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Characterizing Factors Associated with Built-Up Land Expansion in Urban and Non-Urban Areas from a Morphological Perspective

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Abstract: In this paper, built-up land expansion patterns and the associated factors were characterized in urban and non-urban areas across the Wen-Tai region of eastern China. Fractal dimension can be used as a reliable indicator of the complexity of built-up land form, and the increasing trend of fractal dimension indicated a more complex, dispersed pattern of built-up land in urban areas. Spatial regression models were quantitatively implemented to identify the indicators influencing the variation of fractal dimensions. Our findings suggested that the fractal dimension of built-up land forms was positively correlated to the patch density and elevation when built-up land expansion was more concentrated. Both landscape shape index and Gross Domestic Product (GDP) were positively correlated with fractal dimension in urban areas, and total edge, edge density, and connective index had impacts on fractal dimension in non-urban areas. Slope and agricultural population also showed an influence on fractal dimension. This study provided a new way for urban studies in interpreting the complex interactions between fractal dimension and related factors. The combined approach of fractal dimension and spatial analysis can provide the government planners with valuable information that can be efficiently used to realize the influences of land use policies in urban and non-urban areas.

Keywords: fractal measures; built-up land expansion; associated factors; urban and non-urban areas

1. Introduction

As a social phenomenon and a physical transformation of landscapes [1], urbanization has an enormous impact on society and the environment on a local, regional and global scale and can cause the degradation of ecosystem services, alteration of vegetation production, climate, and air quality [2,3]. Anthropogenic impact on the environment is powerful, irreversible, and highly visible [4–6], and it plays in interactions between city areas and global environmental change [7,8]. The rapid urbanization process in Zhejiang (one of the richest province in China), characterized by large-scale rural–urban migration and rapid expansion of built-up land areas, has led to enormous arable land loss and serious environmental problems at an unprecedented rate [9–11]. Former studies in this area reported that cropland was the major land use types converted for urban expansion in recent decades [12,13]. Nowadays, the urban-rural development in the eastern coastal area is entering a new stage of transformation with metaphase industrialization and rapid urbanization [14]. Construction of transportation infrastructures and settlements were the primary driving forces of land-use conversion in the eastern coastal area [14]. Meanwhile, land use underwent a fundamental transition from natural landscape to human-made landscape. Consequently, identification and assessment of built-up land expansion and associated factors in Zhejiang province has become a hot topic, and has recently drawn the attention of many scholars [10,11].

Urban areas have replaced considerable amounts of undeveloped land. This phenomenon is highly correlated with socio-economic development, and has also caused various ecological, environmental and social problems [15]. In recent decades, many Chinese cities became more complex, scattered, and disordered, with rapid urbanization, which has led to waste and unreasonable usage of land resources [11]. Identifying built-up land expansion patterns and its related factors is fundamental to realizing the urban-rural relationship and the influences of rapid urban sprawl on society, economics, environments, ecology, and so on. In this process of urban-rural integrated development, the waste, loss and degradation of arable land resulted in conflicts between conserving limited arable land and increasing demand for the construction of human settlement. However, many urban geographic studies focused on the urbanization and its geographical elements [16,17], while seldom considering the urban sprawl from a morphological aspect. Regional urban development planning in this coastal area is largely based on experience and lacks theoretical support. Using a systems analysis-based approach to describe spatial patterns of city development and morphological measurement is important for regional land use planning and policy making [11,18], and can provide significant evidence for the relationship between built-up land expansion patterns and their associated factors.

Fractal geometry has proven to be a useful method for studying the spatial form of built-up land, because the distribution of built-up land has a non-linear form, and fractal characteristics [16,17,19,20]. The change of scale is represented by the change of fractal dimension, and thus it is a powerful tool to study scale issues [21]. Fractality implies that a city or a county possesses a similar structure at different scales, and has the function to self-organize. Its existence is important since it indicates the presence of some hidden process operating at different spatial scales [16,22]. However, the fractal approach couldn't give spatial context to the built-up land clustering, and does not indicate the variations [23].

In order to characterize the components of built-up land expansion from a morphological perspective, the fractal dimension was employed to classify and quantify clustering in built-up land distribution, and spatial regression was used to identify various factors influencing the distribution patterns of built-up land. Our intention in this paper is to answer these three questions: What are the spatial and temporal patterns of built-up land expansion in the Wen-Tai region? Which areas of this coastal region are suffering due to unreasonable development patterns? How do different associated factors influence built-up land expansion in urban areas and non-urban areas? In order to answer these questions, this study was designed to quantify the transformations in built-up land from 1994 to 2003 in Wen-Tai region (Zhejiang Province, China). The analysis was based on data of residential distribution in Wen-Tai region. Specifically, the research focused on (1) whether different spatial patterns of built-up land can have virtually the same fractal dimensions and urbanization pattern; (2) identifying different factors of fractal dimension of built-up land expansion like landscape metrics, social-economic and topography using regression models; and (3) whether fractal dimension is a reliable measure of spatial distribution of built-up land.

2. Study Area and Data Description

2.1. Study Area

The Wen-Tai region during 1994 and 2003 was chosen because it represents some notable social and environmental problems associated with development [24,25]. The Wen-Tai region is located in eastern coastal China (Figure 1) with a spatial extent of 27°03′–29°08′ N and 119°37′–121°26′ E. With a subtropical monsoon climate, it experiences moderate temperatures, abundant precipitation, low humid atmosphere, visible monsoons, distinct seasons and variable climates. As one of the most developed regions in Zhejiang province, Wen-Tai witnessed rapid social-economic development in recent decades. This development has resulted in degradation of the surrounding natural habitats and environmental conditions. The distribution of residents in this region is the result of interfaces between human activity and environmental change during these years. The Wen-Tai region gives us a typical coastal case study to identify the fractal dimension of built-up land and the associated factors.

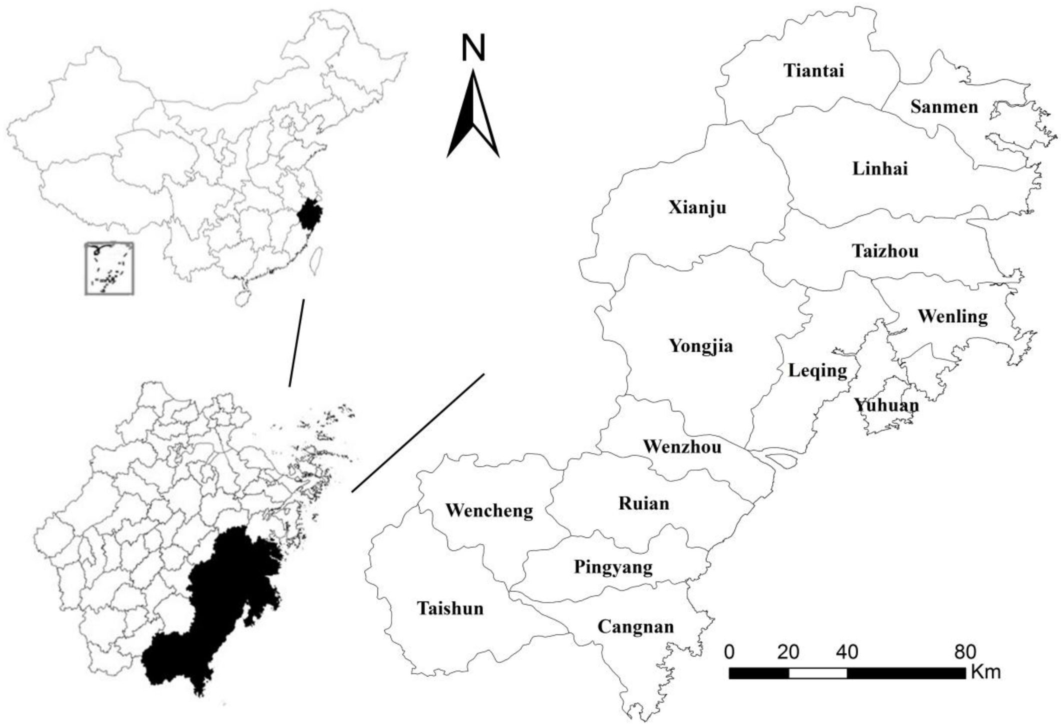

Figure 1. Location of the Wen-Tai region, China.

2.2. Data Preparation and Accuracy Assessment

In this study, built-up land refers to settlements, public facilities, factories and tourist attractions sites. The built-up land use data were generated from Landsat 5 Thematic Mapper (TM) images (Path: 118, Row: 40/41) acquired on 12 May 1994 and 14 July 2003. These images, with a spatial resolution of 30 m, were downloaded from the website of the USGS (United States Geological Survey) Landsat Missions (http://landsat.usgs.gov/index.php). After geometric correction and atmospheric correction, the image in 2003 was rectified to the image of 1994. The maximum likelihood classifier was applied in image classification which only extracted built-up land from these two TM images. Because bare soils and built-up land have similar spectral characteristics, artificial visual interpretation was used to rectify the classification results from TM images. The working window was set at a 1:20,000 scale and then built-up boundaries were corrected [26]. Fifty sampling points for built-up land use were randomly selected to assess the classification accuracy [27]. Google Earth was used to check the accuracy of image interpretation in 1994 and 2003, and an overall Kappa of 0.82 was determined. The classification results are displayed in Figure 2.

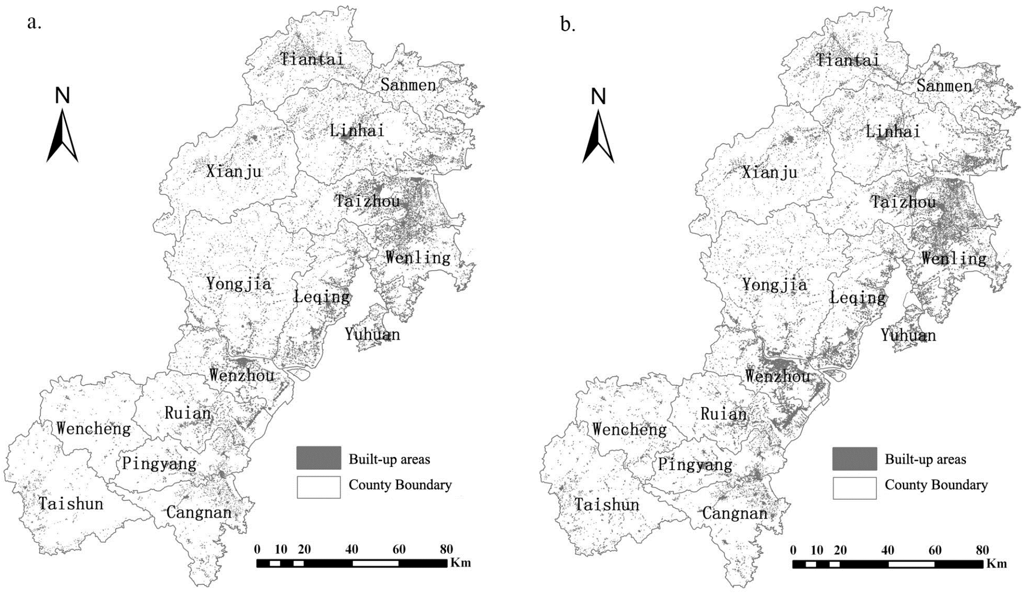

Figure 2. Built-up land map of the Wen-Tai region in 1994 (**a**) and 2003 (**b**).

3. Methodology

3.1. Fractals

A fractal is defined by Mandelbrot & Wheeler [28] as a geometric shape that can be split into parts, and each of the parts is a reduced-size copy of the whole. Fractal analysis provides tools for measuring the geometric complexity of imaged objects. Due to the irregularity and complexity of objects' spatial distribution and the variation of environmental factors at the continuous scales, objects' spatial patterns have spatial variation at different scales. Dimension is used to measure the size of a dataset which is usually made up of images. Objects with one-dimension are line segments, two-dimensional are squares, and three-dimensional are cubes [29].

3.1.1. Fractal Models

There are three kinds of fractal models. Figure 3 shows the Sierpinski carpet (a plane fractal) with each square replaced by $N = 5$ squares, and the base length reduced by the factor $r = 1/3$. Figure 3a calls the initiator with length L. It is then broken down into $N_b = N^1 = 5$ smaller squares with base length $l_b = 1/3$ L (Figure 3b), and they are organized within the area of the initiator which is called a generator. This procedure is repeated in a second step for each of the five squares and it is broken down to $N_c = N^2 = 25$ squares of size $l_c = (1/3)^2$ L (Figure 3c). A spatial hierarchy then emerges, consisting of smaller and smaller clusters in the process of the iteration. We can see that for the generator in the example, the elements are contiguous, so in all the iterations, the fractal consists of one cluster, and this kind of fractal is called a Sierpinski carpet [28,30].

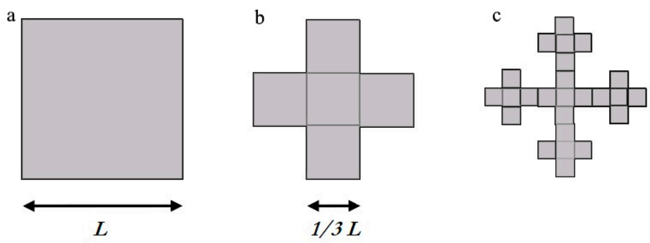

Figure 3. Generating a Sierpinski carpet from a square (**a**) to a fractal result with N = 5 (**b**) and a fractal result with N = 25 (**c**).

Fournier dust is another kind of fractal. This fractal form has a hierarchically organized network of non-occupied spaces [30]. Figure 4 shows the difference between Sierpinski carpets and Fournier dust fractals [31]. A Sierpinski carpet (in the upper) looks different from a Fournier dust (in the below) when the first iteration is processed. All the lanes separating the black squares in Sierpinski carpet have the same width, but in Fournier dust, the lanes follow a well-defined hierarchy. We can see they have different spatial hierarchies and different fractal dimensions. The Fournier dust has stronger hierarchy with lower fractal dimension value than the Sierpinkski carpet (D = 1.50 for Fournier dust and D = 1.89 for Sierpinski carpet).

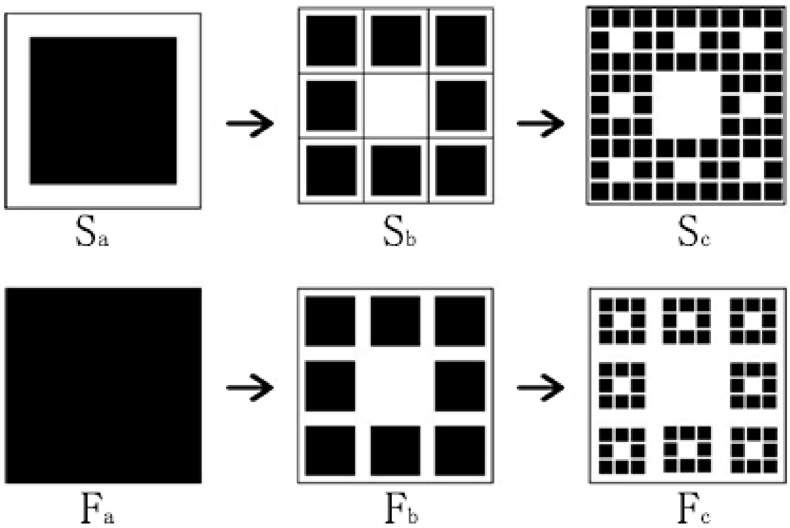

Figure 4. Differences between Sierpinski carpet (**upper**) and the Fournier dust (**below**).

A teragon is another type of constructed fractal that is unlike the Sierpinski carpet and Fournier dust. It is a curve with self-similar fractal that can be produced by replacing each line segment in an initial figure with multiple connected segments [28]. For the urban study, the teragon was a form where the inner black surface remained constant and the borders became more and more complex [30].

3.1.2. Fractal Measurement

Fractals have obvious particularities, and usual geometric measures are not able to describe these structures [26,27]. Fractal measurements can be defined as:

$$N(r) = ar^D \tag{1}$$

This leads to:

$$\mathrm{D} = \frac{\ln \frac{N(r)}{a}}{r} \tag{2}$$

where r is a given side length in a square surrounding each built-up land patch. The number of patches is counted within this square. *N(r)* denotes the mean number of built-up land patches lying within such a square. The exponent D is the fractal dimension that the form-factor measures the general features of the structure [28].

Two methods, the dilation and the correlation analyses [28], were employed to calculate the fractal dimension values of urban and non-urban areas in our research. In the dilation method, the squares surrounded each built-up land patch were gradually expanded so that they became close to each other, and finally the black clusters appeared when they overlapped. *N(r)* denotes the number of squares with size r that are able to cover the whole study surface. Preliminary experiments have presented that dilation method was less dependent linear structures where the mass of the object was small [32].

This method was employed to extract urban boundaries in this study. The surfaces of built-up are spatially distributed according to the same type of rule that holds for constructed fractals, in which case we could identify urban patterns as random fractals [28,30]. The software Fractalyse (downloaded from http://fractalyse.org) is applied for studying the fractal dimension of built-up land.

3.1.3. Surfaces and Borders

The fractal dimension of built-up areas (surfaces), which is denoted D_{Surf}, can be used as an indicator of the complexity of urban form [33,34]. Generally, when a city has higher value of fractal dimension, it would become more complex or disperse. This is the reason that the human settlements patterns exhibit the clear nature of irregularity, scale-independence and self-similarity. The fractal values of borders, which is denoted D_{bord}, show that it is possible to quantify how smooth they are [30]. Urban boundaries were extracted by means of the dilation technique (see details in Frankhauser and Tannier, 2005 [30]; Keersmaecker et al., 2003 [32]). Figure 5 shows the process of boundary extraction. We took the urban area of Wenzhou as an example, Figure 5a is the source image, Figure 5b is the dilation image for five iterations, Figure 5c shows all the outlines of the whole county, and Figure 5d shows the boundary of the urban area. The ratio of D_{Bord} and D_{Surf} was used in this study. This ratio represents the compactness of a structure [31]. Geometrical objects have smooth borders with D_{surf} = 2 and D_{bord} = 1, so the ratio is D_{bord}/D_{surf} = 1/2 = 0.5, which is the minimum value of the ratio. For Sierpinski carpets the ratio had a maximum value of 1 because D_{surf} equalled the D_{bord}. For the teragon, the ratio ranged between 0.5 and 1.0, because D_{surf} = 2 and D_{bord} ranged between 1 and 2. However, this was reflective of the real-world patterns of built-up areas.

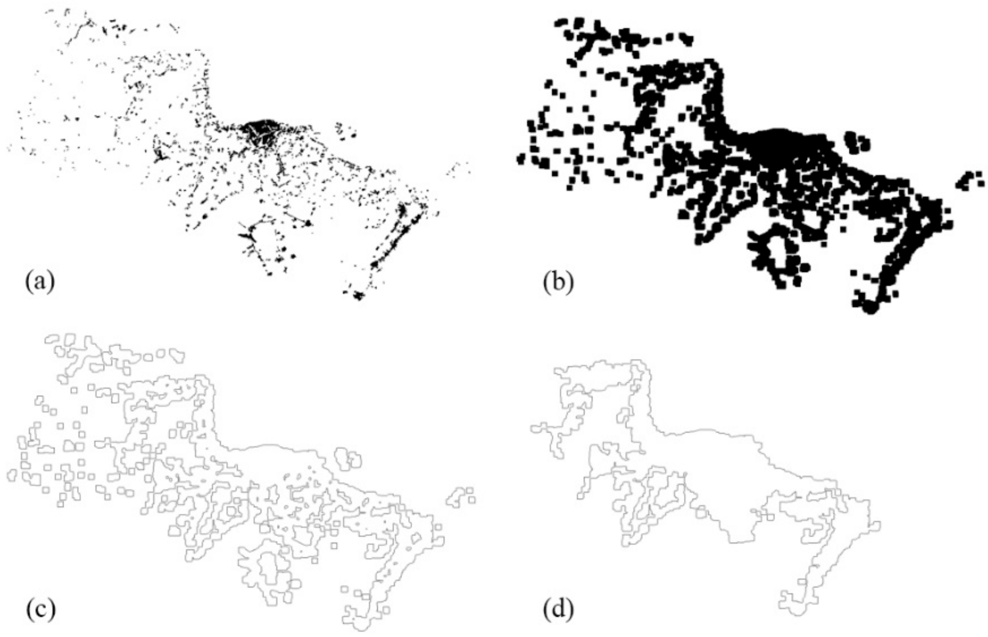

Figure 5. The procedure of extracting the outlines of a county by dilation of the built-up land. (**a**) is the source image; (**b**) is the dilation image; (**c**) shows all the outlines; and (**d**) shows the outline of the main cluster (urban area).

3.2. The Selected Indices

Referring to previous studies, a set of 40 indices focusing on aspects of landscape, socio-economic interactions, and nature were initially generated to identify the associated factors. We selected indices by considering the integrity, simplicity, dynamic response, accuracy and availability of the data [35]. Landscape indices are widely used in the study of spatial landscape patterns and landscape ecology [36]. Social-economic indices such as GDP [37,38] and population [39] have been proven to be effective indicators of built-up land expansion. Natural factors such as elevation [40,41] and slope [41–43] are other potential factors which have been reported in the previous studies. Subsequently, a three-round Delphi Process and principal component analysis were used to eliminate the indices with high correlation by rotating the multidimensional indices into a new group of mutually orthogonal variables [44]. Finally, a total of 13 indices were generated (Table 1).

Table 1. The indices selected in this study.

Item	Category	Indices	Abbreviation
Landscape metrics	Area	Total Area	TA
	Density and size	Patch Density	PD
		Largest Patch Index	LPI
	Edge	Total Edge	TE
		Edge Density	ED
	Shape	Landscape Shape Index	LSI
	Isolation	Connective Index	CI
	Diversity	Shannon's Diversity Index	SDI
Social-economics	Social	Total Population	TP
		Non-agricultural Population	NAP
	Economic	Gross Domestic Product	GDP
Natural	Topographic	Elevation	Ele
		Slope	Slp

3.3. Spatial Analysis

Moran's I index was employed to characterize the spatial autocorrelation of the built-up land expansion patterns. Moran's I has values ranging from -1 to 1, and a zero value indicates a random spatial pattern, which has no spatial autocorrelation. Positive values indicate spatially clustered patterns in adjacent patches, and negative values suggest that samples have different values from the neighbors [45]. Moreover, Local indicators of spatial association (LISA) was further calculated by GeoDa 0.9.5-i (Beta) software to identify the location of clusters and their types of spatial autocorrelation [46,47]. The significant spatial clusters of similar values can be identified by LISA. There exist four categories of LISA: high-high (low-low) means high (low) sampling values are surrounded by high (low) values; high-low indicates high values surrounded by low values; and low-high means a low value has neighbors with high values [46].

Relationships between fractals and the associated factors were quantified by spatial regression. Spatial regression extends the traditional ordinary least squares regression (OLS) by incorporating spatial dependency in terms of error or lag. The dependent variables were the fractal dimension values of each county in the Wen-Tai region for 1994 and 2003. Independent variables included landscape structure, social-economic interactions, and natural factors. Specifically, independent variables obtained from stepwise regression were introduced in order to resolve potential multicollinearity between the variables [42]. Spatial lag regression and spatial error regression were respectively described by Equations (3) and (4),

$$y = \rho W_y + X\beta + \varepsilon \tag{3}$$

$$y = X\beta + \varepsilon,\ \text{with}\ \varepsilon = \rho W_\varepsilon + \mu \tag{4}$$

where y denotes the dependent variable; X is the independent variable; μ denotes stochastic parameters; β are coefficients for X, and ε are the error terms; ρ is the spatial autoregressive coefficient; W_ε and W_y are spatial matrices of the error term and dependent variable, respectively. All spatial regression was performed using GeoDa 0.9.5-i (Beta) software [46].

4. Results

4.1. Spatiotemporal Patterns of Fractals

Maps of LISA are shown in Figure 6 to describe the local autocorrelation of the built-up land expansion in the Wen-Tai region. High-high clusters were mostly concentrated around the urban center, indicating that urbanized areas were focused in the peri-urban areas, not the inner urban areas. Figure 6 shows Taizhou had the largest high-high cluster, suggesting that Taizhou has the most urbanizing intensity. Furthermore, Taizhou had the second largest low-low cluster which was mainly distributed in the inner area, indicating that Taizhou has insignificant built-up land expansion in its inner areas. Xianju had no high-high cluster, indicating that this county has very weak urban sprawling both at outer and inner areas. On the other hand, Wencheng has low-low cluster, indicating that this county has urban sprawling at both outer and inner spaces.

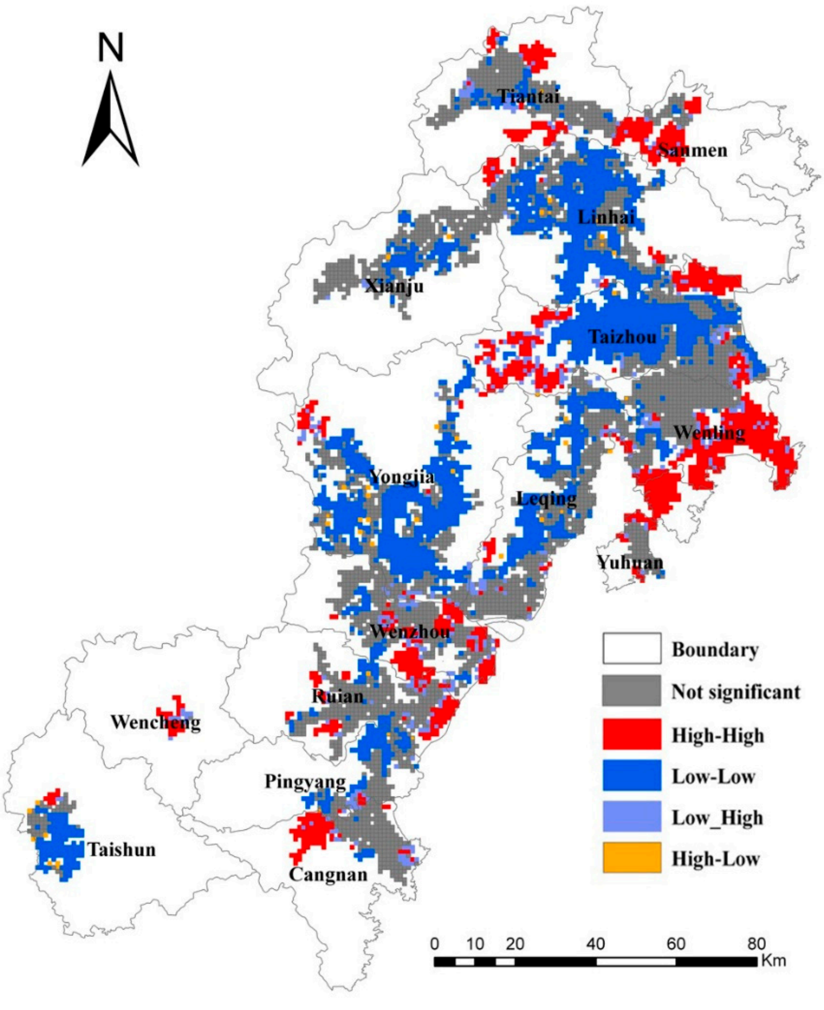

Figure 6. Local indicators of spatial association (LISA) map of the built-up land expansion in Wen-Tai region.

Table 2 shows the fractal dimension value of surfaces and borders for built-up land. For non-urban areas, most counties showed a trend of increasing values of fractal dimensions, while some counties showed decreasing trend values of fractal dimension. This was especially true for Taizhou, which displayed a significant decrease of fractal dimension value (1.10–0.67). The reason for this was that in 2003, the urban area became larger and the non-urban area became smaller with dispersion, so that the distribution of built-up land became loose and the fractal dimension values decreased.

Table 2. Fractal dimension value of surfaces and borders, and their ratios for built-up land in the Wen-Tai region.

Study Area	Urban						Non-Urban	
	D_{Surf}		D_{Bord}		Ratio		D_{Surf}	
	1994	2003	1994	2003	1994	2003	1994	2003
Wenzhou	1.45	1.57	1.24	1.29	0.86	0.82	1.07	1.10
Yongjia	1.29	1.33	1.12	1.10	0.87	0.83	1.14	1.16
Pingyang	1.31	1.36	1.09	1.11	0.83	0.82	1.04	1.16
Cangnan	1.27	1.37	1.05	1.09	0.83	0.80	1.14	1.12
Wencheng	1.24	1.27	1.36	1.25	1.10	0.98	1.06	1.23
Taishun	1.22	1.26	1.1	1.09	0.90	0.87	1.04	1.18
Ruian	1.41	1.45	1.08	1.13	0.77	0.78	0.97	1.09
Leqing	1.37	1.42	1.1	1.14	0.80	0.80	0.91	0.92
Taizhou	1.44	1.47	1.25	1.12	0.87	0.76	1.10	0.67
Yuhuan	1.21	1.41	1.14	1.11	0.94	0.79	1.26	1.26
Sanmen	1.20	1.37	1.14	1.06	0.95	0.77	1.31	1.34
Tiantai	1.33	1.38	1.04	1.04	0.78	0.75	1.14	1.12
Xianju	1.27	1.33	1.06	1.11	0.83	0.83	1.08	1.10
Wenling	1.48	1.51	1.05	1.06	0.71	0.70	1.17	0.87
Linhai	1.40	1.44	1.19	1.08	0.85	0.75	1.18	1.24

Then, borders of the fractal dimension were calculated. The border of those geometrical objects, called a Sierpinski carpet, became more complex, since an increasing number of smaller tentacles appeared at each step. Cangnan, Tiantai and Wenling had D_{Bord} values of 1.0–1.1, which means they are very smooth. Temporally, Wencheng (1.36–1.25), Taizhou (1.25–1.12), Sanmen (1.14–1.06) and Linhai (1.19–1.08) changed greatly for fractal dimension values. This meant that during the ten years, the trend of urban development became smooth, representing the control of the government. Some counties (Wenzhou, Wencheng and Taizhou) showed highly dendritic borders ($D_{Bord} > 1.2$), suggesting that no restrictions were imposed to smoothen the urban outline. For some counties such as Cangnan, Tiantai and Wenling, the fractal dimension value of the borders was lower than 1.1, indicating that these urban areas were considerably smoother than those of other areas. On the other hand, the planning policy in these counties generally tends to limit expansion on the scale of the urban area. The results of fractal dimension values for surfaces and borders showed that for the urban fractal dimension, the values of their surfaces were larger than those computed for their borders. The ratio of borders and surfaces showed that most values for urban were lower than 1 (except Wencheng in 1994).

4.2. Fractal for Urban and Non-Urban Area

We classified the Wen-Tai region into two types (urban and non-urban) with different fractal dimension values. The urban area was extracted through dilation fractal dimension method, and Table 2 shows the range of fractal dimension value increase. The lowest value in 1994 existed in Taishun (1.22), and the highest in Wenling (1.48), while in 2003 the lowest value existed still in Taishun (1.26), and highest in Wenzhou (1.57). A ratio value with a range of 0.5–1.0 is considered urban. The above analysis showed that when the ratio = 0.5 the form of urban was similar to a teragon. The minimum ratio value in 1994 and 2003 both existed in Wenling, which shows the form of this area is more similar to a teragon than other counties. Non-urban areas are the sites around urban areas. Specifically, the non-urban area has much less fractal dimension values than urban areas. The minimum value of the fractal dimension existed in Leqing in 1994 and Taizhou in 2003, both of which were less than 1. The fractal dimension values for Yuhuan and Sanmen in 1994 were larger in non-urban areas than they were in urban areas. This suggested that these two areas had more dispersed distribution of built-up land in non-urban areas in 1994, while urban developments of these two areas showed more dispersed and complex distribution of built-up land in urban areas in 2003.

4.3. Impact of Built-Up Land Expansion on Fractal Dimension

Factors of fractal dimension in different years at both urban and non-urban areas are presented in Table 3. The correlation between fractal dimension and the factors described with spatial regression analysis suggested a close association between them in both 1994 and 2003 in Wen-Tai region. In urban areas, the changes of fractal dimension were significant associated with LSI in both two years. GDP is another significant indicator which presented significant impacts on fractal dimension in both years indicating that the development of urbanization is largely dependent on the development of economics. Moreover, PD and Ele_mean exerted significant impacts on the fractal dimension of urban area in 2003 as both the factors showed a negative correlation with the fractal dimension. The results implied that built-up land expansion mostly occurred in plain areas, and building on high-elevation areas was not suitable. For PD, it meant that the value of fractal dimension increased, while the PD decreased with built-up land expansion. Since NP increased, this means that the increasing rate of patch area surpassed the rate of NP, which accordingly decreased PD. For non-urban areas, the number of influential factors was less than in urban area. Changes in total edge, edge density, and slope acted as the main contributor to dynamics of fractal dimension in non-urban areas for 1994, while changes of TE, LSI, CI and agricultural populations accounted for the dynamics of fractal dimension in 2003. This means that TE is a key factor influencing the fractal of non-urban areas. In addition, in 1994, most people chose settlements in plain areas, showing that slope is a very important factor impacting the fractal dimension. In 2003 most built-ups had been built, with connectedness being a very important factor influencing the fractal dimension.

Table 3. Spatial regression models of fractal dimension in urban and non-urban areas [a].

Year	Y	X	Spatial Regression Models	R^2
1994	Urban	LSI [c]	$Y = 1.093 \times X + 0.302 \times W_Y - 0.196$	0.64 **
		LPI [c]	$Y = -0.366 \times X + 0.841 \times W_Y + 0.154$	0.51 **
		ED [c]	$Y = 0.104 \times X + 0.909 \times W_Y - 0.006$	0.63 **
		GDP [c]	$Y = 0.949 \times X + 0.424 \times W_Y - 0.042$	0.72 **
	Non-urban	TE [c]	$Y = 0.635 \times X + 0.549 \times W_Y + 0.009$	0.65 **
		ED [c]	$Y = -0.271 \times X + 0.855 \times W_Y + 0.159$	0.56 **
		Slp_std [b]	$Y = -0.575 \times X + 0.875$ (lambda = 0.277)	0.53 **
2003	Urban	LSI [c]	$Y = 0.891 \times X + 0.284 \times W_Y - 0.130$	0.66 **
		PD [c]	$Y = -0.480 \times X + 0.835 \times W_Y + 0.209$	0.63 **
		GDP [b]	$Y = 0.781 \times X + 0.218$ (lambda = 0.695)	0.74 **
		Ele_mean [c]	$Y = -0.676 \times X + 0.645 \times W_Y + 0.384$	0.67 **
	Non-urban	TE [c]	$Y = 0.650 \times X + 0.590 \times W_Y + 0.046$	0.61 **
		LSI [c]	$Y = 0.724 \times X + 0.570 \times W_Y - 0.096$	0.75 **
		CI [c]	$Y = -0.811 \times X + 0.229 \times W_Y + 0.634$	0.72 **
		AP [b]	$Y = -0.451 \times X + 0.858$ (lambda = 0.501)	0.51 **

** $p < 0.01$; [a] Abbreviations: landscape shape index (LSI), largest patch index (LPI), edge density (ED), gross domestic product (GDP), patch density (PD), total edge (TE), connective index (CI), mean value of elevation (Ele_mean), standard deviation of slope (Slp_std), and agricultural population (AP); [b] Spatial error regression; [c] Spatial lag regression. W_Y is the weighted mean fractal values of adjacent blocks based on the spatial weight matrix of Y.

Most R square values in these two years reached 0.6, denoting the powerful predictive ability of spatial regression. A higher R^2 (>0.7) in GDP in urban areas implied that the fractal dimension in urban area was better explained by this factor in both years. In addition, the spatial lag model suited most factors. Specifically, it was suitable for predicting the dynamics of all the factors in urban area, but only the landscape metrics in non-urban areas. These results denoted that spatial dynamics of landscape metrics and other associated parameters in urban area depended on not only local independent factors, but also the dynamics of neighboring counties. Differently, spatial error regression was powerful in characterizing the dynamics of slope and agricultural populations in non-urban areas. This implied that associations of slope and agricultural population dynamics omitted from the model are correlated over space in non-urban areas, and unobserved factors should follow spatial patterns.

5. Discussion

5.1. Characteristics of Fractal Dimension in Urban and Non-Urban Areas

Fractal dimension values of borderlines ranged from 1 to 1.5. Values of 1 denoted smooth borderlines and not much spare land in the areas, which may be explained by the strong control of urbanization. Values equal to 1.5 denoted a dendritic pattern similar to a teragon, which can be explained by the rather weak influence from rapid urbanization The surface dimensions observed here were lower than those observed in other areas, especially the European countries [30], indicating that built-up land in Wen-Tai region was less uniformly distributed. This may be explained by the rather weak control of urbanization or the low sustainability of the development. Some counties had significant sprawling with a slight decrease in fractal dimension values (such as Taishun, Wencheng and Xianju) indicating that economic development of these counties are under a general upward trend, and that governments have strong control in these counties. Some counties had an increasing trend for both areas and fractal dimension values. It is important for governments to control urban sprawl, in order to make land use more rational and effective so as to ensure better and faster growth. Traditionally, urban development is accompanied by increasing fractal dimension value and decreasing cluster scale. This indicates that these counties sprawl to the outer spaces with normal and common developing patterns. Similarly, different kinds of built-up land form were identified by fractal dimension values and urban density [48]. Fractal analysis provided insight into the spatial variation of urban sprawl patterns, suggesting that built-up land continuously expanded at most edges over the 10 years.

5.2. Factors Associated with Built-Up Land Expansion Patterns

Over the years, landscape metrics have been used in research on urban morphology [1,49,50]. The relations between the fractal dimension of urban form and landscape patterns were discussed based on fractal theory and urban land-use maps [51,52].Terzi and Kaya [53] found that the fractal dimension of urban areas presented a positive correlation with the urban sprawl index. In this research, it indicated that some landscape metrics showed positive correlations with the fractal dimension (LSI, TE), and some showed negative correlations (ED, CI). It indicated that the changes of landscape structure can significantly influence the value of the fractal dimension, which provides new insights into urban building planning through a landscape approach.

Cai et al. [33] discussed the relationships between fractal dimension and landscape metrics such as compactness index and social-economic components such as GDP and population. Shen [34] discussed the relationships between the fractal dimension and other factors, showing that the fractal dimension has a positive relationship with urbanized areas and is not always positively correlated to urban populations. Similarly, population was not a main indicator for changes of fractal dimension in our study.

Also, socio-economic changes were discussed in the fractal dimension studies [54,55] while no quantitative relationships had been established. Due to convenient transportation, flat terrain and better ecological environment people choose to live near the sea, and most urban areas are located near coastal zones. This leads to economic increase, and urban development depends largely on the sea environment for these coastal counties. The pleasant climate and beautiful natural environment attract people to build their houses near the coastal zones. We will focus on the reason behind this phenomenon using fractals measures in our future research.

5.3. Management Implications

Due to economic reform and the open-up policy, the Wen-Tai region has enjoyed a series of preferential policies that emphasize the development of environment, economy, and society with increased focus on little towns and villages. Built-up lands are specifically located for living close to and engaging in economic, political, and cultural activities, coastal zones are vulnerable to human activities [25]. The rapid urban growth influences new characteristics and new trends for the local urbanization. For coastal areas, the attention is increasingly paid to sustainable district development, thus urbanization development should be sustainable. Since there is an absence of uniform planning for built-up land, the spatial distribution of built-up land is characterized by weak control of urban development. This unplanned urban sprawl can result in severe wastage of land resources, irrational built-up land structures, and restriction on the processes of rural developments. This was especially true for the Wen-Tai region, which is characterized by a majority of hill lands and some small plains. Built-up lands are historically located in the narrow plains near the sea in eastern areas. Yet, low levels of human activity have impacts on the hill land areas. Since the 1990s, the Chinese government has taken many measures to balance development between urban and non-urban areas. The special national conditions in China tells us that the economic increase requires us to pay more attention to science-based built-up land use planning. Managers are willing to develop efficient tools to facilitate the identification of urban sustainability, and therefore quantitative assessment urban morphology is urgently needed [27].

In this study, the general characteristics of built-up land expansion across the Wen-Tai region were identified through fractal dimension analysis. Fractal analysis can provide practical and significant results, thus it can meet the needs of city managers. For example, farmlands are occupied by built-up land in urban areas due to the human activities, and this process can be quantitatively calculated by fractal method. Although economies have developed, the trends of land use multiplicity and fragmentation have also increased along with dominance and concentration. This may restrict the sustainability of agricultural development. The reform and opening-up policy has led coastal China, especially the Wen-Tai region, toward rapid development of the market economy and a good investment environment. The variability of the fractal dimension can indicate the spatial pattern of potential pressure on vulnerability for this coastal region. Rapid and uncontrolled development has occurred in non-urban areas, which resulted in increased urban sprawl. This is the reason why increases in economics, local infrastructure development, and industrialization have made people move from non-urban areas to the urban areas, accelerating urbanization. Under the force of market economic mechanisms, most people leave their rural homes for urban areas, because of their concentration in the urban areas, and the decreasing trend of agricultural activity becoming more and more apparent.

6. Conclusions

This study employed the fractal theory, spatial autocorrelation, and spatial regression methodologies to identify the built-up land expansion and its correlations in eastern coastal China. The main findings were summarized as follows:

(1) Fractal dimension values increased significantly during the ten years, which means that urban growth brought a more complex, scattered and disordered distribution of built-up land patches in Wen-Tai region. If this trend continues, complex and fragmented landscapes will increase rapidly with urbanization, which might lead to the inefficient usage of built-up land resources. Accordingly, the authors suggest that local government implement reasonable built-up land plans by balancing economic growth with the construction of settlements and industrial land in order to guide the city toward sustainable development.

(2) Landscape shape index and GDP played a key role in determining the fractal dimension of urban area. There is a trend in China that governments pay much more attention on improving economics, but ignore the optimization of urban spatial patterns and land utilization structure.

This study showed that the government should give more consideration to the reasonable planning of urban layouts during economic development rather than focusing only on the growth of GDP. In addition, the government should, in future urban planning, consider the impact of landscape shape index, which would play an important role in urban construction.

(3) The application of spatial regression in analyzing the correlation between fractal dimension and its associated factors can also be used for other urban growth research on other spatial scales. Our study implies that long-term management should also be adopted by governments to control the development of urban growth.

(4) This study also incorporates limitations. For one thing, the dataset covered a very limited temporal dimension. For another, the complex interactive relationships among land use and management were not considered. Further studies will be carried out regarding these points.

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