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Article

Fractal Characterization of Settlement Patterns and Their Spatial Determinants in Coastal Zones

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Abstract: Using box-counting and spatial regression, this paper analyzes the morphological characteristics of coastal settlement patterns and their spatial determinants, with a case of the Wen-Tai region on the Chinese eastern coast. Coastal settlement patterns, which reflect the interactions between people and the surrounding environment, can indicate the anthropogenic pressure sustained in the coastal zones. Characterization of settlement patterns in coastal zones is definitely needed for coastal management. Results indicate that coastal settlement patterns in the Wen-Tai region present significant fractal characteristics, and exhibit obvious spatial variations. The morphological characteristics of settlement patterns are significantly correlated with the standard deviation value of elevation and slope, as well as percentage of loam soils. In particular, cities with greater relief amplitude, higher slope variability, and higher percentage of loam soils would present more complexity in form. Proximity to roads and rivers are insignificant determinants. Our study contributes to the understanding of the spatial determinants of the morphological characteristics of settlement patterns in coastal zones. We argue that fractal dimension provides a useful tool to facilitate the identification of vulnerability hotspots for coastal studies.

Keywords: fractal dimension; settlement patterns; coastal zone; spatial determinants; spatial regression

1. Introduction

In geography, settlements are hamlets, towns, villages, and other agglomerations of buildings in which people live. They can range in size from a small number of dwellings grouped together to large cities. Settlement patterns act as one of the most fundamental link between people and the Earth, and reflect the interactions between people with the surrounding environment. Scientists, therefore, always characterize human pressure by analyzing the spatial characteristics of settlement patterns. Settlements are consequently influenced by various environmental factors such as topography, water accessibility, transportation proximity, and so forth [1–3]. Given the significant spatial heterogeneity of these environmental factors, human settlements exhibit great spatial variations across space at various spatial scales [4]. Characterization of settlement patterns and their spatial variations across space in coastal zones can contribute to understanding of the anthropogenic pressure sustained by the coastal zones.

Though literature of human settlements patterns is on the rise [5,6], detailed cases of coastal settlements are quite few. Previous studies mostly focused on certain aspects of settlement spatial characteristics like distribution, density, and size [7,8]. However, the morphological characteristics of human settlements, which indicate the dense or complex degree of population distribution, were not given enough attention. Morphological measurement of human settlements is important for land use planning [7,9–12], since it can provide a systemic analysis to describe spatial form of human settlements. Human settlements usually have complex morphological characteristics at different scales [9,10]. Fractal geometry provides an effective solution to describe the disorder and irregularity of complex systems [7,10,13–16]. Fractal geometry has been explored in interdisciplinary research and applied to analyze problems in ecology [17,18], geology [19], and physics [20]. Additionally, fractal geometry has gradually emerged as a basic tool in characterizing the morphological features in geospatial science, including urban growth [21–23], urban boundary [24], and urban landscape patterns [25–27]. Few studies applied fractal geometry to characterize the morphological features of settlements. In addition, rare studies have been conducted to analyze the spatial determinants of the morphological characteristics of human settlements [28].

Considering the above issues, the primary objective of this paper is to examine the fractal characteristics of human settlements and their spatial determinants in coastal zones. The study was facilitated by data collected from the Wen-Tai region, a typical part of the Chinese eastern coast. Specifically, this study aims to (1) analyze the fractal characteristics of human settlements and their spatial variations in 15 cities across the Wen-Tai region; (2) identify the spatial determinants of the morphological characteristics of human settlements; and (3) discuss some implications for coastal management.

2. Study Area

The Wen-Tai region, with a spatial extent of 27°03′–29°08′N and 119°37′–121°26′E, belongs to Zhejiang province, lies in the southeastern part of eastern coastal China (Figure 1). Constituted by 15 cities, it covers approximately 21,000 km^2 and has a population of 13.7 million in 2008 [29]. With moderate temperatures and abundant precipitation, the region has traditional monsoons, distinct seasons, and changeable climates. High mountains are generally located in the southern part, with the highest value of 1611 meters. The western areas are mostly covered by plains with complex river and road networks.

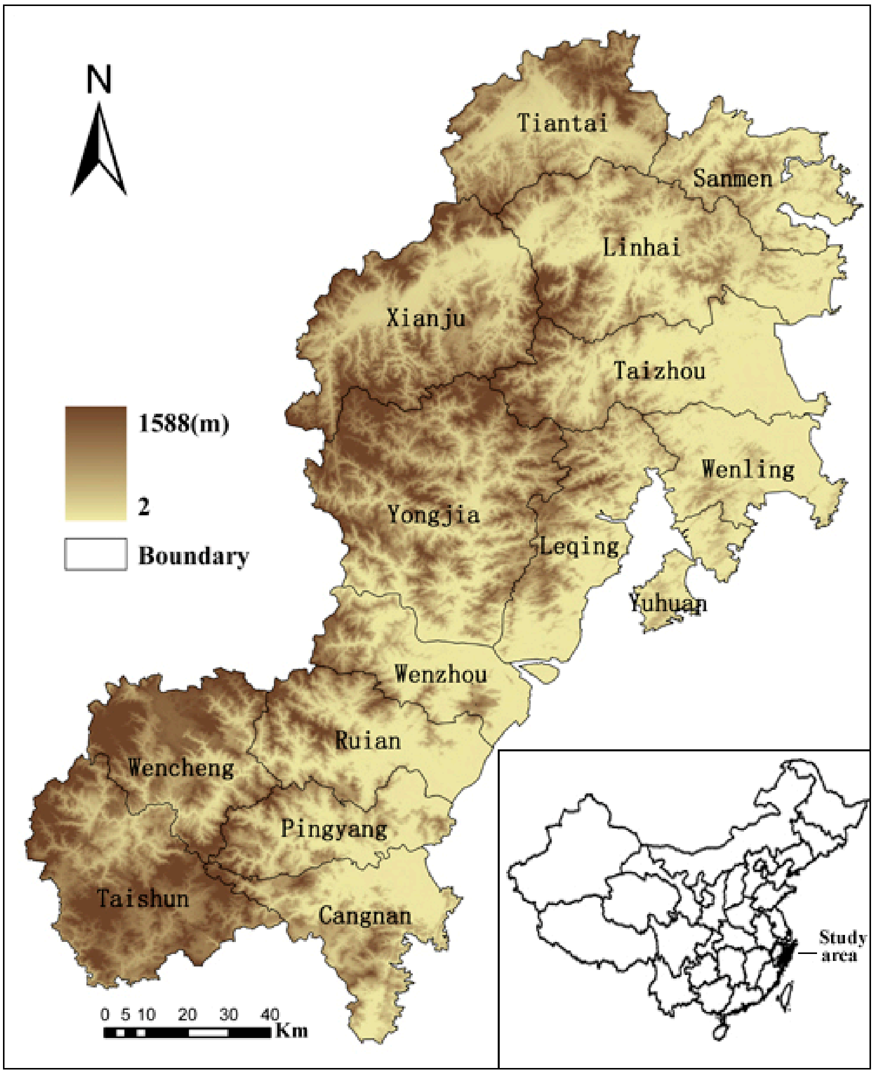

Figure 1. Location of the Wen-Tai region, China.

Since China initiated the economic reform and opening-up policy in 1978, China has focused on the development of the eastern coastal area [30]. The Wen-Tai region witnessed explosive socioeconomic development as other regions in coastal China. For the last twenty years the population in Wen-Tai increased by 16%, and GDP increased by 3475% [29]. Such rapid socioeconomic development can adequately represent the conditions of most coastal regions in China and other parts of the world. The Wen-Tai region, therefore, provides a typical case to analyze the spatial characteristics of coastal settlement patterns.

3. Materials and Method

3.1. Fractal Dimension

3.1.1. Fractal and Fractal Dimension

Fractals are self-similar patterns, in which a fragmented or rough geometric shape is subdivided into parts, and each of the parts is a reduced-size copy of the whole [31], so it can repeat itself on an increasingly smaller scale. Fractal dimension is able to measure fractals by identifying the self-similar characteristics of irregular objectives in different aspects, such as form, function, information and so on, through changing scales. Objects have dimension 0 (points), dimension 1 (line segments), 2 (squares), and 3 (cubes), respectively. Fractal dimension represents its characteristics as the form of a point, a line, or an area feature increases more geometrically complex [32]. Fractal dimensions can be calculated in a variety of ways, including the Calliper method, the box-counting method, the pixel-dilation method, the mass-radius method, and so on [33]. All of these methods are able to analyze spatial objects for a range of scales [9]. Moreover, in spatial pattern analysis, the box-counting method is usually used in computing fractal dimensions [9].

3.1.2. Box-Counting Dimension

Box counting is a data gathering process that analyzes complex patterns. Suppose we have a number of boxes with the same side length r to cover an object in R^n. Let N(r) denotes the number of such boxes. These boxes have area r^n, and they are scaled by a factor of $(1/r)^n$. If we take a simple square of length s and cover it with boxes of area r^n, we can determine N(r) as follows:

$$S^2 = N(r) \times r^n \tag{1}$$

$$N(r) = S^2 / r^n \tag{2}$$

$$N(r) = S^2 \times (1/r)^n \tag{3}$$

Since s^2 is a constant, we can denote it by C, thus:

$$N(r) = C \times (1/r)^n \tag{4}$$

Solving for n yields:

$$n = \frac{\ln N(r) - \ln(c)}{\ln(1/r)} \tag{5}$$

n is the dimension of our object. Since *C* is a constant, we can ignore it for our purposes. If we take the limit of this formula as *r* approaches zero, we get the formula for box dimension:

$$D_B(S) = \lim_{r \to 0} \frac{\ln N(r)}{\ln(1/r)} \tag{6}$$

A graph of log(N(r)) *versus* log(r) is plotted and a linear regression is modeled. If the human settlements have a fractal distribution, the plot gives a straight line with a slope D. In all cases, the largest box size was ignored because the size of the study area can determine its side length r [34]. A random distribution of human settlements points would produce a D value of 2, and as the points become more clustered, the value of D approaches zero. However, this method does not describe how clustering may vary within the study area [35].

In this study, fractal dimensions were calculated on a 50 km grid across the Wen-Tai region. The box sizes used in the four-level box count are 50, 25, 10, 5, 2.5, and 1 km. The 50 km grid spacing is appropriate for the level of geological details in the 1:50,000-scale map of the Wen-Tai region, based on the methodology of Gillespie *et al.* [36], Walsh and Watterson [37] and Raines [38]. The log-log approach was used to find the box counting fractal dimension[33]. In order to obtain a good trend line, it is important to decide the crossover point and which points are useful to model a good function [34]. We selected a cell-size interval that maximizes the R^2 to find trend lines interactively [39]. Typically, the R^2 value close to 0.99 is able to be obtained, thus in our research all the R^2, both before and after the crossover point are higher than 0.99. Then, the model functions are obtained. We used Origin 8 software to calculate FD (Fractal Dimension value) and plot the figures.

3.2. GIS Analysis

Point vector data of settlements (1: 50,000 scale; year 2012) (Figure 2) and digital maps (1:50,000) of road/river networks were obtained from the National Surveying and Mapping Bureau. The centroid coordinate of each village was used to represent its location as a form of points for all villages recorded in the original settlement vector map. We clipped the corresponding data for the Wen-Tai region from the national point data of settlements in ArcGIS 9.3, and it was also used to calculate the box-counting dimension by converting the vector to raster in different appropriate cell sizes to determine the number of cells. Preliminary experiments were carried out for many times, we chose the intervals as 600, 700, 800, 900, 1000, 2500, 5000, 10,000, 25,000, and 50,000 meters. After calculating the different number of boxes at different scales we obtained the log-log plot. Then Origin software was used to model the curves and two straight-line segments to indicate the fractal domain.

Geographic factors were selected to interpret the influences of surrounding environmental situation on the fractal dimension of human settlement patterns. These spatial determinants included mean and standard deviation values of elevation (elevation_mean, elevation_std), slope (slope_mean, slope_std), distance to rivers (river_mean, river_std), distance to roads (road_mean, road_std), and percentage of soil texture (sand%, loam%, clay-loam%, clay%). They were selected because they usually significantly affect the choice of human settlement locations [4,40]. To calculate the distance to roads and rivers for every settlement point, we first generated a set of distance raster surfaces using the Euclidean Distance module in ArcGIS 9.3, and then extracted variable values for each point from the generated distance raster surfaces. In addition, we extracted slope and aspect information from a 30 m digital elevation model (DEM). Through neighborhood statistics operations in ArcGIS 9.3, we generated raster surfaces, and their values were extracted from the generated raster surfaces for all settlement points.

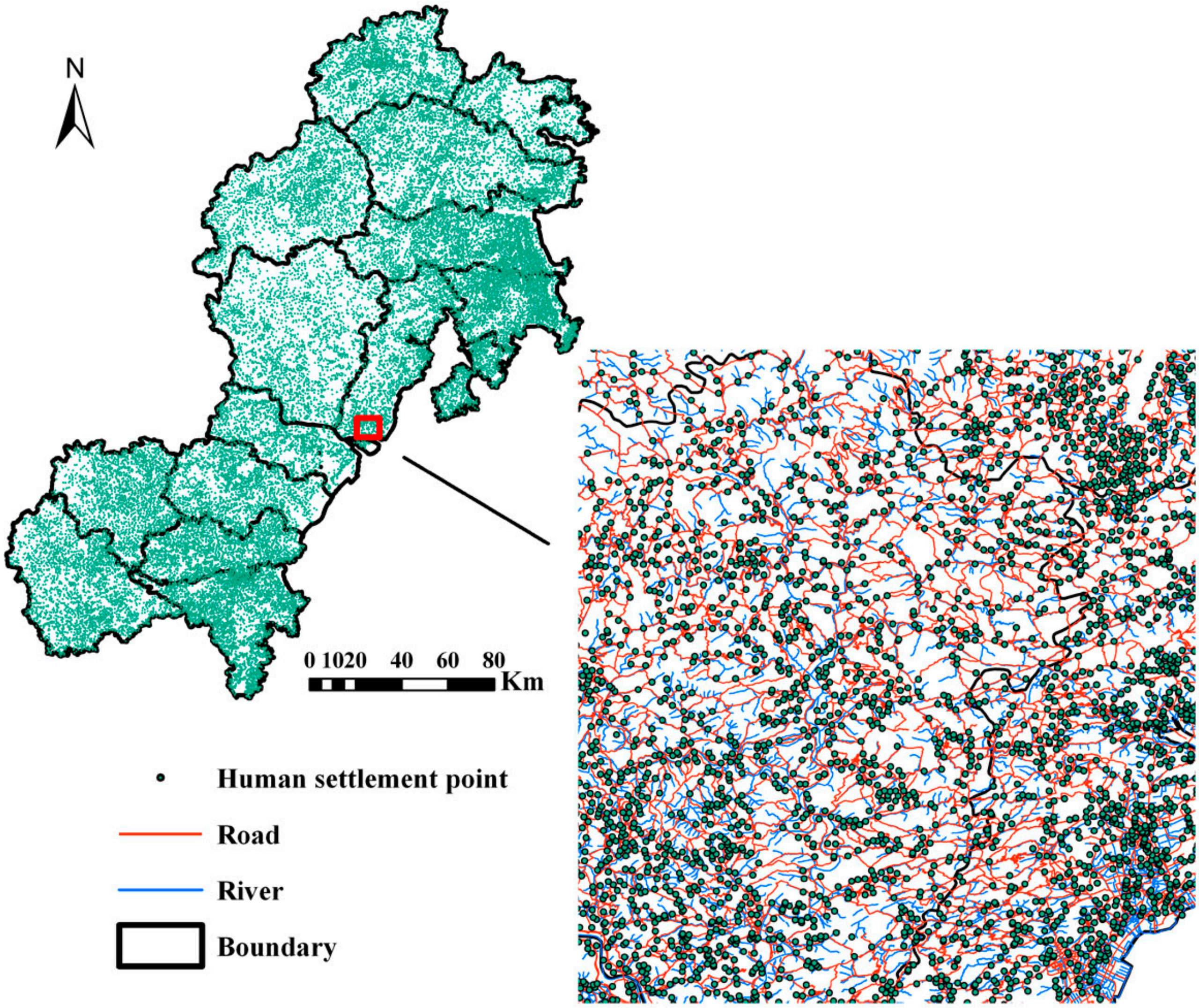

Figure 2. Spatial patterns of settlement locations, roads, and rivers across the Wen-Tai region, China.

3.3. Spatial Regression

Spatial lag/error regression was used to determine the relationships between fractal dimensions of settlement patterns and spatial determinants. The equation of the spatial lag model is given by Anselin [41]:

$$y_i = \rho\sum w_{ij}y_i + x_i\beta + \varepsilon_i \quad (7)$$

where i represents spatial units at different scales, y_i is a vector of observations on the dependent variable, w_{ij} is an element of a spatial weights matrix W, x_i is a matrix of observations on the explanatory variables, ε_i is a vector of error terms, and ρ and β are parameters.

The equation of spatial error model is given by Anselin [41]:

$$y_i = x_i\beta + \varepsilon_i \quad (8)$$

$$y_i = \lambda\sum W_{ij}\varepsilon_i + \mu_i \quad (9)$$

where y_i is a vector of observations on the dependent variable, w_{ij} is the spatial weights matrix, x_i is a matrix of observations on the explanatory variables, ε_i is a vector of spatially auto-correlated error terms, μ_i is a vector of error terms, and λ and β are parameters.

Based on the Lagrange Multiplier diagnostics Anselin [42], application of an appropriate algorithm for spatial regression (error or lag) was performed using GeoDa 0.9.5-i (Beta) software by Anselin [42]. All regression models were performed using the fractal dimension as the dependent variable and spatial determinants as independent variables.

4. Results and discussion

4.1. Fractal Dimension of Human Settlement Patterns

Figure 3 shows the modeling regression of the 15 cities. The slope of each regression function was the fractal dimension value of each city. The linear log-log plots and high R^2 values indicated that settlement pattern in the Wen-Tai region presented significant fractal characteristics. In particular, th ebox-counting dimension was represented by a piecewise function in the log-log plot. All the curves had a crossover point which formed two linear functions and two slopes. The linear function before the crossover point had a smaller slope, which denoted a smaller value of fractal dimension. The linear function after the crossover point had a larger slope, suggesting that at these scales the change of side length of the box had more significant influence on the number of boxes.

The sharp change of human settlements' spatial occupation before and after the crossover point indicated the scale variations and aggregated level in spatial patterns. Fractal dimensions identified the two-dimensional spatial occupation extent of human settlement as an integrated unit, with fractal dimension values ranging from 1 to 2; while fractal dimensions at the small scale represented the two-dimensional spatial occupation extent of points, with fractal dimension value ranging from 0 to 1. Considering these, we focused on the fractal dimensions at large scales.

Table 1 displayed the fractal dimension values of each city. Fractal dimensions ranged from 1.3727 to 1.6177, indicating variations in the clustering of the occurrences. Xianju had the highest fractal dimension value and Yuhuan the lowest value. The fractal dimension of a city can be taken as an indicator of the complexity or dispersion of this city from Cai *et al.* [43]. Based on the results of Tannier and Thomas [21], higher values suggested more complex of fractal dimension. Therefore, the most complex form existed in Xianju, and the most regular form existed in Yuhuan.

A city with a larger number of settlement points usually had higher fractal dimensions, given that human settlements were more space filling and, consequently, had higher dimensions [44]. However, the situation is opposite in our research. For example, Taizhou had more settlement points than Xianju and Taishun, but presented a lower fractal dimension. In addition, Ruian had a lower number of settlement points than Yongjia and Cangnan, but presented higher fractal dimension. This implied that the number of settlements is not the dominant factor of calculating FD.

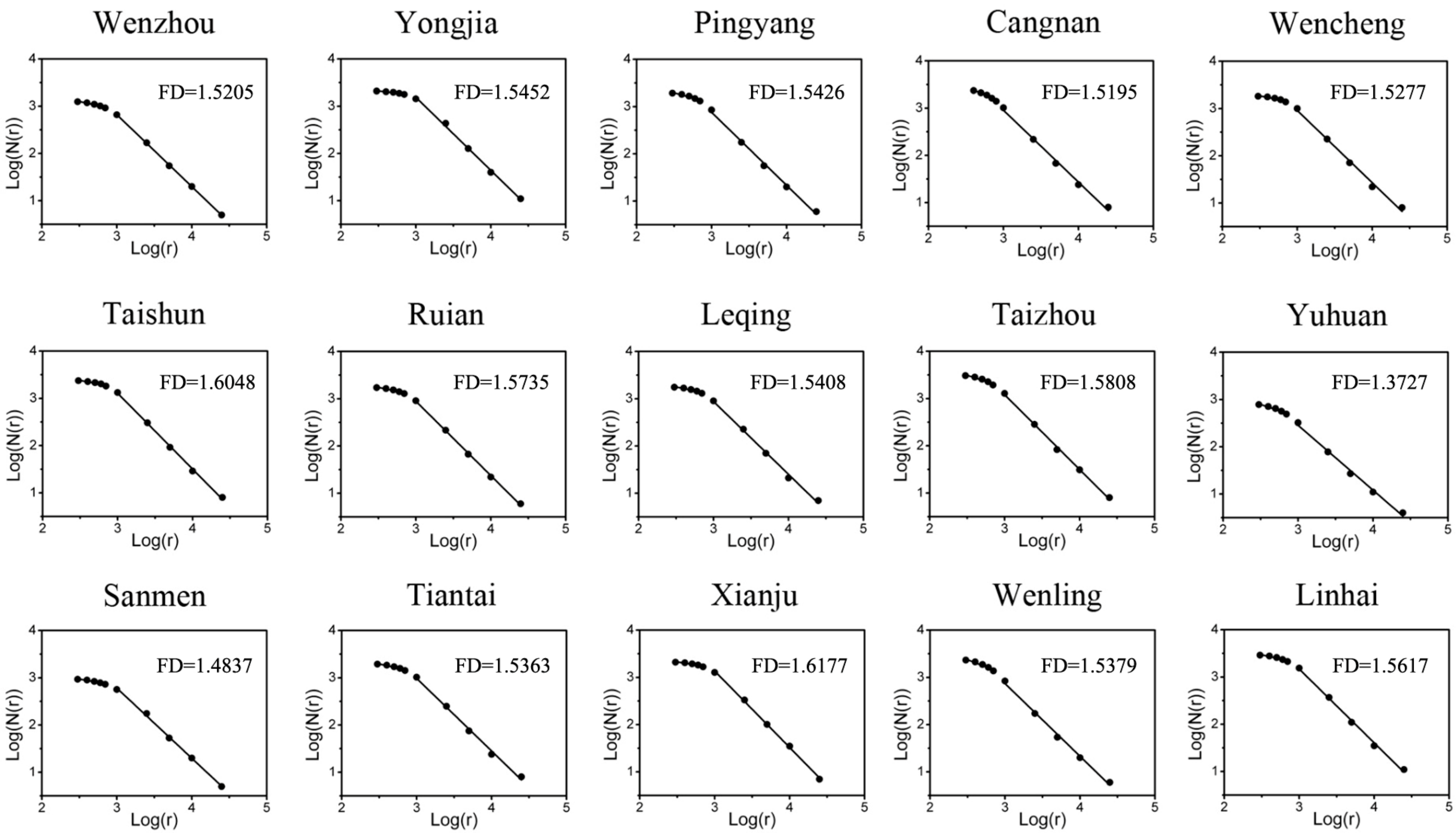

Figure 3. Graphs of number of boxes N(r) against box side length (in meters) on logarithmic scales for each city across the Wen-Tai region, China. (FD = Fractal Dimension value).

Table 1. Fractal dimension values of each city across the Wen-Tai region, China.

Study Area	N	D_B	R^2	Crossover Point (m)
Wenzhou	1330	1.5205	0.9998	995.7264
Yongjia	2152	1.5452	0.9975	1081.909
Pingyang	2096	1.5426	0.9964	665.9738
Cangnan	2709	1.5195	0.9945	535.1751
Wencheng	1925	1.5277	0.9936	841.997
Taishun	2433	1.6048	0.9986	950.6467
Ruian	1805	1.5735	0.9991	940.769
Leqing	1917	1.5408	0.9961	924.269
Taizhou	3568	1.5808	0.9982	845.5723
Yuhuan	905	1.3727	0.9938	526.7021
Sanmen	1050	1.4837	0.9984	995.5408
Tiantai	2217	1.5363	0.9958	897.9551
Xianju	2243	1.6177	0.9989	1020.453
Wenling	2689	1.5379	0.9957	433.6554
Linhai	3371	1.5617	0.9968	925.4678

N is the number of residential points; D_B denotes the line slope

4.2. Spatial Determinants of Settlement Fractal Dimensions

As shown in Table 2, fractal dimensions were significantly associated with elevation_std and slope_std. Such results implied that the city with greater relief amplitude and higher slope variability always exhibited more complex form. Most settlements were aggregated within the plain areas, while those distributed in higher and steeper mountains were quite scattered and disorderly. Therefore, when a city has more steep mountainous lands, human settlements would become more isolated and scattered, and the city pattern would be more complex.

Table 2. Relationships between settlement fractal dimensions and geographical determinants across the Wen-Tai region.

Y	X	Model	R^2	Sig
Fractal dimension	elevation_mean	NS^c		
	elevation_std	$Y^b = 0.0007 \times X + 1.42$ (LAMBDA = −0.33)	0.52	**
	slope_mean	NS^c		
	slope_std	$Y^a = -0.95 \times WY + 0.055 \times X + 2.74$	0.63	**
	road_mean	NS^c		
	road_std	NS^c		
	river_mean	NS^c		
	river_std	NS^c		
	sand%	NS^c		
	loam%	$Y^a = 0.07 \times WY + 0.22 \times X + 1.44$	0.56	**
	clay-loam%	NS^c		
	clay%	NS^c		

** Significant at 99% confidence level. [a]. Spatial lag models; WY = weighted mean of fractal dimension for adjacent stations. [b]. Spatial error models. NS^c. No significant relationships were identified by spatial regression.

Table 2 also shows that loam% displayed positive relation with fractal dimension. This means that a higher percentage of loam soils in these cities would lead to more complexity of urban forms. Loam soils can retain water and nutrients and can also filter excess water, which indicates that loam soils are suitable for gardening and agricultural uses. Some studies pointed out that human settlements usually displayed scattered patterns among agricultural patches in eastern coastal China [4]. Therefore, when loam soils become dominant, the patterns of human settlements across these soils may become more random and dispersed. Considering R^2, this showed that slope and percentage of loam can explain more than 50% of the variations.

Previous studies demonstrated that proximity to road or river had significant impacts on the distribution, density, and size of human settlements. Our results showed that proximity to road or river were insignificant indicators for the morphological characteristics of settlement patterns. Specifically, the spatial lag model was suitable for slope_std and loam%. Such results suggested that settlement fractal dimensions not only depended on slope and soil texture, but also on settlement fractal dimensions of neighboring cities. The spatial error model was suitable for elevation_std. It implied that some environmental factors that were not incorporated in the regression would be auto-correlated over space [45,46].

4.3. Management Implications

Coastal zones are vulnerable to human activities. Disproportionately distributed across the coast, human settlement patterns lead to vulnerability hotspots through interacting with the surrounding resources [47]. Managers are eager to develop tools to facilitate the identification of vulnerability hotspots. Fractal analysis meets management needs, since it can produce results of practical significance. For example, fractal dimension indicates the dispersion and complexity of human settlement patterns. Dispersed settlements are prone to making the adjacent natural area to be consumed, degraded, isolated, and fragmented [48], threatening biodiversity and sustainability [49]. Additionally, complexly-formed settlements are unstable and, therefore, have higher probability to sprawl, increasing more opportunity of adverse ecological effects, such as urban heat island and soil sealing [50]. Variability of fractal dimension, therefore, can indicate the spatial distribution of potential pressure on coastal vulnerability for the Wen-Tai region. In addition, the identified environmental factors governing settlement fractal dimensions can also be employed to map hotspots of vulnerability pressure. For example, cities with higher slope variability and greater relief amplitude are more likely to be vulnerability hotspots along the coast. We consequently argue that fractal dimension provides a useful tool to facilitate the identification of vulnerability hotspots for coastal management.

5. Conclusions

This study employed the fractal theory and spatial regression to analyze the morphological characteristics of human settlement patterns and their spatial determinants in a coastal zone. The main findings were summarized as follows:

1. Settlement patterns in the Wen-Tai region presented significant fractal characteristics and exhibited obvious spatial variations. The pattern of settlements, rather than the number of settlements, was more influential factor for the fractal dimension.

2. Elevation, slope, and percentage of loam soils were the primary spatial determinants of settlement fractal dimensions. Especially, cities with greater relief amplitude and higher slope variability always exhibit more complex form, and cities with a higher percentage of loam soils have more complicated patterns.
3. Proximity to road or river were insignificant indicators for the morphological characteristics of settlement patterns.
4. Settlement fractal dimensions not only depended on slope and soil texture, but also on settlement fractal dimensions of neighboring cities.

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Author Contributions

All authors contributed equally to this work. Zhonghao Zhang and Rui Xiao conceived and designed the experiments. Xiaoqin Yang and Zhonghao Zhang analyzed the data; Zhonghao Zhang wrote the paper.

Conflicts of Interest

The authors declare no conflict of interest.

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