly, the optimal observation scale for studying the farmland landscape is 4 m, and the suitable range for studying the farmland landscape is 3–5 m. The conclusion of optimal observation scale is similar to the research results of Ming et al. (Ming et al., 2011) in which the Average Local Variance (ALV) method is used to analyze the optimal observation scale.

4.2. Experimental results analysis using information entropy

To verify the reliability of modified fractal methods, information entropies of the experimental data are calculated. The information entropy calculation results are shown in Fig. 8.

(1) The information entropy first increases and then decreases with decreasing observation scale, which is consistent with the theoretical analysis result and consistent with the statistical trend of the modified fractal dimension curve shown in Fig. 7. More specifically, the curve of MDBM is more similar to that of information entropy than MFBM.
(2) Similar to fractal dimension curves, there are also inflection points on the information entropy curves changing with spatial resolution. The inflection point for a city landscape is at 4 m, and the suitable scale range is 2–5 m. For farmland, the inflection point is at 4 m, and the suitable scale range is 3–5 m. The optimal feature scale analysis results are basically the same with that of modified fractal dimension method.

5. Discussions

Theoretically, if there is no scale effect or spatial heterogeneity, the fractal dimensions with different scales should be a constant value according to the definition of fractal geometry and its scale should be invariant. However, just because spatial heterogeneity really exists, fractal dimension will change with the spatial scale and the fractal dimension at some certain scale reaches its peak when the spatial resolution is exactly equal to the size of the geo-object.

This paper uses traditional FBM and DBM to calculate fractal dimensions with different scales. Actually, practical calculation results show that neither FBM nor DBM works well on reflecting the scale effects of remote sensing image. As analyzed above, the key to calculating fractal dimensions is to calculate the surface area of the image. However, in calculating the surface area, if scale parameter r is only the number of pixels and the spatial resolution is not involved in the calculation, the numbers of pixels are a group of the same values at different scales (such as 2×2, 4×4……); therefore, the change of fractal dimensions along with spatial resolution cannot be truly and effectively expressed. Contrary to expectations, the obvious peak does not appear, and the fractal dimension graph looks like a variogram (Jupp et al., 1988a, 1988b; Karl and Maurer, 2010) because the calculation of fractal dimension is somewhat similar to that of semi-variance changing with the sample intervals (Journel and Huijbregts, 1978).

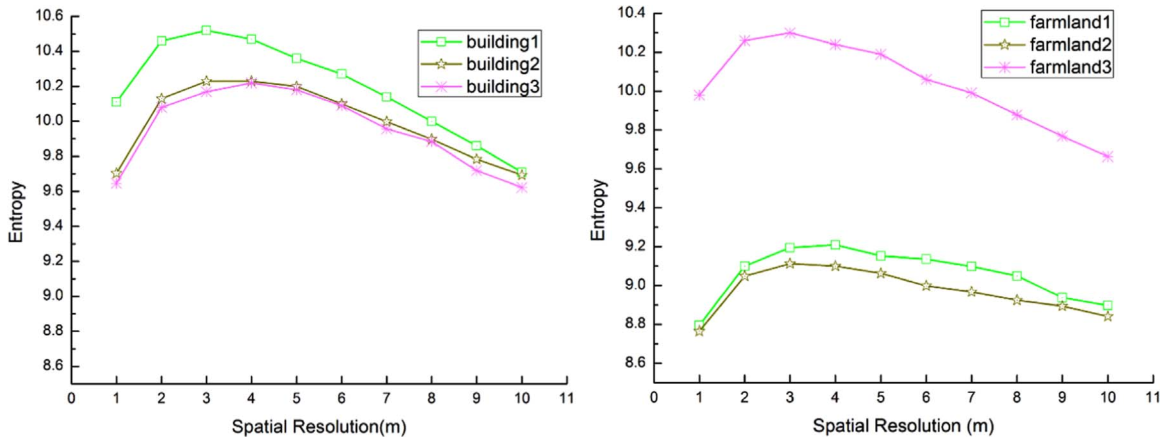

Fig. 8. Information entropy statistics.

Therefore, this paper proposes to use the spatial resolution as the modified scale parameter in calculating the fractal dimension to further analyze the pixel-based scale effect. Compared to FBM or DBM, both MFBM and MDBM can obtain better and reliable statistical results.

From another point of view, Woodcock and Strahler (1987) noted that when the spatial resolution of the study is equivalent to the actual size of the ground objects, this spatial resolution is the optimal observation scale for this landscape. However, it is inappropriate to stress this conclusion with high spatial resolution image data coming into being. The optimal observation scale is no longer equivalent to the actual size of the ground objects. Instead, the actual size of the ground objects is a multiple of the optimal observation scale (i.e., pixel size). In this case, as illustrated in Fig. 9, the number of mixed pixel will be less, while the fractal dimension will be greater and inflection point (i.e., the features scale) will appear at the peak of the fractal dimension curve.

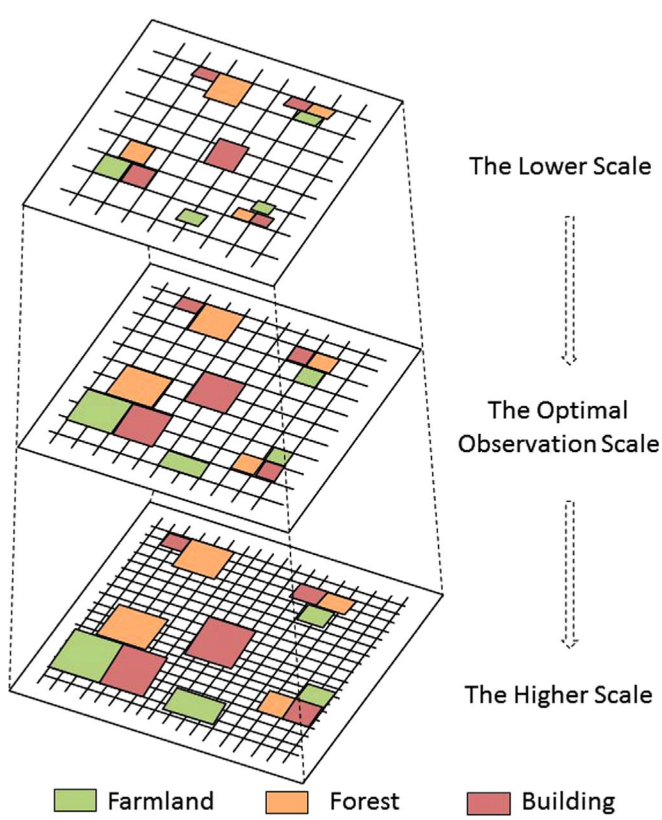

Fig. 9. Relationship between the spatial resolution and the actual size of landscape.

When the scale is below or above the optimal observation scale, more mixed pixels will appear, and the fractal dimension will decrease.

The reasons that each image area has more than one feature scale is that the actual sizes of the dominant objects on the ground might be different (such as the size of the house and the plant canopy area); therefore, a number of feature scales appear on the fractal dimension curves. It is indicated that the larger the number of feature whose actual size on the ground is multiple to the feature scale is, the greater the fractal dimension is. Therefore, this feature scale is the optimal observation scale to analyze this landscape feature.

6. Conclusions

This paper analyzed the connotation of pixel-based scale effect in remote sensing images and summarized the understanding of the scale effect. Fractal dimension is a measurement to reflect the pixel-based scale effect of remote sensing images. In traditional fractal dimension calculations, a major problem is the calculation of the surface area of an image by using a very important scale parameter r. However, in calculating the surface area, the meaning of r is not very clear, and it is always expressed as the number of pixels, which causes the fluctuated change of the surface area to become too slight to highlight the specific details of changes in the regional features (such as feature original size) at different scales.

Therefore, this paper suggests the use of spatial resolution as the modified scale parameter in calculating the fractal dimension. The research presented has demonstrated the utility of modified fractal dimension for further analysis of the pixel-based scale effect. According to experimental results, the conclusions are as follows.

(1) The modified fractal dimension is more sensitive to the change of spatial resolution; therefore, it is more effective in reflecting the pixel-based scale effect of the remote sensing image.

(2) The peaks of modified fractal dimension curves can be regarded as the indicators for the feature scales because the feature scales are somewhat related to the actual sizes of the geo-object.

(3) With the appearance of high spatial resolution image data, the optimal observation scale is no longer equivalent to the actual size of the geo-object. On the contrary, the actual size of the geo-object maybe a multiple of the optimal observation scale (i.e., spatial resolution or pixel size), which is consistent with the Nyquist-Shannon sampling theorem (Nyquist, 1928).

(4) From the sensitivity to the change of spatial resolution, MFBM can produce more inflections that reflect details of geo-object than MDBM, and the latter is more capable of clearly showing the suitable scale range for features than the former. In addition, the curve of MDBM is more similar to that of information entropy. In practice, the use of MDBM to study the pixel-based scale effect is preferred.

Additionally, the following points should be noted:

(1) In this paper, the analysis of scale effect connotation in remote sensing, the understanding of scale effect is just the exploration of scale theory, not the application problem of hard calculation. The solution to scale issues involved in remote sensing will become clear and definite with further analysis.
(2) Through repeated experiments and analysis, the modified fractal methods are more intuitive for analyzing the feature scales of different features. However, there is no single and absolute optimal feature scale to properly describe the shape and size of a complex object.
(3) Due to limited data, this study calculates the pixel-based scale effect only for building areas and farmland areas. In future research, we expect to use multi-source data points to analyze different features or some features of different types. This will fundamentally promote the exploration and cognition degree for remote sensing and the scale aggregation of features.

Conflicts of interest

The authors declare no conflict of interest.

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