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Impacting Factors and Temporal and Spatial Differentiation of Land Subsidence in Shanghai

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Abstract: This paper uses Grey Correlation Degree Analysis (GCDA) to obtain and compare the relationships between major impacting factors and land subsidence, and finds the spatial characteristics of subsidence in the urban centre by Exploratory Spatial Data Analysis (ESDA). The results show the following: (1) Annual ground subsidence in Shanghai has occurred in four stages: slow growth in the 1980s, rapid growth in the 1990s, gradual decline in the first decade of the 21st century, and steady development currently. (2) In general, natural impact factors on land subsidence are more significant than social factors. Sea-level rise has the most impact among the natural factors, and permanent residents have the most impact among the social factors. (3) The average annual subsidence of the urban centre has undergone the following stages: "weak spatial autocorrelation" → "strong spatial autocorrelation" → "weak spatial autocorrelation". (4) The "high clustering" spatial pattern in 1978 gradually disintegrated. There has been no obvious spatial clustering since 2000, and the spatial distribution of subsidence tends to be discrete and random.

Keywords: land subsidence; natural factors; social factors; spatial distribution; clustering pattern

1. Introduction

Land subsidence is the downward displacement of a land surface relative to a certain reference surface, such as mean sea level (MSL) or a reference ellipsoid [1]. Subsidence is mainly caused by the compression of unconsolidated strata, which is due to natural and/or human activities. With a wide impact and long duration, land subsidence is a cumulative, uncompensated permanent loss of environments and resources [2,3]. Subsidence negatively impacts the living environment of human beings, regional ecological security, and the sustainable development of a region. Land subsidence has occurred in more than 50 countries and regions since it was first discovered in Niigata, Japan in 1898 [4]. There are many countries with substantial land subsidence, such as Japan, the United States, Mexico, Italy, Thailand, and China. In China, land subsidence was first discovered in Shanghai in 1921 [5]. According to the estimated result of Zhang et al. (2003), land subsidence caused direct and indirect economic losses of 294.307 billion yuan RMB (35.56 billion USD) in Shanghai from 1921 to 2000, and this number has reached approximately 24.57 billion yuan RMB (2.97 billion USD) from 2001 to 2003 [6]. Shanghai is the economic and financial centre of China and is important for local and national economic development. The land subsidence in Shanghai causes frequent damages of municipal infrastructure and impedes the construction and resource development activities, and is responsible for huge economic and ecological losses. It is the most serious geological disaster that Shanghai is facing at the present stage, and one of the serious obstacles for Shanghai to achieve sustainable development. Therefore, studying the impacting factors and temporal and spatial distribution patterns of land subsidence in Shanghai is important.

As a global, ubiquitous, and long-standing geological problem, land subsidence has attracted worldwide attention. Many studies all over the world pay attention to the causes of land subsidence, monitoring techniques, disaster assessments, and governance measures. Rahman et al. (2018) explored the causes of land subsidence along the coast of Jakarta and found that erection weight and groundwater exploitation are the main causes in the region [7]. Ma et al. (2011) found that high-rise buildings and over-exploitation of groundwater are the main causes in Tanggu [8]. Xu et al. (2016) proposed four main causes in the urban centre of Shanghai: additional loading caused by the construction of infrastructure, the cut-off effect due to construction in aquifers, drawdown of the groundwater level caused by leakage into underground structures, and the decrease in groundwater recharge from neighbouring zones [9]. For monitoring technologies, the current methods for land subsidence include levelling methods, trigonometric elevation methods, digital photogrammetry methods, InSAR methods, ground subsidence monitoring stations, and groundwater monitoring [10,11]. Sun et al. (2017) used the multi-track PS-InSAR technique to monitor land subsidence [12]. Mateos et al. (2017) integrated detailed geological and hydrogeological information with PSInSAR (persistent scatterer interferomtric synthetic aperture radar) data to analyse the land subsidence process in the Vega de Granada in Spain [13]. Liu et al. (2011) found that D-InSAR accurately monitors the deformation of a large area [14]. In terms of disaster assessment, Chen (2016) put forward a conceptual framework for the development of an indicator system for the assessment of regional land subsidence disaster vulnerability [15]. Abidin et al. (2013) concentrated on the roles of geospatial information for risk assessment of land subsidence [1]. Bhattarai and Kondoh (2017) accomplished a comprehensive risk assessment of land subsidence in Kathmandu Valley [16]. In terms of governance measures, Takagi (2018) studied the effectiveness and limitations of coastal embankments in controlling land subsidence in Jakarta [17]. Sun et al. (2011) proposed policy recommendations to control coastal land subsidence in Taiwan [18].

In general, most of the existing studies show the following features: (1) The majority of studies mainly consider natural factors. (2) They commonly adopted methods of traditional mathematical statistics, which had some limitations in chronological and spatial analysis. (3) Most studies with spatial analysis only described spatial distribution in a simple qualitative manner rather than studying spatial information in detail using quantitative methods.

This paper integrates natural factors and socio-economic factors to analyse the dynamic mechanism of land subsidence because a city is a compound natural-social-economic system. The impacting factors selected in this paper are shown in Table 1. The reasons for these factors are selected as follows: (1) Over-exploitation of groundwater reduces the buoyancy of the underground aquifer [19,20] and changes the stress of the stratum. Both of these reactions cause land subsidence [21–24] by affecting the consolidation of the soil. Related studies found that groundwater exploitation is one of the major causes of land subsidence in Shanghai [4]. (2) Sea-level rise is an increase in global mean sea level as a result of an increase in the volume of water in the oceans. Sea-level rise is usually attributed to global climate change by thermal expansion of ocean water and melting of ice sheets and glaciers [25]. It worsens the land subsidence severely. (3) After economic reform and open up, rapid urbanization resulted in a large increase in permanent residents [26] and human activities, which negatively impacted land subsidence. (4) The urban industry has developed rapidly since the 1980s. Undoubtedly, the fast growth of GDP has contributed to dramatic changes in the natural environment [27] and the large consumption of water, natural gas, petroleum, and other resources and energy which are extracted from the ground [28]. Mining activities destabilize stratums, so they have a bad impact on land subsidence [29]. (5) Transportation is an important link that connects regions and transports people and logistics for urban development [30]. The increasing load on the road made the land subsidence more serious by promoting consolidation and compression of topsoil [31,32]. (6) Relevant studies show that the number of high-rise buildings has become a new cause of land subsidence in the process of urbanization [33]. (7) Rapid expansion of high-rise building area has become one of the main causes of the seriously increasing land subsidence in Shanghai [34].

Table 1. The impacting factors of land subsidence in Shanghai.

	Impacting Factors
Natural Factors	Groundwater exploitation Sea-level rise
Social Factors	Permanent resident growth GDP growth Increase of the civil vehicle number Increasing number of high-rise buildings Expansion of high-rise buildings area

Compared with the previous studies, innovations of the study are as follows: (1) It supplements social factors and compares them with natural factors [35]. (2) This paper expands the new perspective by analysing annual growth (i.e., the incremental effect) of impacting factors while most of the existing researches [7–9] analyse the influence of statistics (i.e., the scale effect in the paper) on the land subsidence. (3) GCDA is used in the study instead of mathematical statistics, because of in the analysis of long-term variable data, the GCDA results in an improved integrity and dynamic than those of the traditional mathematical statistics [36]. (4) ESDA was used in the spatial analysis of land subsidence in Shanghai to describe and analyse its spatial characteristics quantitatively in detail.

2. Material and Methods

2.1. Overview of the Study Area

Shanghai is located in the Yangtze River Delta on the south edge of the estuary of the Yangtze on the East Chinese coast. Shanghai faces Kyushu Island with the East China Sea in between. It borders Hangzhou Bay in the south, Jiangsu Province in the north, and Zhejiang in the west [37]. Shanghai is one of the four direct-controlled municipalities of China and one of the most populous cities in the world with a population of more than 24 million in 2016. The city is a global financial centre [38] and transport hub with the busiest container port in the world [39]. Shanghai consists of 16 districts of which there are seven districts in the central city and nine districts in the suburbs (Figure 1).

Figure 1. The administrative regions of Shanghai.

2.2. *Data Source and Methodology*

2.2.1. Data Source

The Shanghai land subsidence data and groundwater exploitation data used in this study are provided by the Shanghai Environmental Geological Bulletin. The land subsidence raster data with a resolution of 30 m × 30 m is obtained by interpolating the Shanghai land subsidence contour maps. The permanent residents, GDP (Gross Domestic Product), and number and area of high-rise buildings are provided by the Shanghai Statistical Yearbook. Sea-level data is collected based on historical tidal level data from the Shanghai tide gauge station shared by the Permanent Service for Mean Sea Level (http://www.psmsl.org/). The civil vehicles data is from the Qianzhan Database (https://d.qianzhan.com/xdata/details/a004230075771a68.html).

(1) Groundwater exploitation

The first deep well was drilled in Shanghai in 1960, which was when the city began to systematically extract groundwater to provide water for human activities. In addition, rapid industrial development in the 1980s led to a rapid increase in groundwater exploitation, though it has been controlled since 1965. Subsequently, Shanghai recharged underground aquifers with tap water to raise the groundwater level and restore soil elasticity. Overall, after economic reform and open up of China, the exploitation of groundwater in Shanghai increased year by year in the 1980s, increased first and then decreased in the 1990s, and then rapidly decreased after 2000 (Figure 2).

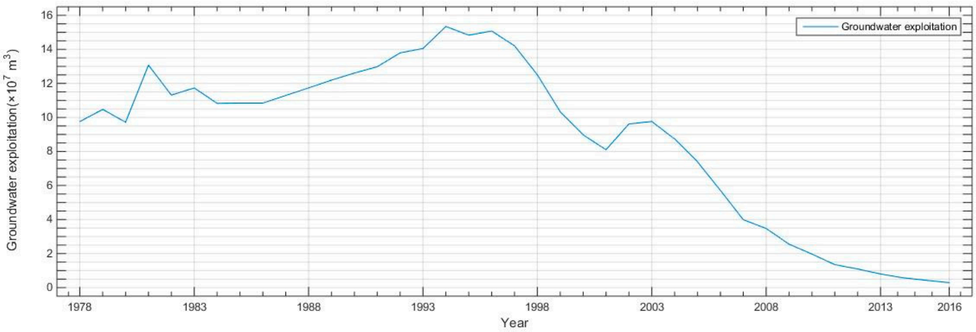

Figure 2. Change in groundwater exploitation in Shanghai.

(2) Sea-level rise

Monitoring data shows that the global sea level has risen by 10–20 centimetres over the past 100 years, and it will rise faster in the future [40]. Obviously, irreversible sea-level rise and serious land subsidence will severely threaten urban development on account of the average ground elevation, which is only slightly higher than sea level in Shanghai [41,42]. According to Figure 3, sea level has been rising with fluctuations since 1978. Sea level rose 96.92 mm from 1978 to 1989, 48.75 mm from 1990 to 2000, and 89.17 mm from 2011 to 2016. Furthermore, sea level was generally stable from 2001 to 2010.

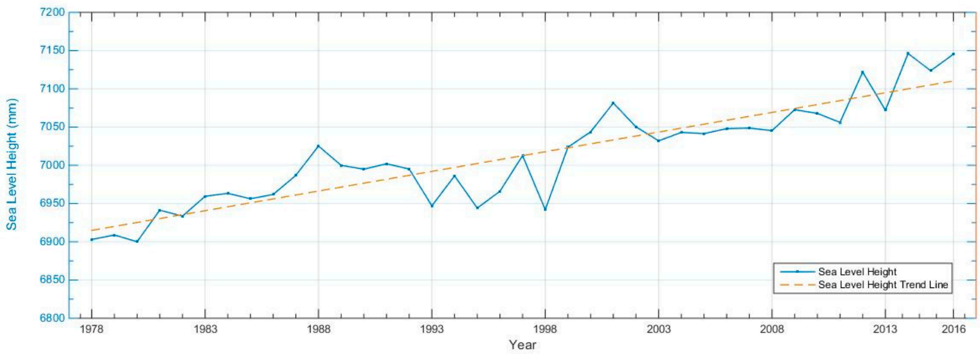

Figure 3. Sea-level change in Shanghai.

(3) Permanent resident growth

The number of permanent residents in Shanghai increased by 2.07 million, with an annual average increase of 186,800 from 1978 to 1989. The permanent residents increased by 2.75 million, reaching an annual average growth of 270,900 from 1990 to 2000 (Table 2). Moreover, the population has increased sharply since 2000 to 23.03 million at the end of 2010 and 24.20 million in 2016.

Table 2. Incremental data of land subsidence and impacting factors.

Year	1978–1989	1990–2000	2001–2010	2011–2016
Average annual subsidence (mm)	3.50	14.30	8.52	5.36
Average annual groundwater exploitation ($\times 10^4$ m^3)	11,149.27	13,154.16	6130.09	756.47
Average annual sea-level rise (mm)	9.26	4.38	2.42	12.92
Average annual permanent resident growth ($\times 10^4$)	18.68	27.09	69.40	19.51
Average annual GDP growth ($\times 10^8$ yuan)	38.85	370.42	1266.20	1790.91
Average annual increase of the civil vehicle number ($\times 10^4$)	1.19	7.70	20.54	8.30
Average annual growth in the number of high-rise buildings	62.70	316.18	1877.20	4279.40
Average annual high-rise building area growth ($\times 10^4$ m^2)	78.70	590.55	1959.20	3329.20

(4) GDP growth

According to statistics and calculations (Table 3), the GDP of 1989 was 2.6 times that of 1978, and by 2000, the GDP increased to 6.1 times that of 1990. Then, GDP growth slowed down. In 2010, the GDP was 3.3 times that of 2001, and in 2016, the GDP was 1.4 times that of 2012.

Table 3. Average of statistics for different periods.

Year	1978–1989	1990–2000	2001–2010	2011–2016
Cumulative land subsidence (mm)	1735.20	1892.20	1977.40	2009.56
Sea-level height (mm)	6953.31	6984.47	7053.08	7110.89
Permanent residents ($\times 10^4$)	1208.42	1444.07	1955.37	2400.62
GDP ($\times 10^8$ yuan)	426.96	2541.51	10,385.45	23,371.34
Civil vehicles ($\times 10^4$)	11.96	46.67	221.18	311.47
Number of high-rise buildings	555.00	3529.00	20,579.00	44,395.00
High-rise building area ($\times 10^4$ m^2)	649.00	6180.00	21,911.00	44,395.00

(5) Increase of the civil vehicle number

This study mainly focuses on civil vehicles because there is a large gap between the number of civil vehicles and the number of public transport vehicles in Shanghai. After economic reform and open up, the number of civil vehicles in Shanghai increased exponentially due to the development of the national economy and the improvement of human living standards (Figure 4).

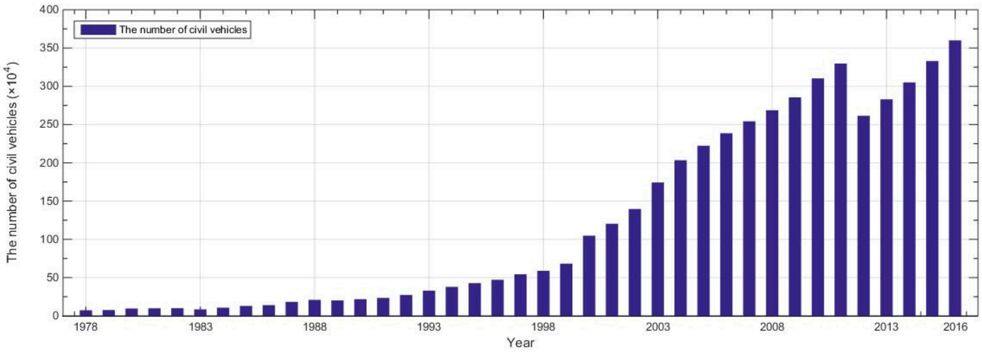

Figure 4. The number of civil vehicles in Shanghai.

(6) Increasing number of high-rise buildings

A high-rise building is a tall construction compared to a low-rise building and is defined by its height differently in various jurisdictions. Emporis Standards defines a high-rise building as "A multi-floor structure between 35–100 m tall, or a building of unknown height from 12–39 floors" [43]. In the U.S., the National Fire Protection Association defines a high-rise building as being higher than 75 feet (23 m) or approximately 7 floors [44]. Most building engineers, inspectors, architects, and similar professionals define a high-rise building as a building that is at least 75 feet (23 m) tall [43]. Buildings with 8 floors or more are defined as high-rise buildings in this paper, considering the average floor height is approximately 3 m [45]. The large number of high-rise buildings in Shanghai has been increasing rapidly since the 21st century according to Figure 4, worsens the land subsidence.

(7) Expansion of high-rise building area

In the 1980s, the high-rise building area in Shanghai increased by nearly 5.22 km^2. In the 1990s, 52.66 km^2 was added, and the total number was up to 61.80 km^2 at the end of 2000. The area reached 219.11 km^2 in 2010 and 436.48 km^2 in 2016.

2.2.2. Methodology

First, we have identified several key time points according to the change in impacting factors since 1978 (Figure 5): 1989, 2000, and 2011. The factors were almost unchanged from 1978 to 1989, and began to grow slowly in 1989. They have grown rapidly since 2000. Year 2011 is very important as factors began to change obviously. For example, the number of civil vehicles reduced, the amount and area of high-rise building and GDP grew at a faster rate, the number of permanent residents began to stabilize. According to these key time points, we divided the land subsidence into four stages: 1978–1989, 1990–2000, 2001–2010, and 2011–2016. Second, Grey Correlation Degree Analysis (GCDA) of land subsidence and seven impacting factors at different stages in Shanghai from 1978 was carried out. According to the grey correlation degree, the influence of each factor was determined. Third, Exploratory Spatial Data Analysis (ESDA) was adopted, and Moran's *I* analysis and Getis–Ord General G analysis were used to explore the spatial autocorrelation and spatial distribution characteristics of the main subsidence area in Shanghai—the urban centre. Spatial autocorrelation refers to the potential interdependence of observations in the same distribution [46], and it is a kind of spatial correlation.

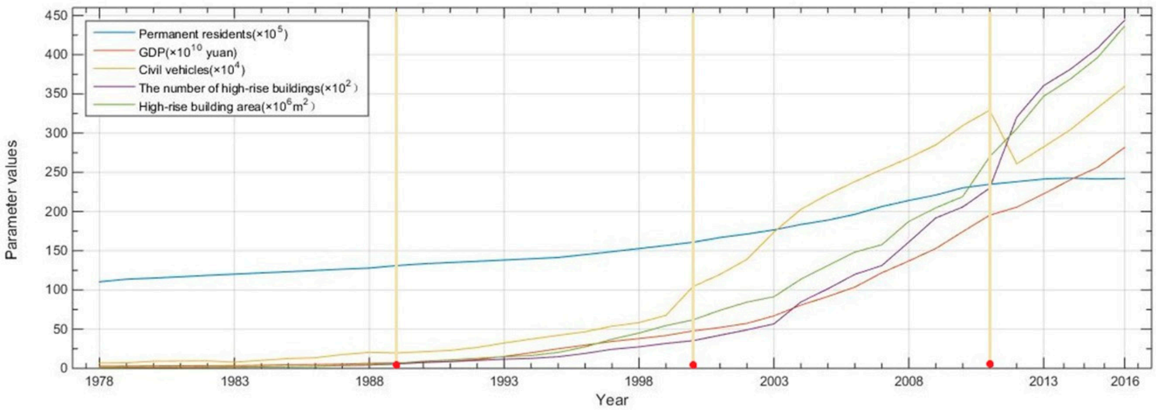

Figure 5. Social factors of land subsidence in Shanghai.

(1) Grey Correlation Degree Analysis (GCDA)

In a complex system affected by multiple factors, the relationship between the factors is unknown [36]. It is difficult to distinguish which factors are dominant and subordinate and which factors are closely related and unrelated. In the past, regression analysis, correlation analysis, variance analysis, principal component analysis, and other traditional statistical methods were commonly used [8,9]. However, these methods have strict requirements on data volume and sample distribution, and there may be problems, such as the quantitative results being inconsistent with the qualitative results and failure of the standard statistical tests.

The theory of grey systems [47] was first introduced in 1982 by Deng (1982). The basic idea [48] is to determine whether the relations between different data sequences are close based on the similarity of the geometry of the data sequence curves. With the application of the linear interpolation method, the discrete observations of system factors can be transformed into segmented continuous polylines, whose geometric characteristics reflect the correlation of the data sequences. The closer the geometry of the polyline is, the greater the correlation between the data sequences, and vice versa. Grey correlation analysis provides a quantified measure of the system's development and is very suitable for dynamic process analysis. There are few requirements for the sample size and distribution and no situation where the quantitative result is inconsistent with the qualitative analysis in grey correlation degree analysis. The formula is:

$$\gamma(x_0(\mathrm{k}), x_i(\mathrm{k})) = \frac{\min\limits_i \min\limits_k |x_0(k) - x_i(k)| + \xi \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max\limits_i \max\limits_k |x_0(k) - x_i(k)|} \tag{1}$$

$$\gamma(X_0, X_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_0(\mathrm{k}), x_i(\mathrm{k})) \tag{2}$$

where $\gamma(x_0(\mathrm{k}), x_i(\mathrm{k}))$ is the grey correlation coefficient at point k, $\gamma(X_0, X_i)$ is the grey correlation degree between data sequences X_0 and X_i, and ξ is the resolution coefficient, with a value between 0 and 1. The smaller ξ is, the greater the difference between the correlation coefficient values of the data sequences and the stronger the discrimination between the data sequences. The calculation process of the grey correlation degree is shown in Figure 6.

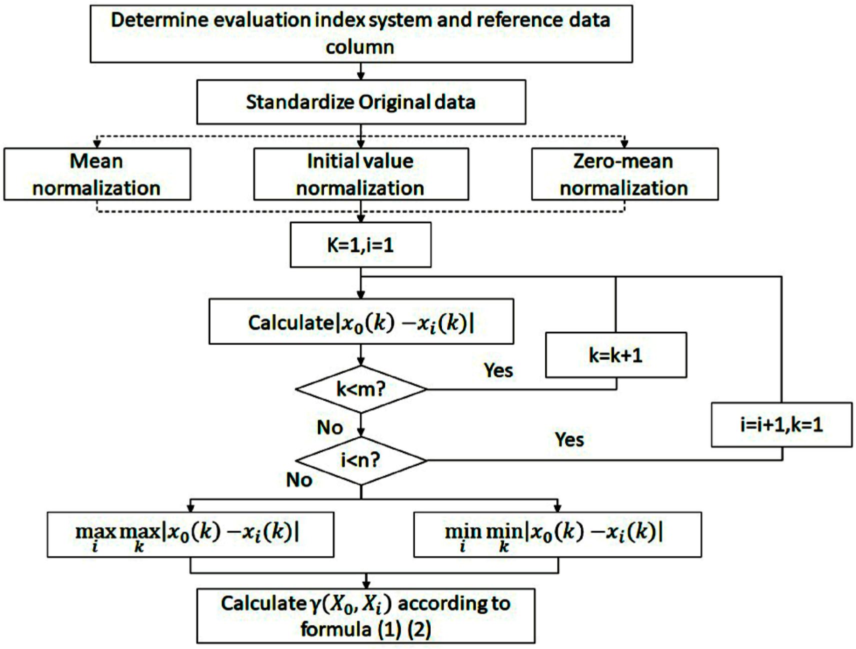

Figure 6. The calculation process of the grey correlation degree.

Different data standardization methods will lead to different grey correlation degrees and deserve special attention. Common methods include mean normalization, initial value normalization, and zero-mean normalization (also called z-score normalization). In general, the initial value normalization is applicable to socio-economic data, because most of these sequences show a steady growth trend, and the initial value normalization makes the growth trend more obvious [49]. Therefore, the initial value normalization is used in this study according to the statistical characteristics.

(2) Exploratory Spatial Data Analysis (ESDA)

Exploratory spatial data analysis (ESDA) is supported by spatial analysis, emphasizes the spatial correlation of events, focuses on the nature of spatial data, and explores the spatial patterns of data. ESDA includes global and local statistical analysis. In this paper, two global statistical analysis indexes, Moran's *I* and Getis–Ord General G [46], are used to carry out spatial autocorrelation and spatial clustering.

(3) Spatial Autocorrelation

Spatial autocorrelation refers to the potential interdependencies among observed data of some variables in the same distribution area. Tobler (1970) once pointed out "the first law of geography: everything is related to everything else, but near things are more related to each other" [50]. Moran's *I* is a good indicator of spatial correlation and was proposed by Moran [51], an Australian statistician. Moran's *I* reflects the degree of similarity among attributes of regional units that adjoin or are adjacent to each other. Moran's *I* is a rational number, and after normalization of variance, the number is normalized between −1 and 1 and is defined as:

$$\text{Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{3}$$

where n is the number of special units indexed by i and j; x is the variable of interest; $\overline{x}$ is the mean of x; and w_{ij} is a matrix of spatial weights.

Moran's $I > 0$ means there is a positive spatial correlation between observations, and the larger the Moran's *I* value is, the more significant the correlation is. When Moran's *I* is close to 1, the observations gather in specific areas. In other words, similar observations (high or low) tend to agglomerate in space. Moran's $I < 0$ indicates that there is a spatially negative correlation between the observations, and the smaller Moran's *I* is, the greater the spatial difference among the observations. When Moran's *I* approaches −1, the observations follow a discrete spatial pattern, and similar observations tend to be distributed. Moran's $I = 0$ means that the observations are spatially random and there is no spatial correlation [52].

(4) Spatial Clustering

Clustering is the grouping of observations according to a similar criterion, which maximizes the intra-group similarities and the differences among groups to discover meaningful structural features. "High/low" spatial cluster analysis (also known as Getis–Ord General G analysis) determines which observations are clustered based on the possibility of data clustering. In the results of General G, high-high cluster shows that observations larger than the mean are spatially clustered, low-low cluster indicates that observations smaller than the mean are spatially clustered, and not significant means that the observations are not spatially clustered. The method was proposed by Ord and Getis [53]. In this method, the z-score and p-value reflect statistical significance and determine whether to reject the null hypothesis which indicates that study objects are randomly distributed.

The z-score is a multiple of the standard deviation. The higher (or lower) the z-score is, the more clustered the observations are. Z being positive and greater than the threshold indicates high-value clustering, z being negative and less than the threshold indicates low-value clustering, and z = 0 indicates no clustering of observations. The *p*-value is defined as the probability under the null hypothesis in which the spatial pattern of the observation is random. The null hypothesis is rejected if any of these probabilities is less than or equal to a small, fixed but arbitrarily pre-defined threshold value, which is commonly set to 0.10, 0.05, or 0.01 (Table 4).

Table 4. Critical *p*-values and critical z-scores under different confidence coefficient values [54].

z-Score	*p*-Value	Confidence Coefficient
<−1.65 or >+1.65	<0.10	90%
<−1.96 or >+1.96	<0.05	95%
<−2.58 or >+2.58	<0.01	99%

3. Results and Discussion

3.1. Development of Land Subsidence in Shanghai

The land subsidence in Shanghai is severe. Land subsidence was noticed in the early 1920s and has a long history of more than 90 years [55]. Compared with 1921, the ground in the urban centre has subsided by approximately 2 m, and the maximum subsidence is approximately 3 m (Figure 7). Land subsidence leads to serious water hazards in urban areas [56], poor inland navigation, frequent damages to municipal infrastructure, and other urban problems. Clearly, land subsidence has become one of the main restrictive factors for efficient and stable economic growth and sustainable development in Shanghai.

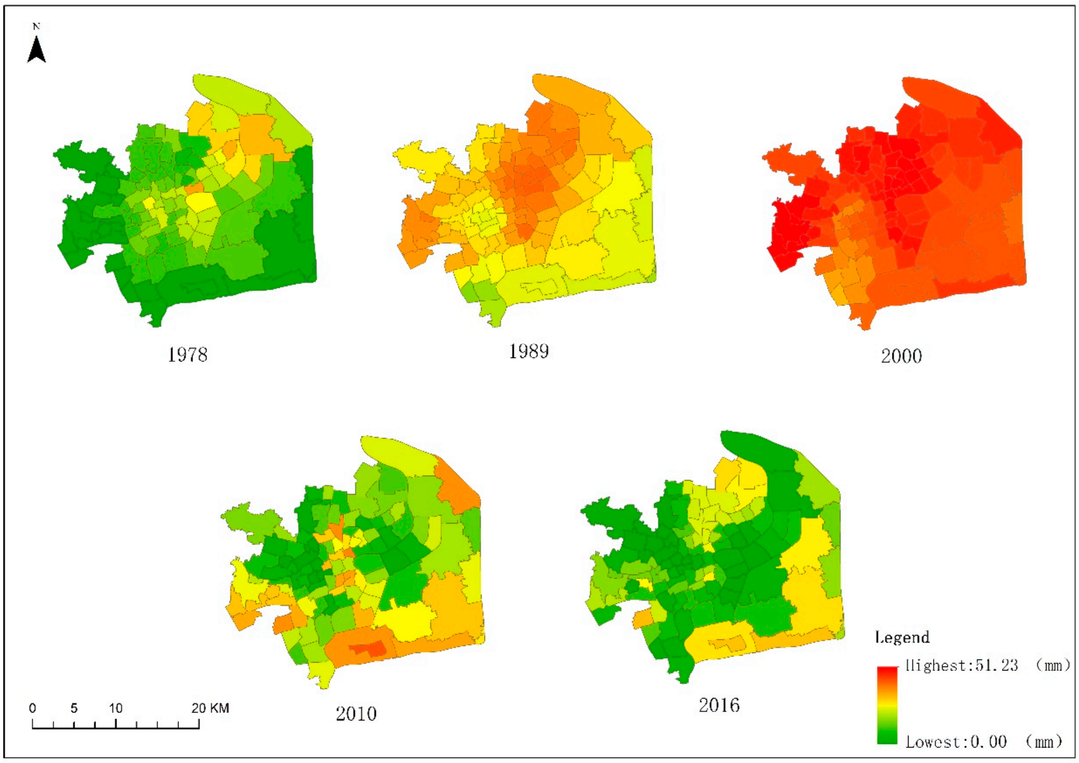

Figure 7. Spatial distribution of average annual land subsidence in the urban central area of Shanghai.

The annual average land subsidence in Shanghai has distinct characteristics at different times: (1) The 1980s (1978–1989) were a period of slow growth, and the annual average land subsidence had an upward trend and a small increase. (2) Land subsidence increased rapidly in the 1990s (1990–2000), and the annual average increase was 4.09 times that in the 1980s. (3) Land subsidence was effectively controlled during the first decade of the 21st century (2001–2010), and the annual average subsidence gradually decreased. In fact, the subsidence decreased from 14.3 (mm/a) in the 1990s to 8.52 (mm/a), with a decrease of 40.42%. (4) The second decade of the 21st century (2011–2016) witnessed the stable development of land subsidence in Shanghai. Land subsidence decreased to 5.36 (mm/a), which was 37.01% lower than that of the previous stage and remained stable (Figure 8). Incidentally, only the statistics from 2011 to 2016 were analysed in the last stage because of the lack of subsidence data after 2016.

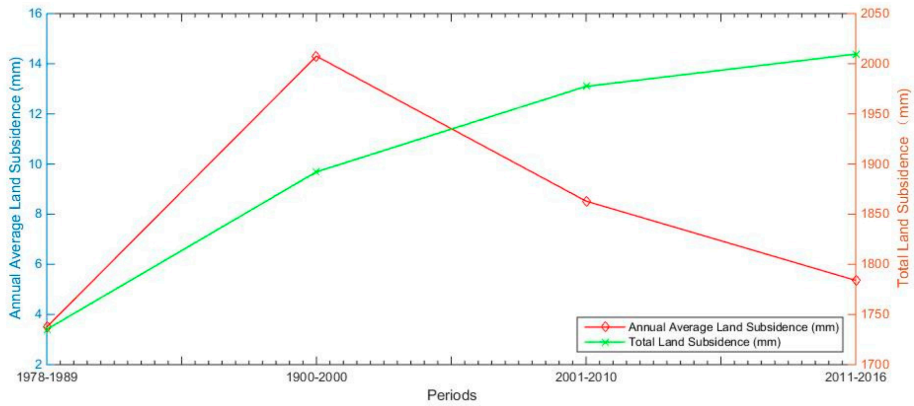

Figure 8. Development of land subsidence in Shanghai.

3.2. Analysis of the Impacting Factors of Land Subsidence

The results of GCDA between the annual average land subsidence and impacting factors, which consist of the annual average growth of groundwater exploitation, sea-level rise, permanent residents, GDP, civil vehicles, the number of high-rise buildings, and high-rise building area, are shown in Table 5.

Table 5. The result of GCDA between the average annual land subsidence growth and the annual increase in the impacting factors.

	Impacting Factors	Grey Correlation Degree r_i	Mean
Natural factors	Average annual groundwater exploitation	0.8241	0.8350
	Average annual sea-level rise	0.8458	
Social factors	Average annual permanent resident growth	0.8719	0.6070
	Average annual GDP growth	0.4655	
	Average annual increase of the civil vehicle number	0.6494	
	Average annual growth in the number of high-rise buildings	0.5402	
	Average annual expansion of high-rise building area	0.5077	

As the incremental effect shows in Table 5, (1) the impact of natural factors is more significant than that of social factors because the mean degree of natural factors is greater than that of social factors. (2) The increase in permanent residents is the most important cause of annual average land subsidence in Shanghai since it has the highest grey correlation degree of 0.8719. (3) The influence of annual average sea-level rise is positive and very strong, similar to that of groundwater exploitation on land subsidence. (4) High-rise buildings, both in quantity and area, deteriorate land subsidence. (5) The grey correlation degree between annual average GDP growth and land subsidence is 0.4655, so there is a small positive impact. (6) The increasing influence all factors have on land subsidence is as follows: permanent resident growth > sea-level rise > groundwater exploitation > increase of the civil vehicle number > increasing number of high-rise buildings > expansion of high-rise building area > GDP growth.

In addition to the annual average growth of these factors, how does their total amount affect land subsidence? In this paper, an incremental effect is defined as the effect of the annual growth of impacting factors on land subsidence, and scale effect is defined as the effect of the total amount of impacting factors on land subsidence. Groundwater exploitation is excluded in the scale effect analysis because it is seriously affected by land subsidence measures such as groundwater recharge.

As the scale effect shows in Table 6, (1) natural factors, mainly sea-level height, are proven to be the major cause of land subsidence. (2) The amount of the permanent residents still has a very large impact, which is slightly less than the sea-level height. (3) Civil vehicles are the third crucial influence factor, with a correlation degree of 0.5725, which is less than that of the incremental effect. (4) GDP, the number of high-rise buildings and high-rise building area have significant influences on cumulative land subsidence. (5) The level of impact of all factors is ordered from high to low as follows: Sea-level height, permanent residents, civil vehicles, GDP, number of high-rise buildings, and high-rise building area.

Table 6. The result of GCDA between the cumulative land subsidence and the total amount of impacting factors.

Impacting Factors		Grey Correlation Degree r_i	Mean
Natural factors	Sea-level height	0.9892	0.9892
Social factors	Permanent residents	0.9586	0.5889
	GDP	0.5001	
	Civil vehicles	0.5725	
	Number of high-rise buildings	0.4676	
	High-rise building area	0.4457	

In conclusion, the impact of natural factors on land subsidence in an urban centre is greater than that of social factors, both of which influence different aspects: (1) In terms of groundwater exploitation, the effect of increasing exploitation is significant, so strict control of groundwater exploitation is essential for land subsidence prevention. (2) There is a strong positive correlation between sea-level rise and land subsidence; thus, sea-level rise should be a focus. (3) Permanent residents have a large positive impact, and their scale effect is greater than their incremental effect. Therefore, the more than 24 million permanent residents, with an annual increase of nearly 200,000, have become a substantial threat to land subsidence in recent years. (4) Increase of the civil vehicle number is one of the most imperative causes of land subsidence in Shanghai because of both its incremental and scale effects. (5) All of the other social factors have significant positive impacts on land subsidence, including GDP, the number of high-rise buildings and high-rise building area. However, there are some differences between their incremental and scale effects, namely, the GDP has a larger scale effect, while the number and area of high-rise buildings have larger incremental effects.

3.3. Spatial Autocorrelation of Land Subsidence in the Urban Centre

The land subsidence in the urban centre has developed as "weak spatial autocorrelation" → "strong spatial autocorrelation" → "weak spatial autocorrelation". (1) It had a weak positive spatial autocorrelation in 1978, as the Moran's I was 0.3607. This spatial distribution pattern was a result of the minor land subsidence; there was only one subsidence funnel (the ground has gradually subsided from the periphery to the centre) in Yangpu District, and no significant subsidence occurred in most areas of the urban centre. (2) There was a strong spatial autocorrelation of land subsidence in the 1980s and 1990s. From 1978 to 1989, Moran's I increased sharply to 0.7095, representing a strong positive spatial autocorrelation. This result shows the subsidence funnel worsened and the subsidence range expanded. By 2000, Moran's I was still as high as 0.5707. There was still a strong positive spatial autocorrelation of land subsidence, indicating that the land subsidence and its spatial expansion in the urban centre were intensified. (3) Land subsidence has followed a weak spatial autocorrelation pattern since 2000. By 2016, Moran's I decreased to 0.20 as effective subsidence prevention measures were taken. During this period, the strong spatial autocorrelation pattern of land subsidence was gradually broken and changed to a weak spatial autocorrelation pattern, indicating that subsidence funnels were dispersed in the urban centre, but their spatial expansion was moderated.

3.4. Spatial Clustering Pattern of Land Subsidence in the Urban Centre

The "high/low" cluster analysis of land subsidence found that the clustering increased in the last century and decreased in the 21st century. This conclusion is consistent with the spatial autocorrelation development law described in the previous section. (1) In 1978, 1989, and 2000, each z-score was greater than 2.58 and each p-value was less than 0.01. According to Tables 4 and 7, the confidence coefficient of the "high clustering" distribution of the land subsidence in the urban centre was 99%. (2) Since 2000, land subsidence has been randomly distributed, and there have been no obvious clustering characteristics.

Table 7. Analysis of clustering characteristics of land subsidence in the urban centre.

	1978	1989	2000	2010	2016
Clustering characteristics	High clustering	High clustering	High clustering	None	None
General G observations (10^{-4})	0.8800	0.7200	0.7100	0.5800	0.6100
General G expected value (10^{-4})	0.6000	0.6000	0.6000	0.6000	0.6000
z-score	5.2490	5.6032	3.3298	−0.3758	0.2443
p-value	0.0000	0.0000	0.0009	0.7071	0.8070

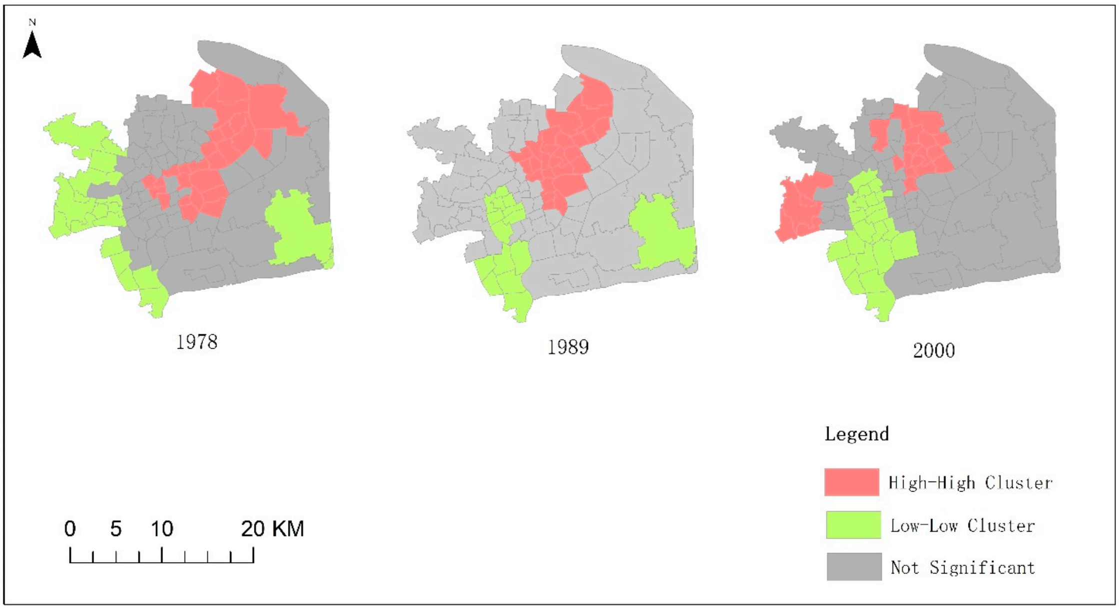

Figure 9. Land subsidence clustering pattern in the central areas of Shanghai.

As seen in Figure 9, (1) land subsidence followed a "high clustering" pattern in 1978, and the "high-high" clustering was mainly in Yangpu District and Huangpu District, while the "low-low" clustering was distributed in four districts—Putuo District, Changning District, Xuhui District, and Pudong New Area. (2) The high subsidence area expanded, and the low subsidence area reduced in the 1980s based on the fact that the "low-low" clustering only occurred in Xuhui District and Pudong New Area in 1989. (3) Land subsidence was high in the urban centre in the 1990s. A new subsidence funnel rapidly formed and the low subsidence area in Pudong New Area was eliminated. Moreover, a new "high-high" clustering area was formed in Changning District, while the "low-low" clustering in Pudong New Area disappeared by 2000. (4) A spatial random distribution pattern was formed after 2000. The trend of the high subsidence area was alleviated, and the "high clustering" pattern was gradually eliminated because of the adoption of various subsidence control measures.

4. Discussion

(1) The study finds that land subsidence is proven to be closely related to human activities and social development and has become a major constraint on sustainable development; therefore, preventing and controlling land subsidence is imperative for the city to be a metropolis of excellence, innovation, humanity, ecology, and culture and an international centre of economy, finance, trade, shipping, science, and technology.

(2) Generally, resources and the environment are the material basis and fundamental guarantee for social progress and economic development. Social factors are the main bearing and direct

drive for wealth creation and civilization. Different impacting factors have different influences on land subsidence in Shanghai. Therefore, in the process of urbanization, industrialization, and modernization, only by considering the comprehensive needs of urban development and enhancing the awareness of "natural-social" protection can Shanghai cooperate and compete better internationally and achieve the goal of sustainable development of the economy, society, culture, and ecology.

(3) The change in spatial interaction shows that the prevention and control of land subsidence in Shanghai achieves remarkable results by gradually weakening the cumulative effect and the geological influence of the subsidence funnel on adjacent areas. These achievements confirm the positive role of subsidence treatment and indicate that the implementation of urban subsidence prevention is effective. However, additional work is needed to fully control the intensification of subsidence and completely eliminate the subsidence risk the city is facing.

(4) The majority of previous studies in China [57,58] and overseas [59,60] analysed only natural factors or a single social factor [56] of land subsidence in Shanghai. Few researchers considered integrated "natural-social-economic" factors; in particular, the link between social factors and land subsidence has been ignored. However, human social activities extraordinarily contribute to a series of complex effects in Shanghai, a metropolis with a large population. This paper demonstrates the considerable relation between social factors and land subsidence and reveals that permanent residents are the most powerful social factor. At the same time, this study is based on two different perspectives, the incremental effect and scale effect, and compares the results from these two research perspectives to explore the differences of various impacting factors. The idea of dual-view research broadens the perspective of this type of research.

(5) In terms of scale effect, groundwater exploitation and sea-level rise are the main impacting factors of land subsidence in Shanghai. This conclusion is consistent with the results of Wang [4], Li et al. [57], and Xu et al. [9].

(6) The analysis of spatial distribution is rare in the existing studies on land subsidence in Shanghai, and most studies do not discuss spatial information. A small part of the research simply describes the objective phenomenon without quantitative spatial data support [61]. The application of ESDA accomplishes numerical spatial analysis and deeply explores the spatial information of land subsidence in Shanghai based on powerful spatial analysis theories and geography calculation methods. A comprehensive and systematic interpretation of spatial information will better serve the sustainable development of the city.

5. Conclusions

(1) Land subsidence is a geological engineering problem that is slowly accumulating. The annual average land subsidence in Shanghai has distinct characteristics during the periods since economic reform and open up of China. Land subsidence has experienced four stages: "slow growth in the 1980s", "rapid growth in the 1990s", "gradual decline in the first decade of the 21st century", and "steady development in the current stage".

(2) Land subsidence in Shanghai is the result of the combined effects of various factors, among which the influence of natural factors is greater than that of social factors. Sea-level rise is the most important natural factor, while the influence of groundwater exploitation has decreased in recent years. At the same time, permanent residents play the most imperative role in social factors—the large quantity and rapid growth of permanent residents are largely responsible for the land subsidence in Shanghai.

(3) The rate of land subsidence in Shanghai is spatially non-uniform, and it has different spatial distributions at different stages. Moran's I analysis proves that the spatial distribution of annual average land subsidence in central urban areas has experienced the development process of "weak spatial autocorrelation" $\rightarrow$ "strong spatial autocorrelation" $\rightarrow$ "weak spatial autocorrelation" since 1978.

(4) The annual average land subsidence has gradually evolved from a "high clustering" pattern to a distribution with no obvious clustering in the urban centre since 1978, and its spatial development tends to be discrete and random. That is, the distribution of subsidence funnels spreads, and an increasing number of regions are facing subsidence risks. This phenomenon deserves much attention in the overall development of the city, and we must stop it from further deteriorating areas where land subsidence occurs. Preventing the spread of subsidence areas and strictly preventing the formation of new subsidence funnels should be the focus.

(5) There are some suggestions for policy makers: ① In the 20th century, the main cause of land subsidence in Shanghai was groundwater exploitation. However, the growing population has worsened the land subsidence severely since the 21st century. The government should shift its focus to control moderate population growth when the exploitation of groundwater has been effectively controlled. ② The most serious land subsidence occurred in Yangpu District, Hongkou District, Jing'an District, and Pudong New Area in 2016, which show government should limit the intensity of development in these areas, especially the strength of high-rise buildings. ③ The study found that sea-level rise is a very important factor in worsening land subsidence. Reducing greenhouse gas emissions is therefore an unshirkable responsibility.

(6) There are some limitations of the research: ① Due to a lack of data for the last two years, the data used in this study was pre-2016. ② Future research needs to further explain the specific influencing mechanism of various impacting factors on land subsidence. ③ How to predict the land subsidence based on its development still needs to be explored further.

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