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Potential and Influencing Factors of Urban Spatial Development under Natural Constraints: A Case Study of the Guangdong-Hong Kong-Macao Greater Bay Area

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Abstract: As urbanization in China progresses, urban spatial development is transitioning from rapid expansion to more intensive and compact growth. This study examined the role of physical geography and environmental factors in shaping the urban spatial development in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA). Based on the current natural conditions, we selected evaluation indices from topography, hydrogeology, climatic conditions, and natural disasters. These indices were used to create a carrying capacity and suitability evaluation system for development land under natural constraints. Finally, the spatial development potential of the city was finalized by taking into account the current state of the built-up area of the city. Meanwhile, we employed the Optimal Parameters-based Geographical Detector and assessed the impact of 14 natural factors on the spatial development of urban built-up areas. In 2020, the GBA had 52,168.77 km^2 of land suitable for construction, of which 34,241.13 km^2 was highly suitable (61.29%) and 17,927.64 km^2 was moderately suitable (32.09%). At the Bay Area level, 90.15% of the development potential remains untapped; at the city level, Zhaoqing City has the highest potential at 99.56%, while Macao has the lowest at 26.83%. Key factors influencing urban development include silty sand content, annual average relative humidity, and cumulative temperature above 0 °C, with varying impacts across different urban scales. At the Bay Area level, the silty sand content, annual average relative humidity, and cumulative temperature above 0 °C are the main influencing factors on the spatial development of urban built-up areas; at the city level, the main factors are annual average relative humidity and cumulative active temperature above 0 °C. This study reveals the important influence of natural environmental factors on urban spatial development, which is conducive to promoting sustainable development of land resources in GBA.

Keywords: urban spatial development potential; construction land carrying capacity evaluation; suitability assessment for development land; geographic detector; Guangdong-Hong Kong-Macao Greater Bay Area

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1. Introduction

Land is an essential non-renewable resource to human survival providing the basic materials for human production and livelihoods. Their sustainable utilization can also be

defined as a critical factor in societal sustainable development [1]. Land carrying capacity refers to the ability of land resources to sustainably support socio-economic activities over a period of time, including the production, living, and ecological functions of the land [2]. Land suitability assessment is an evaluation of the appropriateness of land for specific uses based on its natural conditions and socio-economic demands [1]. Land carrying capacity and land suitability assessment are fundamental bases for assessing land use conditions and planning land utilization. Effective management of urban spatial development is a challenge faced by planners and managers, among which carrying capacity assessment remains one of the useful planning tools [1,3]. Utilizing the carrying capacity to assess the suitability levels of construction land is an effective measure. This approach guides urban development and construction, thereby achieving sustainable urban development. For urban areas with rapid socio-economic development, accelerated urbanization, and significant imbalances in urban–rural land use, there is an urgent need to conduct studies focusing on the carrying capacity assessment of construction land [4–6].

In recent years, most scholars have initiated research into land-carrying capacity, focusing on the interactions among population, land, and food. As land development progressed, issues such as spatial imbalances in land use became apparent, prompting more comprehensive studies on overall land carrying capacity. In recent years, various methods, techniques, and frameworks have been used to assess land-carrying capacity [7]. The evaluations of land-carrying capacity typically concentrate on urban [8], regional [9], and specialized areas [5]. Common methodologies for assessing land-carrying capacity were utilized in various ways including systems dynamics [10], ecological footprint models [11], and multi-criteria evaluation [12]. The primary indicators selected for these assessments often relate to environmental capacity [13], population density [14], and ecological capacity [15]. However, existing studies predominantly focus on the carrying capacity of pre-urban development, relying on natural constraints like topography, climate, and hydrology to gauge the development potential of undeveloped land. These studies frequently overlook the link between existing urban areas and the potential for urban expansion under natural constraints. Clarifying this relationship is significant for understanding the dynamics between urban development and the natural environment.

The concept of urban spatial development potential refers to the economic growth, social progress, and environmental improvement of inherent conditions and potentials over a specified period. This interdisciplinary concept includes the economy, society, and environment, aiming to evaluate and predict a city's future development opportunities. Researchers assess urban development potential across several domains. In the economic domain, scholars focus on factors such as a city's growth potential [16], the optimization of its industrial structure [17], and innovation capabilities [18]. In the social domain, studies emphasize the urban population structure [19], cultural development [20], and public health [21]. In the field of technological innovation, the focus is on the city's capacity for innovation [22], low-carbon development [23], and smart industries [24]. Additionally, natural environmental factors, such as geographical location, climate, and natural resources, not only influence the quality of the urban ecological environment but also the city's capacity for sustainable development [25,26]. Previous assessments of urban development potential have predominantly concentrated on social, economic, and technological factors, often neglecting the complex interactions between natural environmental elements and urban development.

Assessing land suitability based on land-carrying capacity facilitates the effective utilization and management of land resources, thereby promoting sustainable development. Although various scholars have explored land-carrying capacity and land suitability from diverse perspectives, in-depth investigations into the alignment between natural constraints and current urban development are still scarce. Exploring the impacts of physical geography and environmental factors on urban spatial development offers insights into current and future potentials, which can provide a scientific basis for national spatial planning and the evolution of urban forms. Currently, China's urban spatial development

is transitioning from rapid expansion to a more intensive and compact form. This transition underscores the importance of analyzing the effects of physical geography and environmental factors on both present and future urban spatial potentials, providing a scientific basis for national spatial planning and the evolution of urban forms. This study focuses on the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) to develop an evaluation index system for the carrying capacity of construction land under natural constraints. It assesses the connection between the current state of urban construction land and its potential for suitable development under these constraints, attempting to answer the following two scientific questions: (1) Is the developed urban area in GBA fully utilizing the "urban spatial development potential" under natural constraints? (2) How did the different natural constraints impact the urban development space?

2. Materials and Methods

2.1. Study Area

The GBA is recognized as one of the world's four major bay areas, situated in the southern coastal region of China, spanning from 21°26′ to 24°28′ N latitude and 111°14′ to 115°24′ E longitude (Figure 1). It encompasses nine cities in the Pearl River Delta (including Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing) and two Special Administrative Regions, Hong Kong and Macao. Collectively, these areas cover approximately 56,000 km^2, which constitutes 31.2% of Guangdong Province and only 0.6% of China's national territory. By the end of 2022, the GBA housed roughly 86.3011 million people and generated an economic output surpassing CNY 13 trillion, making it one of the most open and economically dynamic regions in China. This area is pivotal to the Belt and Road Initiative and China's broader national development strategy.

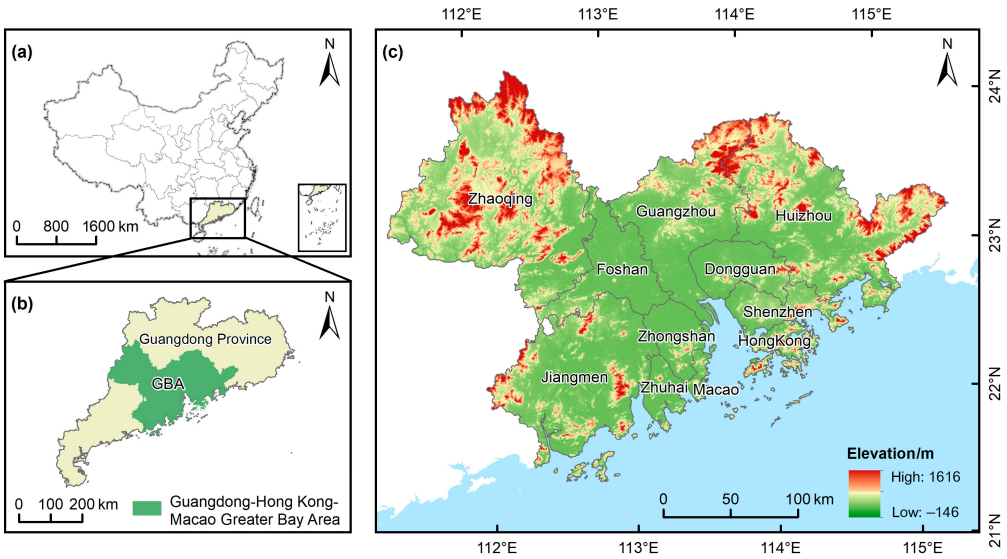


Figure 1. Location of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA). (**a**) Location of Guangdong Province in China. (**b**) Location of GBA in Guangdong Province. (**c**) GBA administrative division and elevations.

The geographic landscape of the GBA features high terrain in the northwest and lower elevations in the southeast, with mountains predominantly in the northern sections near Zhaoqing, Guangzhou, and Huizhou, and plains chiefly in the central and coastal regions. The area benefits from a unique geographical setup, which is "surrounded by mountains on three sides and where three rivers converge", complemented by an extensive coastline, numerous ports, and a large sea area. It experiences a subtropical monsoon climate with an average annual temperature of 22 °C. The rainy season lasts from April to September, providing ample sunlight, warmth, and water resources which enrich the region.

The favorable natural geographical conditions have supported significant development; between 1990 and 2020, residential and construction land in the GBA expanded by 115.21%, reaching 9183.47 km^2. This land type has seen the greatest increase in the area and the fastest rate of change within the region [27]. Since 2010, the scale of construction land has tended towards stabilization, with improvements in the regularity and compactness of its form. Urban construction has thus entered a transitional phase from rapid expansion to intensive and compact development [28].

2.2. Data Sources

This study utilized elevation, soil, hydrology, climate, climatic zoning data, and built-up area data (Table 1) to develop a framework for assessing the carrying capacity and suitability of urban development land under natural constraints. This framework also facilitated the mapping and analysis of urban spatial development potential within the study area. All data were standardized to a uniform projection coordinate system, WGS_1984_Web_Mercator_Auxiliary_Sphere, and resampled to a 30 m resolution using the resampling tool in ArcGIS. Table 1 provides detailed information on the multi-source data utilized in this study.

Table 1. Data sources.

Dataset	Sources	Type of Dataset	Spatial Resolution	Time of Dataset	Note
Elevation data	Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences. (http://www.gscloud.cn, accessed on 15 November 2023)	tif	30 m	2009	Extraction of elevation, slope, and aspect data.
Soil data	Harmonized World Soil Database, HWSD (https://data.tpdc.ac.cn/en/data/, accessed on 15 November 2023)	tif	1:4 million	2009	Extraction of silty sand content
Drainage data	OpenStreetMap (https://www.openstreetmap.org, accessed on 15 November 2023)	shp	——	2020	——
Climatic zoning data	Resource and Environmental Science Data Platform of Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 21 November 2023)	shp	——	1978	——
Active accumulated temperature	Swiss Federal Institute for Forest, Snow and Landscape Research (https://chelsa-climate.org/downloads/, accessed on 15 November 2023)	tif	1 km	1981–2010	For extracting data on active cumulative temperatures greater than 0 °C
Meteorology data	Resource and Environmental Science Data Platform of Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 21 November 2023)	tif	1 km	1960–2010	Extraction of mean annual wind speed, mean annual air temperature, mean annual sunshine hours, mean annual relative humidity, and annual precipitation data
Fault data	National Earthquake Data Center (https://data.earthquake.cn/index.html, accessed on 15 November 2023)	shp	——	——	——
Built-up area data	Science Data Bank (https://www.scidb.cn/en, accessed on 15 November 2023)	shp	——	2020	——
Administrative division data	Resource and Environmental Science Data Platform of Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 15 November 2023)	shp	——	2022	——

2.3. Methods

2.3.1. Construction of a Land-Carrying Capacity and Suitability Evaluation System under Natural Constraints

Evaluation Index Selection

The development of urban built-up areas is complex and influenced by multiple natural factors. Previous studies have highlighted several critical factors affecting urban development. (1) Topography: Plains and river valleys, characterized by flat terrain and fertile land, are generally more conducive to agriculture and construction, resulting in rapid urban expansion. Conversely, challenging topographic conditions such as mountains, hills, or deserts impose limitations on urban growth. (2) Water Resources: Essential for urban development, an adequate water supply supports residential life, industrial production, and agricultural irrigation. Consequently, cities near rivers, lakes, or other bodies of water tend to expand more rapidly. (3) Climate Conditions: Mild climates are favorable for human habitation and agriculture, attracting more population and investment, which in turn promotes urban expansion. In contrast, extreme climates—such as high temperatures, severe cold, or drought—can hinder urban development. (4) Natural Disasters: Earthquakes, floods, typhoons, and other natural disasters can severely damage cities and affect their expansion. In areas prone to disasters, urban planning and construction must be carried out more cautiously to mitigate risks.

Considering previous studies and the specific characteristics of the GBA, along with data availability and the quantifiability of indicators, we established a system comprising eight criteria to evaluate the carrying capacity of development land under natural constraints within the GBA. Combined with the existing research [29–31], we determined the evaluation system. The evaluation system includes (1) slope; (2) aspect; (3) silty sand content; (4) water resources; (5) climatic zone; (6) accumulated temperature above 0 °C; (8) wind effect index; (9) distance from fault lines.

Evaluation Metrics Quantification and Grading

Each indicator is classified into three to five levels, as outlined in Table 2. These levels correspond to five categories of carrying capacity: high, relatively high, moderate, medium, and relatively low. These categories are assigned scores of 9, 7, 5, 3, and 1, respectively. For instance, the "slope" indicator uses the following classifications: ≤3° (9 points), 3 to 8° (7 points), 8 to 15° (5 points), 15 to 25° (3 points), and >25° (1 point).

Table 2. Evaluation factors and indicators for grading the carrying capacity of development land.

Evaluation Factor	Indicators for Grading the Carrying Capacity of Development Land				
	High (9 Points)	**Middle-High (7 Points)**	**Middle (5 Points)**	**Middle-Low (3 Points)**	**Low (1 Point)**
Slope	≤3°	3 to 8°	8 to 15°	15 to 25°	>25°
	Corrected elevation and relief [1]				
Aspect	Southern slope	Southwest-facing slope, Southeast-facing slope	West slope, East slope	Northeast slope, Northwest slope	Northern slope
Silty sand content	<60%	— —	60% to 80%	— —	≥80%
Precipitation	>1400 mm	800 to 1400 mm	400 to 800 mm	200 to 400 mm	<200 mm
Distance to rivers and lakes [2]	≤1 km	1 to 2 km	2 to 5 km	— —	>5 km

Table 2. *Cont.*

Evaluation Factor	Indicators for Grading the Carrying Capacity of Development Land				
	High (9 Points)	**Middle-High (7 Points)**	**Middle (5 Points)**	**Middle-Low (3 Points)**	**Low (1 Point)**
Climatic zone	Boreal zone, Temperate zone, Subtropical zone	Northern subtropical zone, Central subtropical zone, Southern subtropical zone	Plateau climate, Subtropical climate	— —	— —
Accumulated temperature above 0 °C	≥7600 °C	5800 to 7600 °C	4000 to 5800 °C	1500 to 4000 °C	≤1500 °C
Wind efficiency index	−299 to −100	— —	−99 to −10, −400 to −300	— —	>−10, <−400
Distance to fault lines	>36,000 m	8300–36,000 m	1600–8300 m	<1600 m	— —

Note: [1] Elevation adjustment: Areas with elevation above 4900 m are degraded by two levels, while those between 3000 and 4900 m are degraded by one level. Terrain Undulation Correction: Locations with more than 200 m of terrain undulation have their construction land carrying capacity reduced by two grades, and those with undulations between 100 and 200 m are reduced by one grade. [2] Water resource adjustment based on precipitation and proximity: Sites rated as 3 for distance to rivers and lakes have their water resource rating degraded by one level. Sites rated as 1 for proximity see their precipitation rating degraded by two levels.

Assessment of the Indices

Each 30 m resolution pixel unit is used as an evaluation unit. To calculate the cumulative impact score for each evaluation unit, the quantification and grading results of the previously mentioned evaluation factors are combined. The formula used is as follows:

$$S_j = \sum_{j=1}^{n} X_{ij} W_j \quad (1)$$

In this formula, *Si* represents the composite carrying capacity score for the *i*-th cell. The score contributed by the *j*-th evaluation indicator in the *i*-th cell is weighted by *W*, which is the weight value of the *j*-th evaluation indicator. The total number of evaluation indicators is denoted by *n*.

In ArcGIS 10.8, the eight evaluation indicators for the GBA are analyzed using the raster calculator and an equal weight method to sum all indicators. The total scores of these indicators produce grid values ranging from 49 to 97. We further classified these scores into five categories by the natural breaks method. The intervals for these categories are detailed in Table 3. Additionally, the water system in the GBA was considered a no-development zone, received the lowest scores, and was automatically categorized as areas with low carrying capacity. Urban areas that achieve high or middle-high carrying capacity scores are identified as highly suitable for urban construction. Conversely, areas with middle or middle-low capacity scores are considered moderately suitable, while those with low carrying capacity are deemed unsuitable for urban development. The categories of high suitability and middle suitability are collectively referred to as "suitable areas".

Table 3. Carrying capacity and suitability classification criteria.

Value	Carrying Capacity Grade	Suitability Grade
49–70	Low	Unsuitable
70–76	Middle-low	Middle
77–82	Middle	Suitability
83–87	Middle-high	High
88–97	High	Suitability

2.3.2. Evaluation of Urban Spatial Development Potential

Urban spatial development potential quantifies the extent of land within the urban administrative boundaries that is suitable for development, excluding current built-up areas. This potential is directly related to the proportion of the remaining suitable areas within these boundaries compared to the total suitable areas in the city. The potential can be quantified using the following formula:

$$M = \frac{C - C_1}{C} \tag{2}$$

where M represents the urban development potential. C is the area of land suitable for construction within the administrative boundaries of the study area, and C_1 is the area of land suitable for construction currently within the built-up areas of the study area.

2.3.3. Optimal Parameters-Based Geographical Detector

The geographic detector is a novel spatial statistical method developed by Wang Jinfeng et al. (2020) [32] to examine the effects of various factors and their interrelationships across multiple spatial units. The traditional model of this detector necessitates manual adjustments for discretizing continuous data, a process that may introduce subjectivity and issues with inadequate discretization. To address these challenges, this study employed the Optimal Parameters-based Geographical Detector [29] to analyze the driving forces behind urban development in the GBA. This approach evaluates factors such as elevation, slope, temperature, and humidity to discern spatial differentiation in urban built-up areas and identify the principal driving forces. The formula used for the calculation is presented below:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{3}$$

where q represents the detection value of factor X on the dependent variable Y; L is the number of categories for factor X; N_h and N are the numbers of units in category h and the study area, respectively; ${\sigma_h}^2$ and σ^2 are the variances of the y-values in category h and the entire study area, respectively. The range of q is [0, 1], where a higher q value indicates a greater influence of the selected factor X on the change in variable Y, and vice versa.

This study evaluated the influence of 14 natural factors on the spatial differentiation of urban built-up areas using geographic detectors. The factors analyzed were as follows: elevation (*X1*), slope (*X2*), aspect (*X3*), terrain undulation (*X4*), silty sand content (*X5*), distance from water bodies (*X6*), average annual temperature (*X7*), annual precipitation (*X8*), average annual wind speed (*X9*), annual sunshine duration (*X10*), average annual relative humidity (*X11*), accumulated temperature above 0 °C (*X12*), wind effect index (*X13*), and distance from fault lines (*X14*).

The calculation was performed using the "GD" package [29] in R version 4.3.1, where each continuous factor was discretized for geographic detector analysis. This study calculated the q values for each variable under different categorization methods: equal interval, natural breaks, quantile, geometric interval, and standard deviation. The method yielding the highest q value was deemed the optimal discretization for that variable, with categorizations ranging from 3 to 7 categories. For example, the optimal discretization of the accumulated temperature above 0 °C in Guangzhou in 2020 was achieved using the quantile classification method with six categories (Figure 2). Similarly, the accumulated temperature above 0 °C in Guangzhou in 2020 was classified into six categories using the same quantile interval method. This approach of selecting the optimal discretization method based on the highest q value is consistently applied across different continuous factors and across other years.

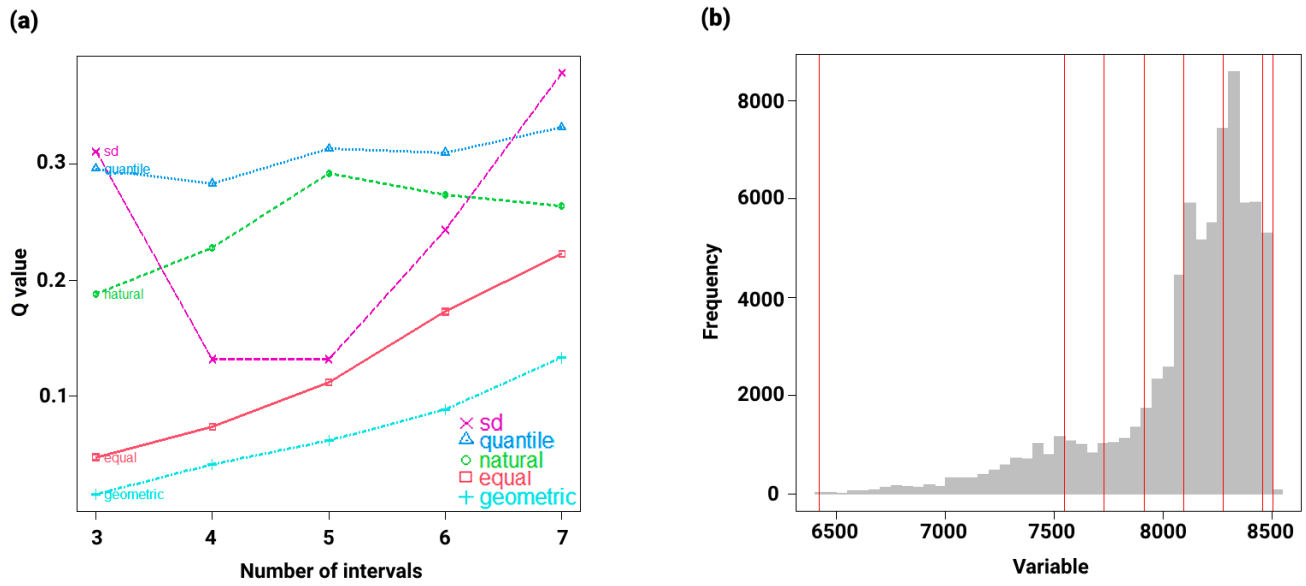


Figure 2. (**a**) Classification method of accumulated temperature above 0 °C in Guangzhou in 2020. (**b**) The optimal interval of accumulated temperature above 0 °C in Guangzhou in 2020.

3. Results

3.1. Distribution of Suitability and Carrying Capacity for Development Land under Natural Constraints

The results from the single-factor assessments were spatially overlaid. This process generated the final carrying capacity assessment for construction land in the GBA, as shown in Figure 3a. The results showed that the GBA has been categorized into five distinct zones based on the carrying capacity: low, middle-low, middle, middle-high, and high. Subsequently, these zones were further grouped into three categories reflecting their suitability for development: unsuitable, moderately suitable, and highly suitable areas, which are illustrated in Figure 3b. The areas and proportions of each carrying capacity and suitability zone are detailed in Table 4.

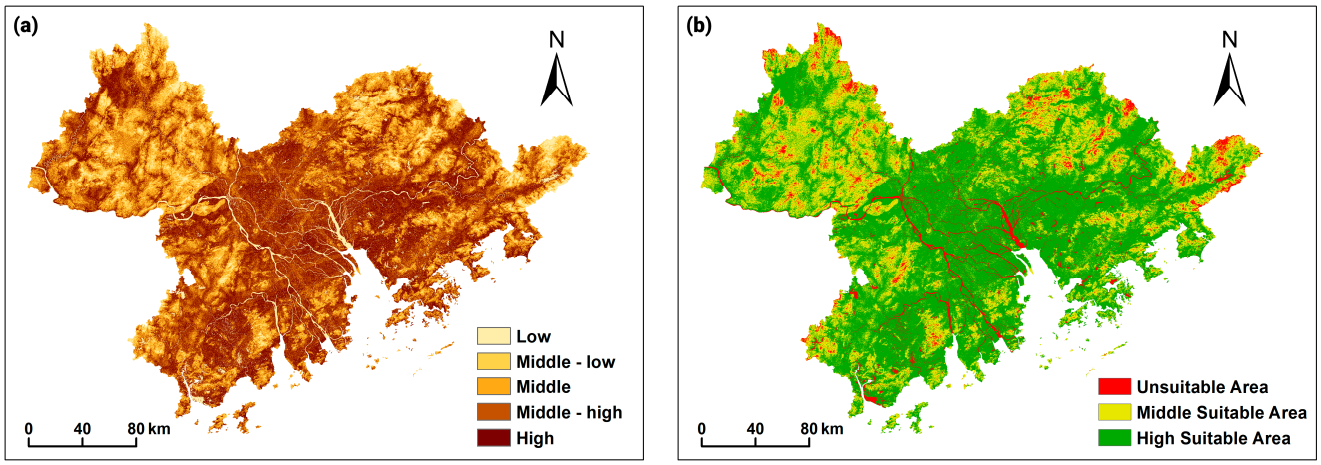


Figure 3. (**a**) Distribution of the carrying capacity grade in the GBA; (**b**) distribution of the carrying capacity and suitability grade in the GBA.

Table 4. Summary of carrying capacity and suitability grade area.

Carrying Capacity Grade	Area/km^2	Proportion/%	Suitability Grade	Area/km^2	Proportion/%
Low	3694.99	6.61	Unsuitable	3694.99	6.61
Middle-low	5515.54	9.87	Middle Suitable	17,927.64	32.09
Middle	12,412.10	22.22			
Middle-high	20,871.65	37.36	High Suitable	34,241.13	61.29
High	13,369.48	23.93			

The highly suitable areas are the most extensive, covering 34,241.13 km^2 and comprising 61.29% of the total area. The moderately suitable areas measure 17,927.64 km^2, comprising 32.09% of the total area. The unsuitable areas, being the smallest, occupy 3694.99 km^2, which represents 6.61% of the total area.

3.2. Analysis of Urban Spatial Development Potential under Natural Constraints

The overall urban spatial development potential of the GBA and its constituent cities is detailed in Figure 4 and Table 5. In 2020, the area of suitable zones already utilized in the urban built-up areas was 5137.15 km^2, which accounted for 9.85% of the total suitable area within the administrative boundaries of the GBA. The remaining suitable area within the administrative region amounted to 47,031.62 km^2, representing 90.15% of the total suitable area. This indicates that as of 2020, 90.15% of the areas suitable for urban development within the GBA remained undeveloped, highlighting the significant potential for further urban spatial development.

At the city level, Zhaoqing still has 99.56% of urban spatial development potential, which ranks first in the GBA, followed by Huizhou (98.99%), Jiangmen (98.04%), Zhuhai (88.96%), Hong Kong (86.48%), Zhongshan (86.41%), and Guangzhou (81.93%), which have urban spatial development potentials beyond 80%. Foshan has 76.72% of urban spatial development potential. Dongguan (49.09%), Shenzhen (45.28%), and Macao (26.83%) have urban spatial development potential of less than 50%. Macao (26.83%) has the lowest urban spatial development potential among all the cities in the GBA.

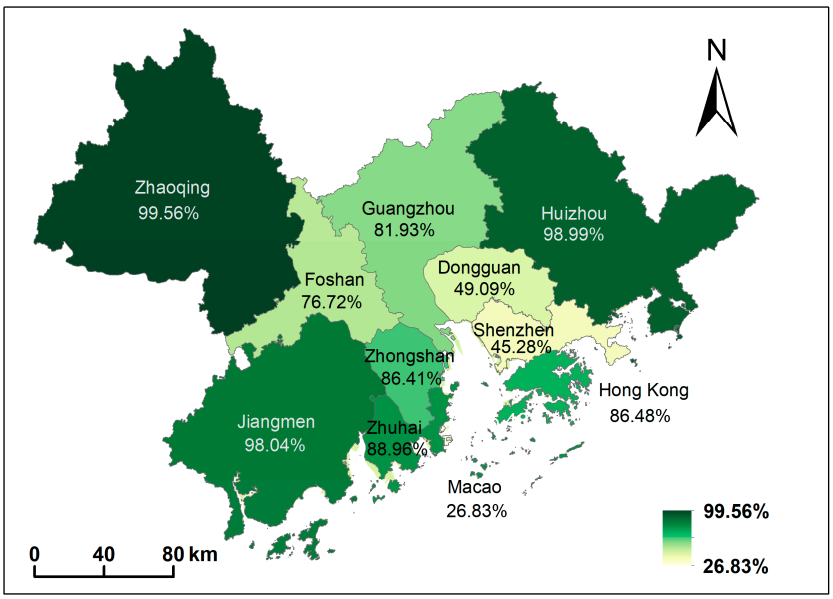


Figure 4. Urban spatial development potential of the GBA.

Table 5. Summary of suitable areas in the GBA.

Area	Built-Up Area		Administrative Division	
	Area of Suitable Area/km^2	% of Suitable Areas	Remaining Suitable Area/km^2	% of Suitable Areas
GBA	5137.15	9.85	47,031.62	90.15
Guangzhou	1235.37	18.07	5602.84	81.93
Shenzhen	1026.34	54.72	849.29	45.28
Zhuhai	162.91	11.04	1312.70	88.96
Foshan	826.95	23.28	2725.43	76.72
Huizhou	107.47	1.01	10,513.77	98.99
Dongguan	1159.19	50.91	1117.92	49.09
Zhongshan	222.07	13.59	1412.51	86.41
Jiangmen	171.05	1.96	8535.81	98.04
Zhaoqing	61.41	0.44	14,047.08	99.56
Hong Kong	141.57	13.52	905.89	86.48
Macao	22.82	73.17	8.37	26.83

3.3. Analysis of Urban Development Area Driving Forces under Natural Constraints

The results of the optimized parameter geographic detector from 2020 indicate that, within the GBA, all influencing factors, except aspect (*X3*), had *q* values above 0 and *p* values below 0.05. This demonstrates that, aside from aspect(*X3*), the remaining factors significantly explain the spatial heterogeneity of urban built-up areas, as detailed in Table 6 and Figure 5. The ranking of the explanatory power of each influencing factor is as follows: silty sand content (0.5669), average annual relative humidity (0.2208), growing degree days above 0 °C (0.1642), annual precipitation (0.1442), wind effect index (0.1137), average annual wind speed (0.1125), terrain undulation (0.1073), elevation (0.1043), average annual temperature (0.0858), slope (0.0621), annual sunshine duration (0.0523), distance to water systems (0.0485), distance to fault lines (0.0319), and aspect (0.0001).

Regional variations affect how these factors influence the spatial heterogeneity of urban built-up areas. For example, silty sand content (*X5*) exhibits strong explanatory power over 0.4 in the overall GBA, as well as in Foshan and Jiangmen, marking it as the most influential factor in these areas, but its explanatory power is notably weaker in Hong Kong, Macao, Zhaoqing, Zhongshan, and Zhuhai, where it falls below 0.1. Terrain undulation (*X4*), average annual relative humidity (*X11*), and accumulated temperature above 0 °C (*X12*) are significant explanatory factors in at least two regions each. In particular, terrain undulation (*X4*) is the most influential in Shenzhen and Dongguan, with values of 0.3838 and 0.2278, respectively. Average annual relative humidity (*X11*) holds significant influence in Zhuhai and Zhongshan, with values of 0.2282 and 0.2021, respectively. Accumulated temperature above 0 °C (*X12*) shows strong influence in Guangzhou and Hong Kong, with values of 0.3799 and 0.2036, respectively.

The *q* values of the influencing factors for each prefecture-level city, as well as the Special Administrative Regions of Hong Kong and Macao, were ranked from highest to lowest, and the top three factors, along with their frequency of occurrence, were tabulated (Table 7). The factors appearing in the top three are *X11*, *X12*, *X8*, *X5*, *X1*, *X4*, *X9*, *X13*, *X7*, and *X10*. Factors *X11* and *X12* appeared six times each; X8 appeared four times; *X4*, *X5*, and *X9* appeared three times each; *X7* and *X13* appeared twice; and *X10* appeared once. This indicates that at the city level, the development of urban built-up areas is predominantly influenced by the annual average relative humidity (*X11*) and the accumulated temperature above 0 °C (*X12*).

Table 6. Summary table of q values of each factor.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
GBA	0.1043 *	0.0621 *	0.0001	0.1073 *	0.5669 *	0.0485 *	0.0858 *	0.1442 *	0.1125 *	0.0523 *	0.2208 *	0.1642 *	0.1137 *	0.0319 *
Guangzhou	0.1992 *	0.0651 *	0.0005 *	0.1458 *	0.1206 *	0.0534 *	0.3453 *	0.3600 *	0.2256 *	0.0845 *	0.2053 *	0.3799 *	0.3253 *	0.0813 *
Shenzhen	0.2582 *	0.2239 *	0.0008	0.3838 *	0.1605 *	0.0180 *	0.1175 *	0.2684 *	0.2269 *	0.2152 *	0.1410 *	0.3135 *	0.2259 *	0.1294 *
Zhuhai	0.0547 *	0.0233 *	0.0010	0.0535 *	0.0213 *	0.0098 *	0.1381 *	0.0599 *	0.0943 *	0.1386 *	0.2282 *	0.1598 *	0.0893 *	0.0207 *
Foshan	0.0511 *	0.0303 *	0.0019 *	0.0622 *	0.6427 *	0.0643 *	0.1229 *	0.2020 *	0.3473 *	0.3125 *	0.4642 *	0.2857 *	0.2706 *	0.0274 *
Huizhou	0.0407 *	0.0208 *	0.0001 *	0.0350 *	0.4618 *	0.0111 *	0.1137 *	0.0758 *	0.0362 *	0.0293 *	0.2106 *	0.0755 *	0.0796 *	0.0036 *
Dongguan	0.2237 *	0.1454 *	0.0012 *	0.2278 *	0.1137 *	0.0428 *	0.0794 *	0.1637 *	0.2324 *	0.2185 *	0.1579 *	0.2519 *	0.1081 *	0.0453 *
Zhongshan	0.0573 *	0.0257 *	0.0018	0.0704 *	0.0654 *	0.0043 *	0.1869 *	0.0509 *	0.1867 *	0.1211 *	0.2021 *	0.0715 *	0.1482 *	0.0153 *
Jiangmen	0.0122 *	0.0063 *	0.0001	0.0123 *	0.5258 *	0.0042 *	0.0538 *	0.0234 *	0.0871 *	0.0622 *	0.1369 *	0.1143 *	0.0376 *	0.0143 *
Zhaoqing	0.0266 *	0.0068 *	0.0000	0.0171 *	0.0069 *	0.0071 *	0.0169 *	0.0443 *	0.0186 *	0.0177 *	0.0264 *	0.0265 *	0.0350 *	0.0183 *
Hong Kong	0.1512 *	0.0912 *	0.0009 *	0.1408 *	0.0304 *	0.0368 *	0.1315 *	0.1392 *	0.0483 *	0.0897 *	0.1720 *	0.2036 *	0.1620 *	0.0325 *
Macao	0.3710 *	0.1335 *	0.0363 *	0.2750 *	0.0958 *	0.0971 *	0.2406 *	0.1860 *	0.2687 *	0.2412 *	0.2704 *	0.2117 *	0.1145 *	0.2254 *

Note: "*" indicates $p < 0.05$.

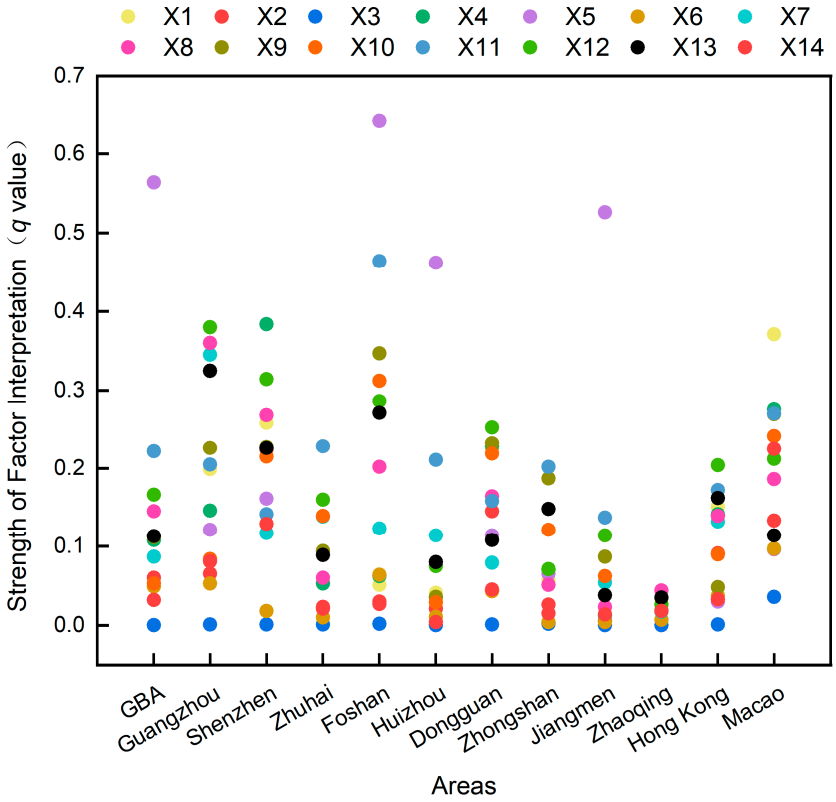


Figure 5. *q* value ranking map of the GBA.

Table 7. Summary of the frequencies of the main factors.

Factor	*X11*	*X12*	*X8*	*X1*	*X4*
Frequency	6	6	4	3	3
Factor	*X5*	*X9*	*X7*	*X13*	*X10*
Frequency	3	3	2	2	1

4. Discussion

From a regional perspective, the GBA has not yet fully tapped into its urban spatial development potential. Macao utilized 22.82 km^2 of suitable area in its urban built-up areas, which constituted 73.17% of all suitable areas within the Macao Special Administrative Region. This makes it the city with the highest proportion of utilized suitable areas in the GBA. Consequently, Macao has only 26.83% of its suitable construction area remaining, indicating the lowest urban spatial development potential at 26.83%. In contrast, Zhaoqing utilized only 61.41 km^2 of suitable area, a mere 0.44% of the total suitable area within administrative boundaries, marking the lowest proportion in the GBA. Accordingly, Zhaoqing possesses the highest urban spatial development potential among all cities in the GBA, at 99.56%. Meanwhile, the Hong Kong Special Administrative Region possesses a development potential of 86.48%, challenging prior studies that highlighted a scarcity of urban land [33–35]. Despite significant development in Hong Kong Island and in the Kowloon districts, substantial areas suitable for development still exist under natural constraints, particularly in the New Territories.

At the municipal level, average relative humidity and accumulated temperature above 0 °C significantly influence urban built-up areas. Previous studies have indicated that higher humidity exacerbates physiological stress from high temperatures, subsequently increasing mortality rates [36–38]. These findings suggest that humidity and temperature substantially affect human health and indirectly influence urban development. At the

overall level of the GBA, silty sand content is the primary factor affecting spatial heterogeneity in urban areas. Similar to Zurui Ao et al. (2024)'s findings, the geological structure beneath cities plays a crucial role in urban subsidence, impacting surface stability and leading to structural damage [39]. This underscores the importance of soil conditions in urban development at the Bay Area level. Additionally, Juan Huang (2015) and other researchers partly attribute Hong Kong's limited built-up area to flawed land development policies [40,41], indicating that both natural conditions and urban policies significantly shape urban built-up areas [42], meriting further research.

This study's evaluation of urban spatial development potential under natural constraints presents several limitations. Firstly, there is significant room for improvement in the multi-indicator comprehensive evaluation approach. The selection, grading, and assignment of indicators introduce substantial uncertainty in the results. Despite efforts to objectify these processes, they inherently reflect subjective decisions by the evaluator, aiming to fulfill specific evaluation objectives but not necessarily capturing land suitability accurately. Secondly, the research data lacked refinement. First, the soil and elevation data are not synchronized in time, which, due to the absence of up-to-date officials, could impact the accuracy of the study. Furthermore, the spatial resolution of the data is insufficient for detailed analysis. Different sizes of spatial statistical grids affect the results of the model. Although the Optimal Parameters-based Geographical Detector is employed in this study, the selection of grid size for data extraction still directly influences data discretization and consequently impacts the analytical outcomes. Finally, the study does not consider the impact of other complex influences on urban areas. While it utilizes the differentiation and factor detection sub-models of the geographic detector model, which effectively identify key variables impacting urban development, it overlooks the complexity of urban systems. The urban environment is a complex and dynamic system, characterized by constant evolution and uncertainty. Its trajectory is influenced by a variety of factors, including climate change, technological innovation, and social unrest [43–45]. Urban development under natural constraints is typically influenced by multiple interacting factors, not just isolated variables. Moreover, in addition to external influences on cities, internal changes in cities also play a significant role in urban development [46].

To address the deficiencies identified in this study, future research should focus on several key areas: First, enhancing the evaluation indicator system is crucial. Further extensive research is necessary to refine the selection, grading, and assignment of land evaluation indicators, ensuring that they align with the evaluation's objectives and enhance both the comprehensiveness and accuracy of the indicators. Second, more refined data can be applied in future research. Employing finer grids would provide more detailed data, improving the model's accuracy in capturing local characteristics and dynamics in urban spatial development. Third, there is a need to consider the impact of different factors on urban built-up areas. For example, climate change would affect urban built-up areas, leading to changes within these areas themselves. This will enable a more comprehensive analysis and understanding of the complex interrelationships in the urban environment.

5. Conclusions

This study conducted a quantitative analysis of urban spatial development potential in the GBA, elucidating the relationship between the region's current urban space and its potential for future development under natural constraints. The findings indicate that Zhaoqing has the highest development potential at 99.56%, followed by Huizhou (98.99%), Jiangmen (98.04%), Zhuhai (88.96%), Hong Kong (86.48%), Zhongshan (86.41%), Guangzhou (81.93%), Foshan (76.72%), Dongguan (49.09%), and Shenzhen (45.28%), with Macao having the least at 26.83%. This ranking highlights significant variability in available urban development space across GBA cities under natural constraints. Further analysis reveals that different cities are affected by natural constraints to varying degrees. At the Bay Area level, urban development is predominantly influenced by silty sand content, average annual relative humidity, and accumulated temperature above 0 °C, contributing 0.5669,

0.2208, and 0.164 to spatial heterogeneity, respectively. At the city level, the same factors of relative humidity and temperature are the primary influences on urban built-up areas. The results of this study provide a scientific foundation for urban land space planning and the future development of urban forms in China during its transitional period. Future research should explore the effects of various influencing factors, including interactions between natural constraints and the impact of human policy factors, to promote sustainable and efficient urban spatial development.

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