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# Assessing the scale effect of urban vertical patterns on urban waterlogging: An empirical study in Shenzhen

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ABSTRACT

Waterlogging disasters seriously affect residents' lives. Investigating the factors affecting waterlogging is crucial for mitigating waterlogging. Although waterlogging is closely related to land-use patterns, most of the previous studies have analyzed only the impact of urban horizontal patterns on waterlogging at a single scale. Few studies have focused on the role of urban vertical patterns from a multiscale perspective. Therefore, this study investigated the influence of various factors on the density of waterlogging points at grid scales of 1–5 km using Pearson correlation analysis and the random forest model. We conducted a case study for Shenzhen City, and the results show that the building coverage ratio, building crowding degree, building density, proportion of impervious surfaces, proportion of green space, and population density are the most important factors. Moreover, the urban horizontal and vertical patterns have significant scale effects on waterlogging. The influence of horizontal patterns on waterlogging is maximum at a scale of 3 km, while the influence and dominance of the vertical patterns increase with scale. Therefore, controlling building congestion is necessary for alleviating waterlogging, and the rational planning of urban horizontal and vertical patterns is important for the construction of sponge cities. Our results provide decision support for urban land-use optimization and waterlogging mitigation, thereby facilitating sustainable environmental management.

## 1. Introduction

Human activities have a profound impact on urban environments (Janizadeh et al., 2021; Lourenço et al., 2020; Ma et al., 2024; Pal et al., 2022). Urban waterlogging is a frequent and severe disaster that occurs in major cities worldwide, causing socioeconomic and environmental losses that hinder sustainable development (Chen et al., 2023; Peng et al., 2024; Shi et al., 2020; Su et al., 2018). Governments have proposed various policies for addressing waterlogging problems. For example, the United States suggests the implementation of the "Low Impact Development" strategy (Ahiablame et al., 2012; Pyke et al., 2011), and China promotes sponge city planning (Li et al., 2017; Xia et al., 2017). In this regard, clarifying the factors affecting waterlogging is fundamental for sustainable environmental management (Chen et al., 2015; Liu et al., 2023b; Shan et al., 2021; Thanvisitthpon et al., 2020; Yuan et al., 2020).

Previous studies have shown that urban waterlogging is significantly affected by both natural and anthropogenic factors (Hettiarachchi et al., 2018; Li and Bortolot, 2022; Li et al., 2023a; Tran et al., 2020; Wu et al., 2019). In terms of natural factors, Tehrany et al. (2019) stated that topographic features (e.g., slope and elevation) have a significant impact on waterlogging. Wang et al. (2023b) indicated that extreme rainfall is the main factor affecting urban waterlogging. Fowler et al. (2021) reported that short-term extreme rainfall is highly likely to cause waterlogging. Zhang et al. (2020b) identified vegetation abundance and cumulative precipitation as the main driving factors for waterlogging. Several studies have shown how various anthropogenic factors, particularly urban spatial patterns, significantly affect waterlogging (Gu et al., 2023; Qian et al., 2021; Wu et al., 2020; Yang et al., 2022; Zhang et al., 2023; Zhang et al., 2020a).

In fact, urban spatial patterns are the physical characteristics of the built environment in both horizontal and vertical dimensions (Al-Kodmany, 2018; Wang et al., 2023c; Zheng et al., 2017). The horizontal dimension of urban spatial patterns refers to the layout and components of land use in cities, specifically the composition and configuration of land use parcels, while the vertical dimension of urban spatial patterns

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refers to the vertical arrangement and design of buildings in cities (Cao et al., 2021; Guo et al., 2023; Salvati et al., 2013). Urban vertical patterns not only affect a city's appearance (Chen, 2022; He et al., 2017), but also exert a substantial influence on the local environment and economy (Chen et al., 2020; Lin et al., 2023).

However, previous studies have focused mainly on the relationship between urban horizontal patterns and waterlogging. Notably, the probability of waterlogging increases with the proportion of impervious surfaces. Areas with a higher proportion of impervious surfaces, such as intersections and overpasses, are prone to waterlogging (Du et al., 2022; Liu et al., 2023a). Furthermore, the risk of waterlogging is generally positively related to factors such as the proportion of built-up areas (Wang et al., 2022), the proportion of high-density residential and industrial areas (Qi and Zhang, 2022), the patch density of impervious surfaces and road density (Li et al., 2022). Conversely, the risk of waterlogging is negatively related to the proportion of green spaces (Yang et al., 2023) and the proportion of water bodies (Li et al., 2024). In summary, all these studies demonstrate that horizontal urban patterns play an important role in waterlogging.

Some studies have shown that urban vertical patterns are also closely related to waterlogging. Li et al. (2023b) found that building indicators have a significant impact on waterlogging at the subbasin scale. Son and Ban (2022) suggested that optimizing building layouts in high-density cities can reduce waterlogging risks better than improving drainage facilities. Li et al. (2021) observed that the distribution, flow depth, and flow velocity of waterlogging are affected by building layouts. Lin et al. (2021) developed a regression model that considers building indicators to explain the waterlogging risk. Bruwier et al. (2018) analyzed the relationship between urban patterns and surface runoff and concluded that the primary factor affecting waterlogging was the building coverage ratio. However, all these studies have yielded inconsistent conclusions. This inconsistency may be attributed to the research scale; that is, the influence of the same influencing factor may vary at different scales. The scale effect of urban vertical patterns on waterlogging is still unknown from the international literature.

It is difficult to comprehensively reveal the factors that affect waterlogging based on a single research scale and several studies have investigated the factors affecting waterlogging at multiple scales. For example, Zhang et al. (2018) reported that impervious surfaces explained 5.0–48.1% of the variability in urban waterlogging risk spots, with increasing explanatory power observed at the 1 km, 3 km, and 5 km grid scales. Lu et al. (2022) found that radar fusion data are effective for urban-scale typhoon pluvial flood modeling, while station observation data are better suited for neighborhood-scale modeling. Zhang et al. (2020b) revealed that topographic factors dominate at small scales (1–2 km), while land cover composition and spatial configuration become more important for waterlogging at larger scales (3–5 km). Therefore, the optimal waterlogging management scale should be carefully determined. Although previous studies have analyzed the factors influencing waterlogging from a multiscale perspective (Fewtrell et al., 2008; Taramelli et al., 2022), much less effort has been devoted to determining the differences in the impacts of urban vertical patterns on waterlogging at different research scales.

Failing to acknowledge the scale effect could lead to underestimating the waterlogging hazards in high-density urban environments and misunderstanding the effectiveness of mitigation strategies. If the nonlinear scale effect of urban vertical patterns on waterlogging is properly assessed, then more informative support can be provided for waterlogging management by policymakers. Therefore, this study aims to reveal the scale effect of urban vertical patterns on waterlogging. We first explored the spatial patterns and agglomeration effects of waterlogging events. Next, machine learning methods were used to discover the relationship between the density of waterlogging points and possible influencing factors at multiple grid scales. These results provide multiscale planning guidance for regions experiencing severe waterlogging issues.

## 2. Data and methods

### 2.1. Case study

We selected Shenzhen, which has severe waterlogging issues and a high building density, as a case study (Fig. 1). By the end of 2020, built-up areas accounted for 45.76% of the city's total land area. Shenzhen is located in a subtropical monsoon climate zone with a high frequency and intensity of extreme rainstorms (Lin et al., 2024). For example, the recent extreme rainstorm on September 7, 2023, caused a severe waterlogging disaster. Therefore, the Shenzhen government is committed to improving strategies for preventing and controlling waterlogging. Understanding the factors that influence waterlogging at different scales can provide reasonable support for waterlogging prevention and control in Shenzhen and other cities with severe waterlogging issues.

### 2.2. Data sources and processing

The data used in this study included the spatial distribution of the waterlogging points and potential influencing factors. Detailed data are shown in Table 1, Fig. 2, and Table S1. It should be noted that a building indicator system can facilitate the quantitative analysis of urban vertical patterns. Building indicators are considered primary metrics for evaluating urban vertical patterns and have been extensively employed to characterize urban vertical development (Cao et al., 2021; Chen et al., 2020; Guo et al., 2023; He et al., 2017; Salvati et al., 2013; Wang et al., 2023c). For example, Chen (2022) used building footprints to compute vertical metrics of urban land parcels and simulate dynamic changes in urban vertical patterns. Zheng et al. (2017) investigated the changes in urban vertical patterns (i.e., building heights) in Beijing over time and analyzed their relationships with urban horizontal patterns. Al-Kodmany (2018) considered buildings with four or more floors as indicators of vertical urban growth. Therefore, this study characterized urban vertical patterns based on a series of building indicators.

The scale of analysis was determined by considering the spatial distribution of waterlogging points, the number of grid units, and the applicability to planning. This approach allows us to accurately assess the situation and make informed decisions. First, we performed an average nearest-neighbor analysis of the waterlogging points and found that the observed mean distance between the waterlogging points was approximately 830 m. Because the grid size should be greater than the observed mean distance, the minimum grid size was determined to be 1 km. Subsequently, with an interval of 1 km, we successively constructed 2–5 km grids. This resulted in 2181 grids of 1 km size and 117 grids of 5 km size. This indicates that the number of available grids will be too small if the scale size continues to increase as the grids with null records need to be excluded. Therefore, 1-, 2-, 3-, 4-, and 5 km grids were adopted in this study (Fig. 3). Only grids with both buildings and waterlogging points were included in the analysis. It is important to note that the selection of a 1 km interval is important for the development of comprehensive scales that cover different levels of urban planning units, including communities (approximately 1–2 km), subdistricts (approximately 3–4 km), and districts (approximately 5 km). These grids facilitate the assessment of the scale effect on waterlogging and the formulation of planning recommendations at each level.

### 2.3. Methods

The procedure used in this study is illustrated in Fig. 4. First, we measured urban vertical patterns (Table S1) based on building information. Second, we analyzed the spatial characteristics of the waterlogging points. Third, machine learning methods were used to investigate the multiscale relationships between the waterlogging point density and influencing factors. Finally, suggestions for urban planning are provided based on the scale effects of the urban vertical patterns on

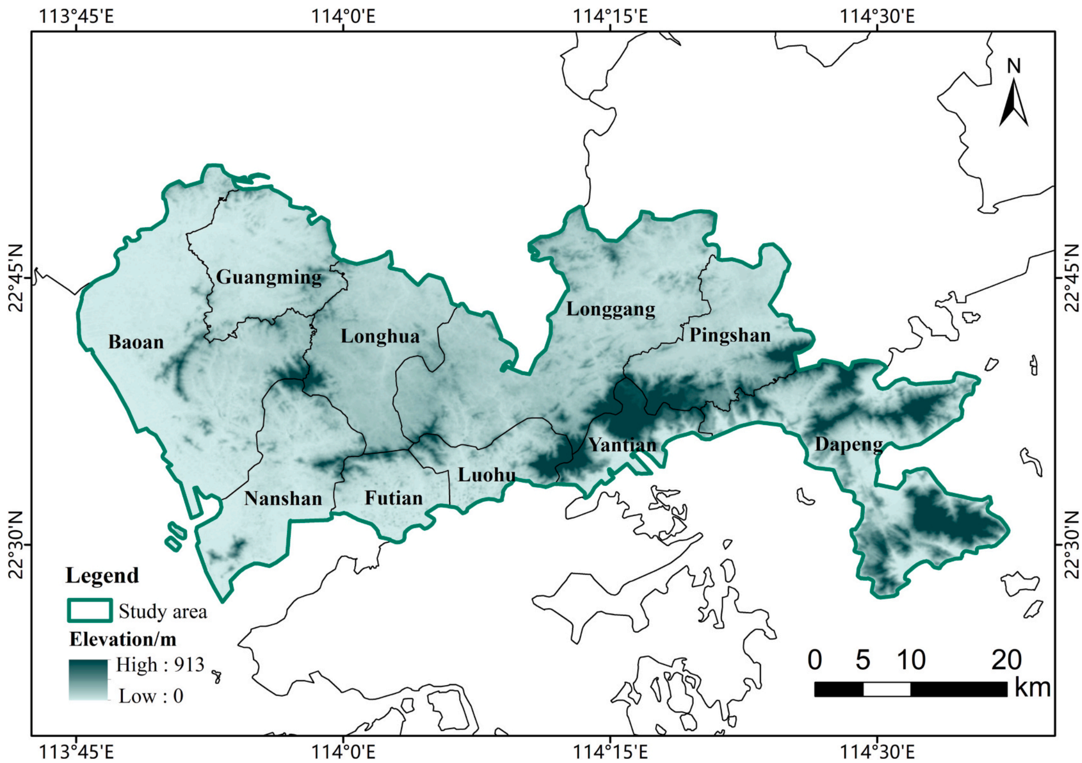


**Fig. 1.** Overview of the study area.

**Table 1**
Detailed data used in this study.

| Primary data | Secondary data | Detailed information | Source |
|---|---|---|---|
| Waterlogging points | – | – | Shenzhen Water Affairs Bureau, Shenzhen Meteorological Bureau, and the Atlas of Sponge City Planning in Shenzhen |
| Building | Building indicators | Building location, number of floors | Map of Gaode |
| Land use | Impervious surface ratio<br>Green area ratio<br>Waterbody ratio | 10 m resolution | Tsinghua University (Gong et al., 2019) |
| DEM | Elevation<br>Slope<br>Surface relief<br>Ground roughness | 30 m resolution | Geospatial data cloud platform |
| Population | Population density | 100 m resolution | WorldPop |
| NDVI | – | 1000 m resolution | Chinese academy of sciences |
| Extreme rainstorm | Number and peak volume of rainstorms | 1000 m resolution | China Scientific Data Network |
| Overpass | Distance to overpass | – | Map of Gaode |

waterlogging.

### 2.3.1. *Kernel density of waterlogging points*

The kernel density estimation method is used to calculate the density of the objects in the surrounding neighborhood. We used this method to reflect the kernel density and the spatial pattern of the waterlogging points in Shenzhen. The kernel density estimation formula is as follows:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \tag{1}$$

where $f_n$ is the estimated kernel density of the waterlogging points, $n$ is the number of waterlogging points within the bandwidth, $k$ is the kernel function, $x$-$x_i$ is the distance between waterlogging points $x$ and $x_i$, and $h$ is the radius.

### 2.3.2. *Spatial autocorrelation of waterlogging points*

The spatial autocorrelation method reveals the distribution patterns of geographic objects based on their locations and features, and both global and local spatial autocorrelations are used. The global spatial autocorrelation describes the spatial characteristics of geographic objects in the study area and can be evaluated using Moran's $I$ index, the $z$ score, and the $p$-value. We used the global Moran's $I$ index to determine the spatial correlation of the waterlogging points in Shenzhen at 1–5 km grid scales. The calculation is as follows:

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

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2, \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

where $n$ is the sample size, $x_i$ and $x_j$ are the observed values at locations $i$ and $j$, respectively, $w_{ij}$ is the spatial weight between $i$ and $j$, and $S^2$ is the standard deviation.

Local spatial autocorrelation identifies the spatial clustering of geographic objects with high or low values within an area. In this study, local spatial autocorrelation was used to evaluate the aggregation and differentiation characteristics of waterlogging points at the local scale. The calculation is as follows:

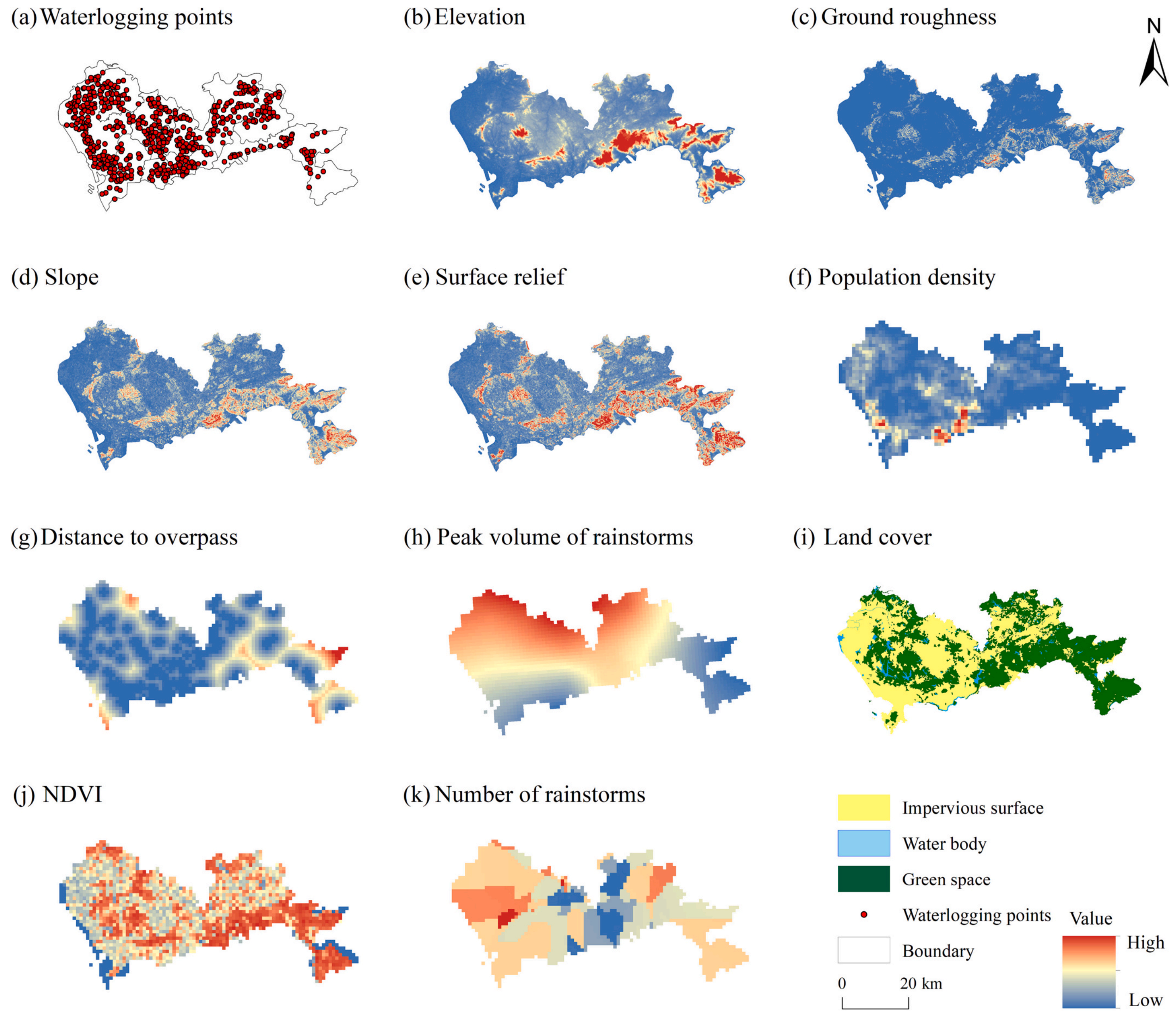


**Fig. 2.** Spatial data used in this study.

$$I_i = \frac{(x_i - \overline{x})}{S^2} \sum_{i=1}^{m} w_{ij}(x_i - \overline{x}) \tag{4}$$

where $I_i$ is the local Moran's $I$ index, and $m$ is the number of adjacent units of unit $i$. There were five types of local autocorrelation, namely "high–high agglomeration", "high–low agglomeration", "low–high agglomeration", "low–low agglomeration", and "not significant".

#### 2.3.3. Pearson correlation analysis

In this study, Pearson correlation analysis was conducted to measure the correlation coefficient between the density of waterlogging points and possible influencing factors. The calculation is as follows:

$$\rho_{XY} = \frac{N\sum_{I=1}^{N} x_i y_i - \sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{\sqrt{N\sum_{I=1}^{N} x_i^2 - \left(\sum_{I=1}^{N} x_i\right)2}\sqrt{N\sum_{I=1}^{N} y_i^2 - \left(\sum_{I=1}^{N} y_i\right)2}} \tag{5}$$

where $\rho_{XY}$ is the Pearson correlation coefficient, $X$ and $Y$ represent the two sets of variables with $X = (x_1, x_2 \ldots, x_N)$ and $Y = (y_1, y_2 \ldots, y_N)$, and $N$ is the sample size. In this study, $X$ denotes the influencing factors (e.g., urban vertical pattern indicators), and $Y$ denotes the density of the waterlogging points.

#### 2.3.4. Random forest

The multivariate linear regression model is commonly used to reveal the effects of independent variables on dependent variables; however, the presence of multicollinearity degrades its performance. To overcome the limitations of multivariate linear regression, we used random forest regression to identify the factors influencing waterlogging. The random forest model is not sensitive to multicollinearity. In addition, this model reduces the risk of overfitting through random sampling and random feature selection (Rafiei-Sardooi et al., 2021; Tang et al., 2021; Zhao et al., 2023).

The random forest algorithm is a decision-tree-based machine learning approach that combines different decision trees to form an ensemble model. Random forests can process high-dimensional nonlinear datasets and effectively handle regression and classification problems. In addition, out-of-bag samples that were not selected in the random sampling process can be used to evaluate the performance of the model and measure the importance of different independent variables. Generally, three types of indicators can be used to evaluate the

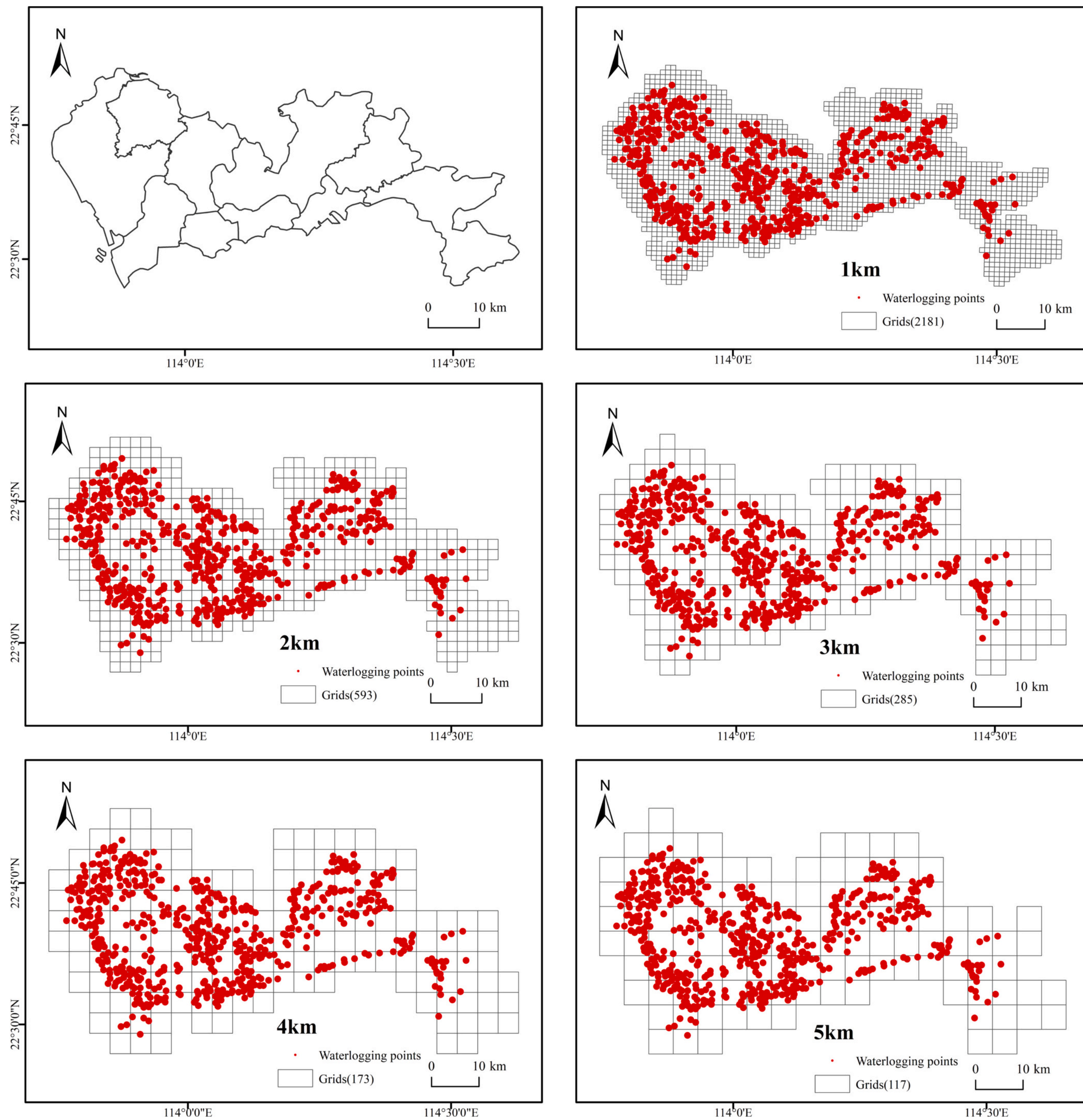


**Fig. 3.** Scale size and corresponding grids.

performance of a model: root mean square error (RMSE), mean absolute error (MAE), and goodness of fit ($R^2$). A larger $R^2$ and smaller RMSE and MAE values indicate more accurate results.

## 3. Results and analysis

### *3.1. Spatial characteristics of the waterlogging points in Shenzhen*

We first analyzed the spatial pattern and agglomeration effects of waterlogging events in Shenzhen. The results provide insights into the spatial characteristics of waterlogging and support the implementation of disaster prevention and reduction measures.

#### *3.1.1. Kernel density of the waterlogging points in Shenzhen*

The kernel density analysis (Fig. 5) revealed multicore aggregation among the waterlogged areas in Shenzhen, with varying degrees of aggregation across different regions. The western part was classified as a high-density area, the central part as a medium-density area, and the eastern part as a low-density area. Within the high-density area, three major agglomerations were identified: a belt-shaped agglomeration in the western part of Shenzhen, an agglomeration located at the junction of Longhua District and Longgang District, and an agglomeration spanning Futian District, Luohu District, and Longgang District. The medium-density area consisted of the northeastern part of Longgang District and the northwestern part of Pingshan District, while the low-density area was mainly distributed in southeastern Shenzhen.

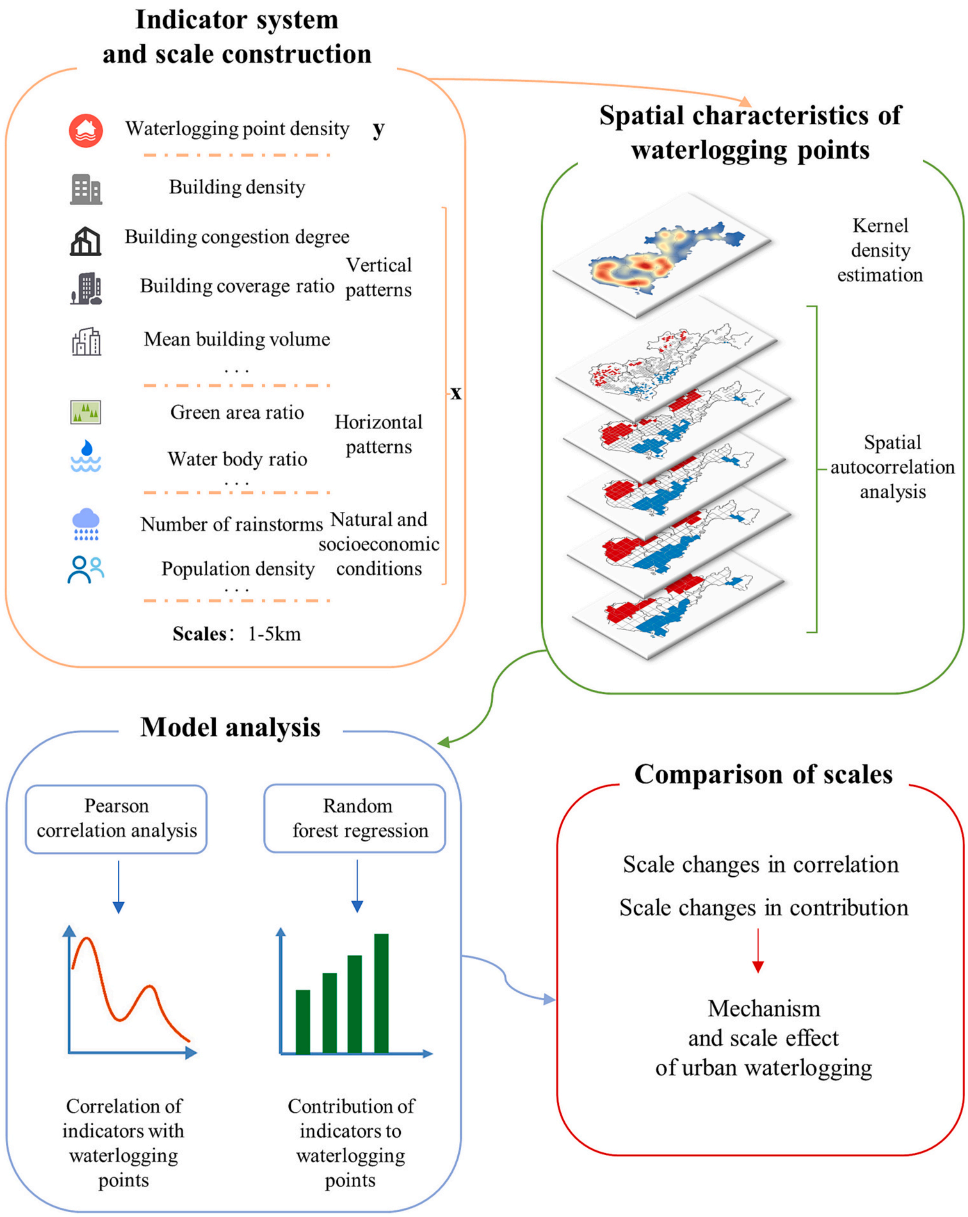


**Fig. 4.** Assessing the influencing factors of waterlogging at multiple scales.

The western agglomeration close to the Pearl River Estuary has a flat topography, rendering it vulnerable to tidal influences that hinder the effective drainage of stagnant water. In addition, numerous industrial manufacturing parks are located in this region, resulting in a greater proportion of impervious surfaces and imperfect drainage systems. Longhua and Longgang districts mainly experience extreme rainfall because of their low and flat terrain, high industrial concentration, and high proportion of impervious surfaces. Futian and Luohu districts are the central urban areas of Shenzhen, with dense populations and concentrated building clusters, but their drainage systems have not kept up with the increasing construction. Therefore, these areas are at great risk of waterlogging during extreme rainstorms.

*3.1.2. Spatial autocorrelation of waterlogging points in Shenzhen*

The global spatial autocorrelation results (Table 2) indicated a significant agglomeration effect of waterlogging points at 1–5 km grid scales. However, the Moran's $I$ values varied at different scales, with the highest values observed at the 2 km grid scale, indicating that the agglomeration trend of waterlogging points in Shenzhen was the strongest at the 2 km scale. This suggests that the implementation of disaster prevention and mitigation measures should be conducted at this scale.

In addition, we utilized local spatial autocorrelation to examine the clustering patterns of waterlogging points across multiple grid scales, and the results are presented in Fig. 6. Only two local clustering patterns, namely, "high–high cluster" and "low–low cluster", were identified across all the scales. The northern part of Shenzhen exhibited a significant degree of a "high–high cluster", while the southern part showed an apparent "low–low cluster" pattern. Overall, the distributions of waterlogging hot spots and cold spots in Shenzhen remained relatively equivalent across all grid scales. The "high–high cluster" patterns were mainly identified in the northern Bao'an District, Guangming District, northern Longhua District, northern Longgang District, and northwestern Pingshan District. The "low–low cluster" was primarily concentrated in the southern Bao'an District, Nanshan District, Futian District, and southwestern Luohu District.

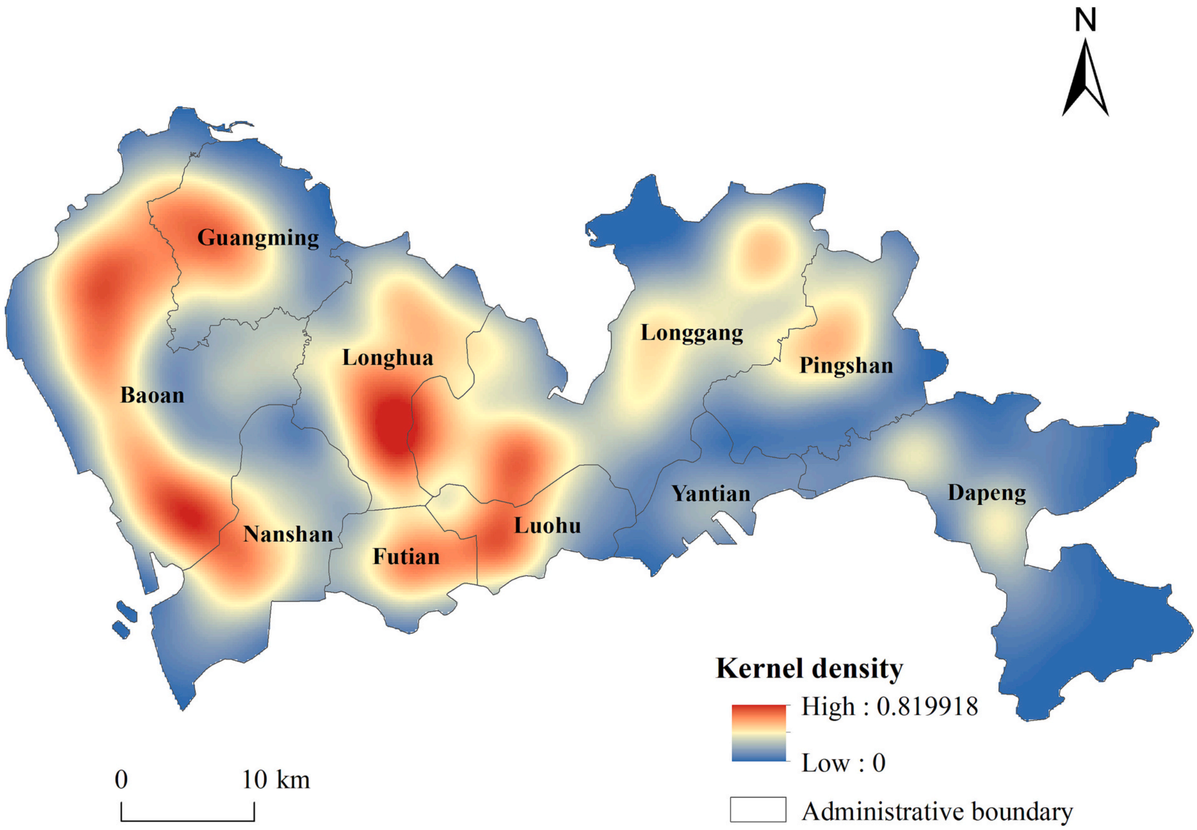


**Fig. 5.** Results of kernel density analysis for waterlogging points in Shenzhen.

**Table 2**
Global Moran's *I* index of waterlogging points in Shenzhen at different scales.

| Grid size (km) | Moran's *I* | *z* score | *p*-value |
|---|---|---|---|
| 1 | 0.9684 | 28.1494 | 0.0000 |
| 2 | 0.9735 | 31.5285 | 0.0000 |
| 3 | 0.9533 | 24.9647 | 0.0000 |
| 4 | 0.9219 | 19.9755 | 0.0000 |
| 5 | 0.7768 | 16.0988 | 0.0000 |

### 3.2. Correlations between the density of waterlogging points and influencing factors

The results of Pearson correlation analysis at 1–5 km grid scales were compared, as shown in Table 3 and Fig. 7. Population density exhibited statistical significance at all grid scales, and elevation, slope, and NDVI passed the significance test at 2–4 km grid scales. Based on the changes in correlation coefficients, elevation, slope, and NDVI peaked at the 3 km grid scale. In addition, the correlation coefficient of population density peaked at the 4 km grid scale. Furthermore, the distance to the overpass increased from 0.162 at the 2 km grid scale to 0.370 at the 4 km grid scale. These results demonstrate that the 3–4 km grid scales are the best management units for natural and socioeconomic influencing factors. Although the absolute values of the correlation coefficients for the influencing factors were relatively close at the 1 km grid scale, the absolute values for the proportions of impervious surfaces, green space, building density, building coverage, and building crowding were greater than those for elevation, slope, NDVI, and distance to the overpass at the 2–5 km grid scale. Therefore, it can be concluded that land use and vertical patterns have a greater influence on waterlogging than natural factors.

Among the land-use factors, the correlation coefficients for the proportions of impervious surfaces and green spaces passed the significance test at all grid scales. Overall, the correlation coefficients (absolute values) for the proportions of impervious surfaces and green spaces increased with increasing grid scale, peaked at the 3 km grid scale, and then declined.

In terms of vertical patterns, the HBH (highest building height), BCR (building coverage ratio), and BCD (building crowding degree) all passed the significance tests at grid scales of 1–5 km. Furthermore, highly significant positive associations were found between BD (building density) and the density of waterlogging points at grid scales of 2–5 km. As the scale size increased, the correlation coefficients for the BCR, BCD, and BD increased and surpassed those for the proportions of impervious surfaces and green spaces. The highest correlation was observed at a grid scale of 5 km. Therefore, the vertical patterns gradually replaced the horizontal patterns as the primary determinant of waterlogging with increasing scale size.

We compared the influencing factors that passed the significance test at different grid scales. The results showed that the number of influencing factors significantly associated with waterlogging point density at grid scales of 1 km and 5 km was less than that at the 2–4 km grid scales. This indicates that a small scale may be inadequate for capturing the impact of agglomeration, whereas a large scale may overlook the differences within finer statistical units. Both situations are unfavorable for revealing the complex mechanisms underlying waterlogging. In addition, the correlation coefficients for the influencing factors varied at different scales. Therefore, it is crucial to prioritize the dominant influencing factors in spatial planning across different control units. Particularly, the rational arrangement of urban vertical patterns at larger scales requires greater attention. This approach provides practical and comprehensive recommendations for the prevention and control of waterlogging.

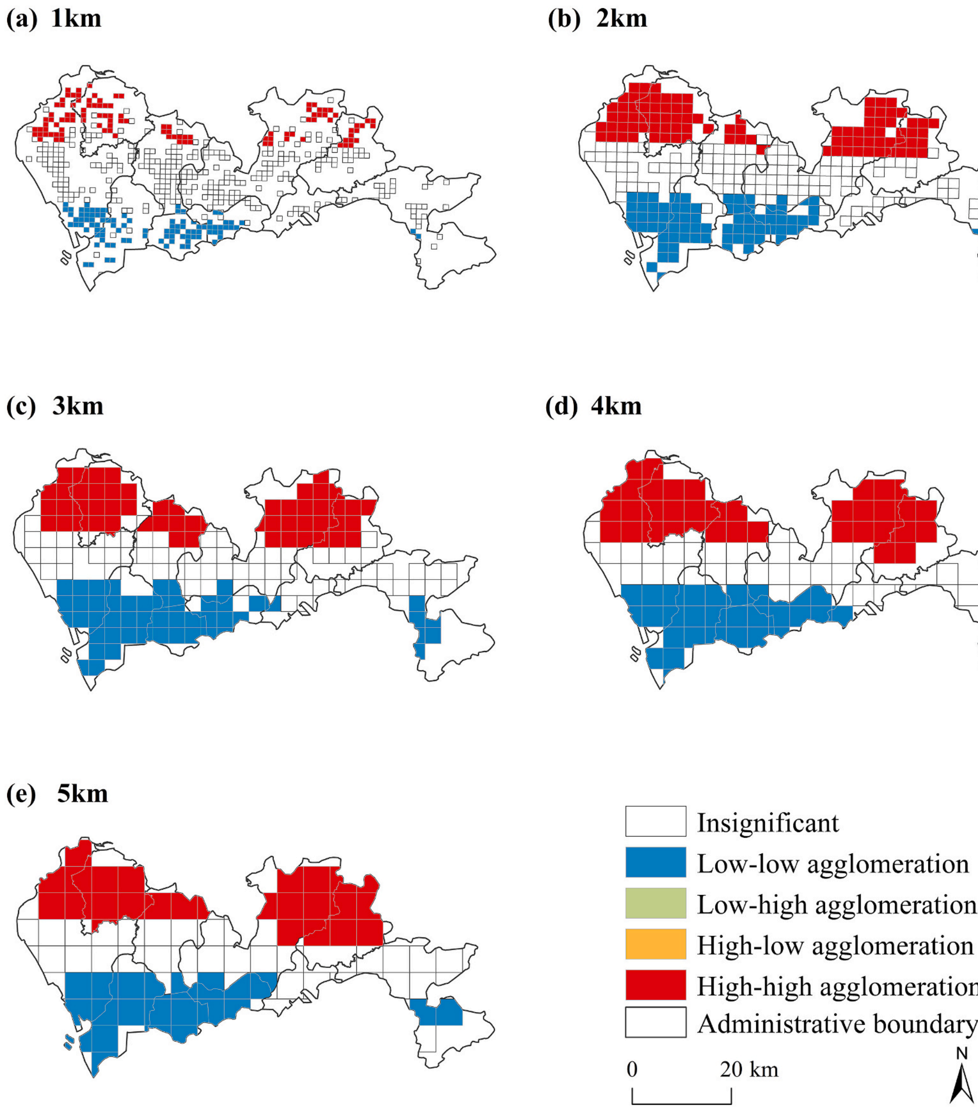


**Fig. 6.** Local spatial autocorrelation of waterlogging points at 1–5 km grid scales.

**Table 3**
Correlation between the density of waterlogging points and influencing factors at 1–5 km grid scales.

| | Influencing factors | Scale | | | | |
|---|---|---|---|---|---|---|
| | | 1 km | 2 km | 3 km | 4 km | 5 km |
| | Water body proportion | −0.001 | −0.136* | −0.157 | −0.179 | −0.225 |
| Land use | Impervious surface proportion | 0.148** | 0.369** | 0.528** | 0.507** | 0.458** |
| | Green space proportion | −0.151** | −0.356** | −0.522** | −0.494** | −0.423** |
| | BD | 0.093 | 0.308** | 0.483** | 0.532** | 0.583** |
| | TBH | 0.147** | 0.204** | 0.231** | 0.225* | 0.362** |
| | SDBH | 0.081 | 0.096 | 0.105 | 0.081 | 0.219 |
| | BCR | 0.186** | 0.374** | 0.491** | 0.519** | 0.575** |
| Vertical patterns | BCD | 0.151** | 0.379** | 0.511** | 0.565** | 0.577** |
| | BSC | −0.080 | −0.077 | −0.157 | −0.003 | −0.100 |
| | MBH | 0.023 | 0.024 | 0.002 | −0.051 | 0.073 |
| | MBV | 0.046 | −0.009 | −0.022 | −0.143 | −0.061 |
| | SDBV | 0.084 | 0.087 | 0.025 | −0.034 | 0.036 |
| | Elevation | −0.086 | −0.236** | −0.320** | −0.270** | −0.184 |
| | Slope | −0.086 | −0.244** | −0.398** | −0.337** | −0.233* |
| | NDVI | −0.029 | −0.186** | −0.244** | −0.216* | −0.084 |
| Natural, socioeconomic conditions | Distance to overpass | −0.091 | −0.162* | −0.260** | −0.370** | −0.359** |
| | Population density | 0.183** | 0.344** | 0.488** | 0.526** | 0.470** |
| | Number of rainstorms | 0.044 | 0.026 | 0.088 | 0.056 | −0.027 |
| | Peak volume of rainstorms | −0.075 | −0.049 | 0.029 | 0.006 | 0.075 |

Note: "**" represents a significant correlation at the 0.01 level (two-sided); "*" represents a significant correlation at the 0.05 level (two-sided). The vertical pattern factors are introduced in Table S1.

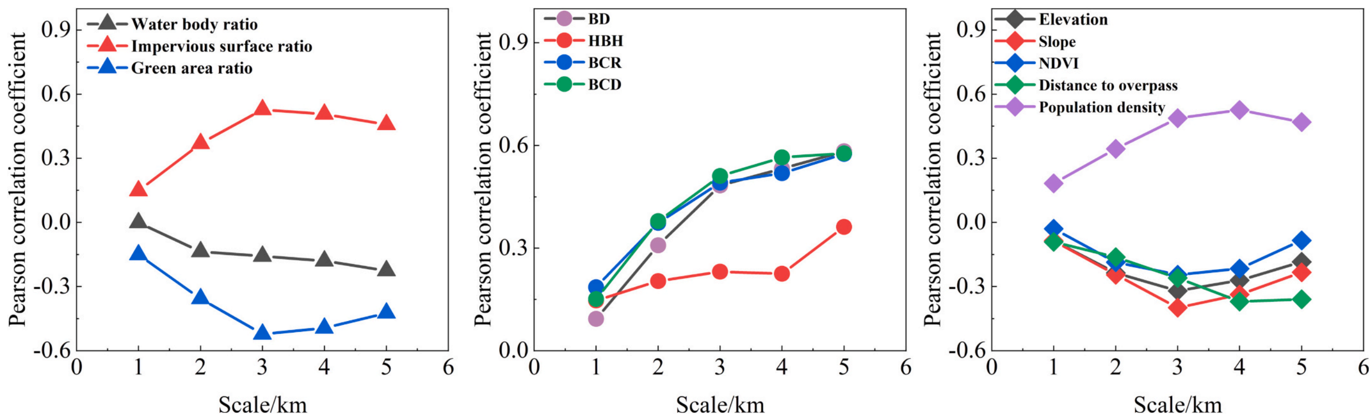


**Fig. 7.** Comparison of correlation coefficients for all factors at different scales.

### 3.3. Contribution rate of the influencing factors

The results in Table 4 show that the coefficients of determination for the random forest regression models are >0.96 at all grid scales, suggesting favorable model-fitting outcomes. Furthermore, the random forest regression models exhibited low MAE and RMSE values, indicating a high level of reliability.

Fig. 8 shows the contribution rates of all the influencing factors at the five grid scales. Based on their contribution rates, the factors were arranged in descending order within each scale. They were added cumulatively, starting with the highest contributing factor until the contribution rate reached 50%. At this point, the influencing factors included were considered dominant for that particular scale. The dominant influencing factors at each grid scale were as follows: BCR, SDBV (standard deviation of building volume), HBH, population density, MBV (mean building volume), BSC (building shape coefficient), distance to overpass, BCD, and MBH (mean building height) (1 km); BCD, BCR, population density, proportion of impervious surfaces, BD, the proportion of green space, HBH, and SDBH (standard deviation of building height) (2 km); BD, the proportion of impervious surfaces, the proportion of green space, population density, BCD, and BCR (3 km); BCR, BCD, population density, the proportion of green space, the proportion of impervious surfaces (4 km); and BCD, BCR, BD, population density, and HBH (5 km).

We analyzed the occurrence frequencies of the 13 dominant influencing factors at all grid scales (Fig. 9). The results revealed that building coverage, building crowding, and population density were present at all five scales, whereas building density, highest building height, proportion of impervious surfaces, and proportion of green spaces were observed three times. The remaining dominant influencing factors were observed only once. Therefore, BCD, BCR, BD, population density, the proportion of impervious surfaces, the proportion of green space, and HBH can be regarded as critical factors affecting waterlogging in Shenzhen. The cumulative contribution rates of these seven key influencing factors at 1–5 km grid scales were 52.16%, 51.50%, 37.80%, 35.88%, 32.59%, 31.36%, and 26.77%, respectively (Fig. 10).

In the order of contribution rates, the seven most significant influencing factors are BCD, BCR, BD, population density, the proportion of impervious surfaces, the proportion of green space, and HBH (Figs. 9 and 10). In other words, vertical patterns and land use have a significant influence on waterlogging, with the former having an even greater influence.

We further compared the changes in the contribution rates of the seven factors at different grid scales. Fig. 11 shows that the influencing factors with the highest contribution rates are the BCR (1 km and 4 km), BCD (2 km and 5 km), and BD (3 km). As the grid expanded, the contribution rate of the BCD showed an upward trend, whereas that of HBH showed a decrease. The contribution rates of the BCR, BD, population density, the proportion of impervious surfaces, and the proportion of green space exhibited upward trends, peaked, and then declined significantly.

Although there was an overall increase in the contribution rates of the vertical patterns, distinct vertical pattern factors exhibited variations in their changes. Furthermore, most of the influencing factors contributed significantly to waterlogging at the grid scale of 3 km, suggesting that this particular scale can be considered the primary planning unit for each influencing factor. Urban planning departments must carefully select the research scale and undertake prudent planning of urban vertical patterns at an appropriate scale.

**Table 4**
Accuracy of the random forest regression models at different scales.

| Indicator | 1 km | 2 km | 3 km | 4 km | 5 km |
|---|---|---|---|---|---|
| $R^2$ | 0.9773 | 0.9684 | 0.9667 | 0.9718 | 0.9689 |
| MAE | 0.2878 | 0.2810 | 0.2382 | 0.2481 | 0.2303 |
| RMSE | 0.3840 | 0.3460 | 0.3028 | 0.3070 | 0.3031 |

## 4. Discussion

### 4.1. Influence mechanism of urban vertical patterns on waterlogging

Previous studies have primarily focused on the influence of urban horizontal patterns on waterlogging. For example, Jiang et al. (2023) analyzed the effects of land-surface changes on waterlogging in Kunming City, from 2012 to 2020, and reported that the risk of waterlogging increased when the land surface permeability dropped below 35%. Lin et al. (2022) identified specific land-use factors, such as the proportions of impervious surfaces and green spaces, as major contributors to waterlogging disasters. It is essential to account for the dynamic changes in land use when forecasting future waterlogging-prone locations. The ongoing expansion of built-up areas destroys pre-existing river networks and water systems, disrupting the hydrological and ecological equilibrium of cities. This intensifies the burden on drainage systems, thereby increasing the frequency of waterlogging events (Feng et al., 2020; Houghton and Castillo-Salgado, 2020; Mustafa et al., 2020; Zhao and Huang, 2022). However, changes in urban horizontal patterns also result in alterations in urban vertical patterns. Therefore, an in-depth investigation of the influence of urban vertical patterns is essential to fully understand the mechanisms underlying waterlogging.

Zhou et al. (2022) and Li et al. (2023b) suggest that building crowding is the most important factor in urban waterlogging. Bruwier et al. (2018) report that building coverage ratio has the greatest influence on waterlogging. According to Son and Ban (2022), the proportion of detached buildings contributes significantly to waterlogging. Wang et al. (2023a) demonstrated that controlling the maximum building

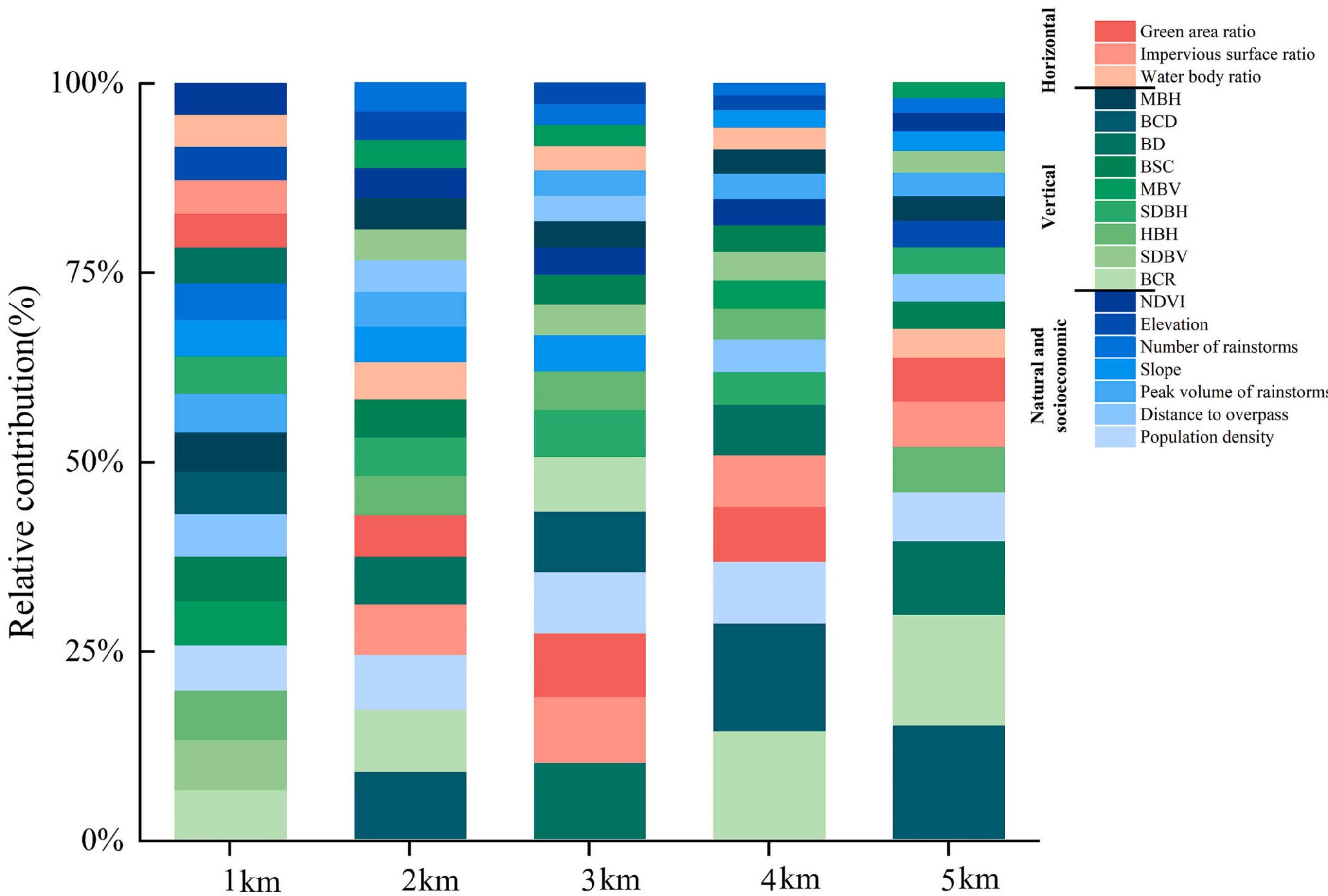


**Fig. 8.** Contribution rates of all influencing factors at different scales.

volume and building density within certain ranges can mitigate the risk of waterlogging. Thus, different studies have drawn inconsistent conclusions, possibly because of the varying contributions of the same influencing factors across different research scales. For example, this study reveals that the building coverage ratio is the most important influencing factor at scales of 1 km and 4 km, whereas the degree of building crowding has a great impact at scales of 2 km and 5 km. Furthermore, the dominant waterlogging factors vary across different scales. Even if a strong correlation is found between a specific building indicator and waterlogging at a particular scale, there is no guarantee that the correlation will remain significant upon adjusting the research scale.

Therefore, we conducted a multiscale analysis with 1–5 km grid scales and found that the building crowding degree, building coverage ratio, and building density are the most influential factors across all scales. Among these factors, the building crowding degree represents the proportion of space occupied by buildings in an urban space, while the building coverage ratio and building density measure the concentration of buildings. These factors indirectly reflect the influence of building agglomerations on urban waterlogging. These factors affect urban waterlogging in two ways regarding water production and drainage. First, an increase in building crowding degree, building coverage, and building density allows more people and human activities in the region. Simultaneously, the compact vertical patterns alter the airflow in the city, aggravating the "heat island effect" and "rain island effect" and amplifying the frequency and intensity of extreme weather events. Second, an increase in the degree of building crowding, building coverage, and building density implies a larger proportion of impervious surfaces in the region (Liu et al., 2020; Voskamp and Van de Ven, 2015; Yu et al., 2021). This weakens water infiltration and increases the pressure on the drainage system, causing an increase in the amount and rate of water produced and a decrease in the amount and rate of water drained (Fowler et al., 2021; Kim and Park, 2016; Wu et al., 2020; Zhang et al., 2015). In this regard, we investigated the effect of urban vertical patterns on urban waterlogging across multiple spatial scales. The findings provide valuable insights for urban planning departments to mitigate waterlogging through building planning and facilitate the effective implementation of disaster prevention and reduction strategies.

### *4.2. Scale effect of urban vertical patterns on waterlogging*

Most previous studies have explored the factors that affect urban waterlogging exclusively at a single scale. In contrast, this study conducted a multiscale analysis to examine the spatial aggregation of waterlogging points at grid scales ranging from 1 km to 5 km. Furthermore, this study explored the influence of vertical patterns on waterlogging from a multiscale perspective. Urban waterlogging is a complex process and the influence of urban vertical patterns on waterlogging is scale-dependent. Identifying the critical scale at which building indicators affect waterlogging is important for national land use planning and related policy adjustments. Identifying the scale effect of the influence of urban vertical patterns on waterlogging can facilitate the rational regulation of urban planning and building design across different management and control units from a macroscopic perspective. This approach provides essential decision-making support for multilevel urban planning and management.

The correlation coefficients of waterlogging with the highest building height, building coverage ratio, building crowding degree, and building density are relatively high at grid scales of 1–5 km. The random

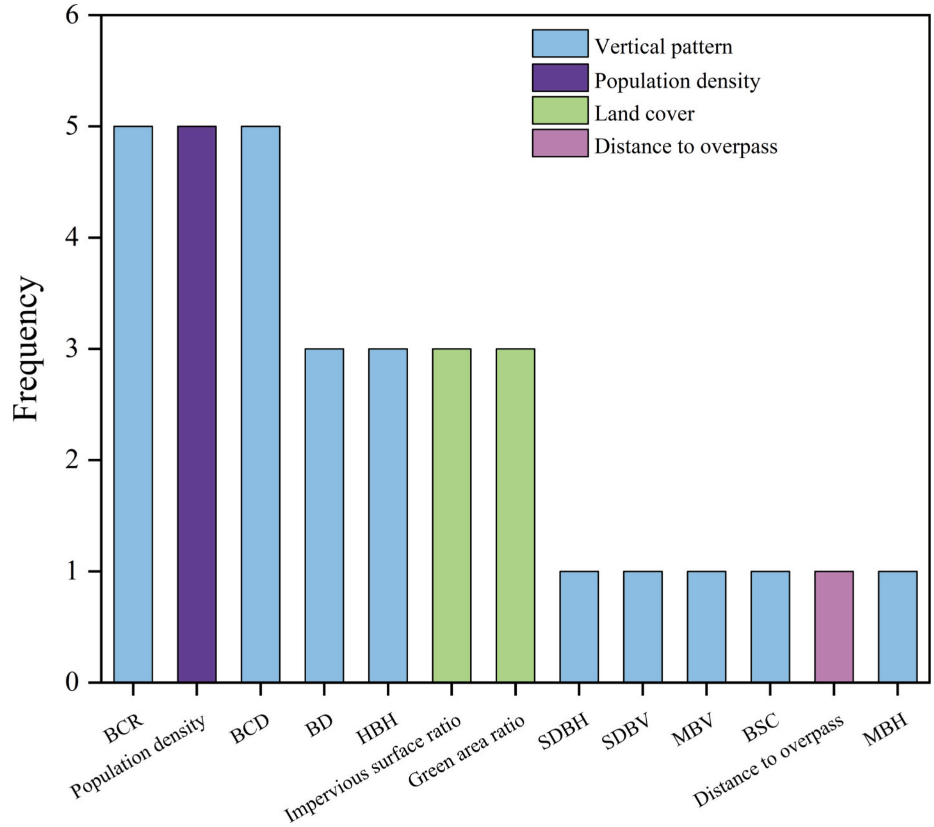


**Fig. 9.** Occurrence frequencies of dominant influencing factors at different scales.

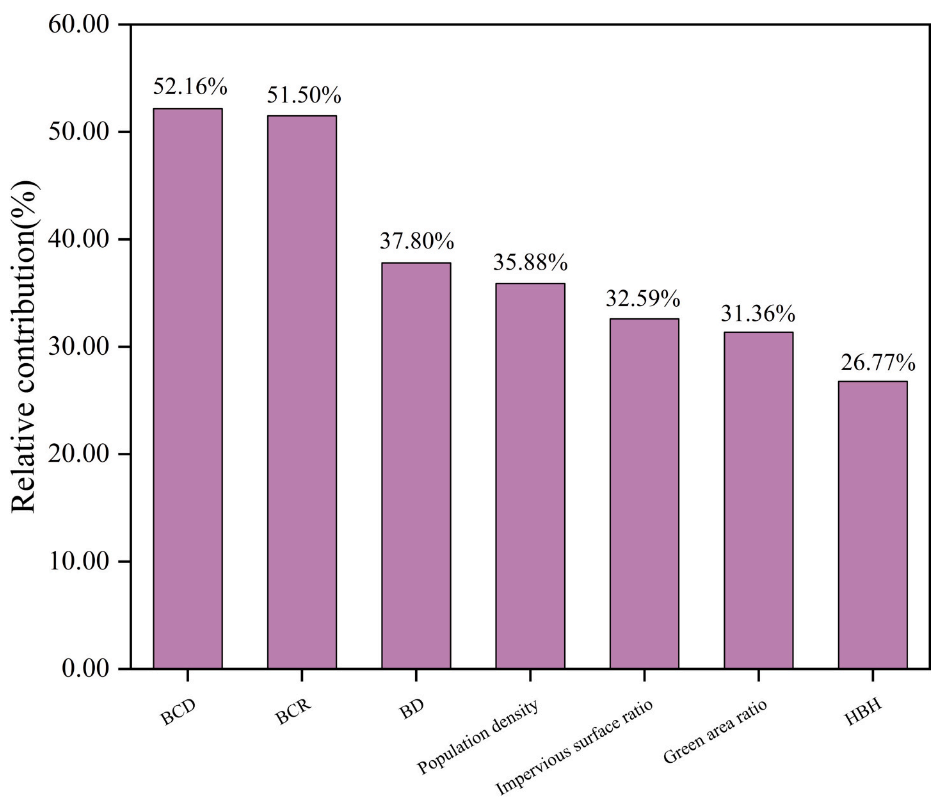


**Fig. 10.** Cumulative contribution rates of seven key influencing factors at different scales.

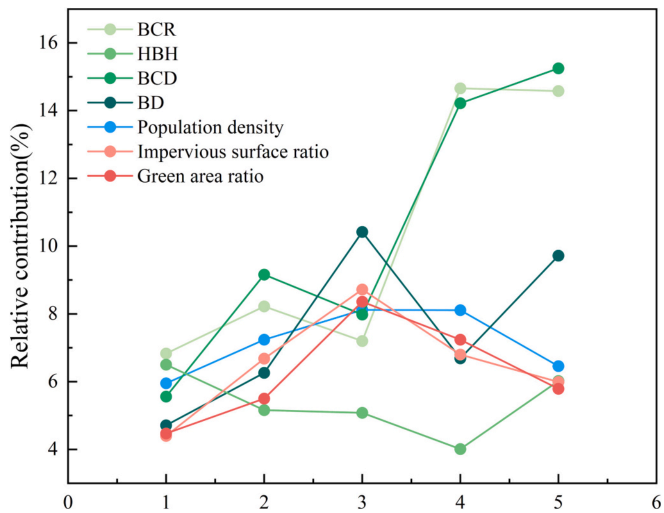


**Fig. 11.** Changes in the contribution rates of seven key influencing factors at different scales.

forest regression model also reveals the significant contribution of these factors, identifying them as the dominant influencing factors of waterlogging. However, the sensitivity of these factors to different scales varies. The correlation between the highest building height and waterlogging was significant only at a small scale (1 km). This result may be attributed to the fact that the tallest buildings pose the greatest challenges to drainage systems at smaller scales. Furthermore, the correlation between the number of buildings and waterlogging increased when the research scale was expanded to 3 km. This indicator directly reflects the agglomeration effect of the buildings. The drainage efficiency in building-dense areas is low, which increases the risk of waterlogging. When the research scale was expanded to 5 km, the negative effects of the urban vertical patterns on various environmental problems increased. As building crowding can directly affect urban airflow movement and heat dissipation, this indicator is the primary factor affecting waterlogging. In conclusion, our multiscale analysis effectively reveals the complex mechanisms behind urban waterlogging and identifies optimal research scales for land-use optimization.

Our findings highlight the importance of considering the scale effect when addressing waterlogging issues. In addition to urban vertical patterns, landscape configuration and topography also have varying impacts on waterlogging at different scales. Topographic factors are more significant at smaller scales (200 m and 400 m), while landscape indices of built-up areas (e.g., total edge) have a stronger correlation at larger scales (600 m and 800 m) (Wang et al., 2022). In addition, urban vertical patterns also exhibit non-linear scale effect on various other urban environmental factors, such as land surface temperature, air temperature, and wind speed. Notably, it has been observed that urban vertical patterns have a greater impact on land surface temperature at small scales (<105 m) (Guo et al., 2023). The building morphology is closely related to the wind speed at 500 and 1000 m scales, and the correlation between the building morphology and air temperature increases with scale. These findings suggest that the 500–1000 m range is the most effective scale for predicting urban air temperature and wind speed (Cao et al., 2021). The above studies demonstrate the importance of investigating scale effect in urban environmental impact assessments and policy formulation.

### *4.3. Suggestions for waterlogging mitigation considering scale effects*

Based on the analysis conducted, this study recommends the following measures for the construction of sponge cities in large urban areas. First, planning departments should avoid the stereotypical thinking that relies solely on sewer pipes and pumping stations for drainage. Instead, the optimization of urban vertical patterns should be prioritized. Local governments should strictly regulate the planning and design of high-rise and super high-rise buildings to control the unregulated expansion of cities in the vertical direction. In addition, it is necessary to optimize the spatial layout of buildings at an appropriate scale, limit the number of buildings, and manage the concentration of built-up areas in the horizontal dimension. Special consideration should be given to constructing urban "blue–green spaces" as a solution for waterlogging risks through a combination of human intervention and natural regulation.

Second, planning departments should implement precise disaster prevention and reduction strategies based on optimal management and control units and the most critical influencing factors. The effects of various factors on waterlogging should be considered when formulating disaster prevention and mitigation measures at different scales. Specifically, the correlation coefficients and contribution rates of each influencing factor exhibit similarities at a small scale. In comparison, significant differences are observed when these values are examined at a large scale. Therefore, it is crucial for small-scale areas to conduct a comprehensive evaluation of multiple factors and implement integrated control measures, including the development of a comprehensive flood resistance indicator system at the community level and the assessment of the collective impacts of these indicators (Zhong et al., 2020). For large-scale implementation, centralized control of the dominant influencing factors is necessary to improve the overall effectiveness of disaster prevention through accurate implementation of appropriate measures.

Finally, it is essential to carefully consider the appropriate scale for different planning objectives. For example, a 3 km grid is recommended as the optimal management unit for impervious surfaces and green spaces, suggesting that the development of gray–green infrastructure should be planned at this scale. In addition, a 4 km grid is appropriate for assessing the building coverage rate, while a 5 km grid is preferable for assessing building crowding degree. The scale effect is important in urban waterlogging mitigation, and tailoring strategies to different scales and planning objectives can significantly improve waterlogging management. Our findings provide precise and effective recommendations for implementing emergency strategies against waterlogging, thereby enhancing the effectiveness of waterlogging control.

Moreover, it is also important to consider other aspects, such as the collaborative optimization of impervious surfaces and drainage systems in urban renewal (Ke et al., 2024), the enhancement of rainwater management through green and gray infrastructure (Li et al., 2024), and the improvement of dynamic urban flood modeling for better flood warning systems and emergency response (Xia et al., 2017). These efforts collectively promote the development of "sponge cities" and "resilient cities".

### *4.4. Limitations and future research directions*

This study has several limitations that require further improvement. First, we focused mainly on natural and socioeconomic conditions, land use types, and urban vertical patterns as influencing factors without considering the planning of drainage networks. Second, this study only examined Shenzhen, a city with frequent waterlogging and high building density, as a case study. However, further research is required to evaluate the relevance of these findings to other regions. Third, while the study assessed the influence of current land use conditions, it did not consider the potential impact of future land use changes on waterlogging. Fourth, the impact of building function type on urban waterlogging was not considered due to data availability. Finally, although the study analyzed the impact of different factors on waterlogging at different scales, it did not explore the interaction effects of these factors or their combined contributions to waterlogging.

Consequently, future research should collect comprehensive and detailed information on building functions and urban drainage networks in diverse urban settings. Moreover, future research should include various types of cities to draw more generalized conclusions. Additionally, further research could investigate the potential impacts of different climatic conditions, urban planning strategies, policy interventions, and future land use changes on the observed scale effect. It is also important to consider the cumulative impacts of these factors on waterlogging. Finally, future research could benefit from a more in-depth examination of the nonlinear relationship between urban vertical patterns and waterlogging, as well as an exploration of potential variations in critical thresholds across different scales.

## 5. Conclusions

Because the influence of urban vertical patterns on waterlogging is subject to an obvious scale effect, precise management and control of waterlogging are essential. Failing to acknowledge the scale effect could lead to the underestimation of waterlogging hazards in high-density urban environments and misunderstanding the effectiveness of mitigation strategies. To address the limitations of previous studies, we first analyzed the spatial distribution and clustering patterns of waterlogging events. We then investigated the influence of urban vertical patterns on waterlogging based on Pearson correlation analysis and a random forest model, highlighting their scale effects.

The results revealed a multinuclear aggregation pattern of waterlogging points in Shenzhen, with three main agglomeration areas; the waterlogging points in northern Shenzhen displayed a significant agglomeration effect. Correlation analysis and random forest regression models demonstrated that the building crowding degree, building coverage rate, and building density were the most important factors influencing waterlogging. These factors increase the frequency of extreme rainstorm events mainly by exacerbating the “heat island effect” and the “rain island effect”. In addition, a sharp increase in these factors lowers the proportion of blue–green space and leads to greater surface runoff.

Notably, urban vertical patterns exhibit a discernible scale effect on waterlogging, and a grid of approximately 3 km is the optimal research scale. When the research scale was increased to 3 km, the influence of urban horizontal patterns on waterlogging reached a certain limit, whereas the influence of urban vertical patterns increased with scale. Therefore, effective urban planning requires a research scale suitable for uncovering the influence mechanisms behind waterlogging. Our study thoroughly assessed the nonlinear scale effect of urban vertical patterns on waterlogging and thus can provide informative support on waterlogging management for policymakers.

### Author Statement

**Yuqin Huang**: Writing - Original Draft, Formal analysis, Methodology. **Jinyao Lin**: Writing – Review & Editing, Conceptualization, Funding acquisition, Resources. **Xiaoyu He**: Methodology, Validation, Data Curation. **Zhuochun Lin**: Validation, Visualization. **Zhifeng Wu**: Project Administration, Supervision. **Xinchang Zhang**: Supervision.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2024.107486.

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