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Modelling Horizontal and Vertical Urban Development Using Parcel-Based Cellular Automata and Artificial Neural Networks

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ABSTRACT

The uncontrolled horizontal sprawl of urban development and the lack of management in high-rise construction, both inside and outside cities, highlight the need for an integrated modeling approach to urban development that addresses both horizontal and vertical dimensions. Existing models have struggled to simultaneously predict these two types of development, resulting in unreliable planning outcomes.

This research addresses this gap by developing a novel approach that combines weighted linear combination (WLC) and artificial neural networks (ANN) models. The proposed model is designed to predict both horizontal and vertical development likelihoods simultaneously.

The results indicated that the WLC model achieved 60% accuracy for horizontal development and 30% for vertical development. In contrast, the ANN model achieved 67% accuracy for horizontal development and 65% for vertical development, with an overall suitability accuracy of 66.3% for simultaneous modeling.

This study contributes to the field by providing a robust and integrated model that effectively addresses both horizontal and vertical urban development. The approach enhances land use optimization and supports sustainable urban growth planning.

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1. Introduction

Over half the global population now lives in urban areas, which occupy a small part of the Earth's surface but accommodate high population densities. This expansion has led to improper building construction and environmental degradation due to urban sprawl (Koziatek & Dragićević, 2017; Nikbayan & Karimi, 2017). Effective land use planning can mitigate these impacts by regulating horizontal development and building heights (Taleai et al., 2007).

Vertical development, or high-rise construction, involves increasing building floors or constructing multi-story buildings in cities(Shamai, and Jahani, 2011). It transforms urban morphology and functions, promoting smart growth and sustainable development (Lin et al., 2014). This approach helps manage urban sprawl and protects natural resources (Razzaghi. Asal, Mahdavinia, 2010). However, poorly constructed high-rises can cause traffic congestion, overcrowding, and limited access to amenities (Karimi, 2010).

Over time, changes occur under specific factors, influencing other phenomena. Factors impacting both horizontal and vertical urban development can be positive, promoting growth, or negative, hindering it. Research indicates that various factors influence both horizontal and vertical urban development.

Over the past two decades, Cellular Automata (CA)-based urban models have undergone significant development and have become essential tools in urban studies (Chen, 2022; Liu et al., 2021). These models are particularly valuable for scenario analysis, offering a framework to explore and understand the complexities of urban systems (Clarke, 2019; Feng et al., 2018). By leveraging the simplicity of CA, researchers have effectively modeled both horizontal and vertical urban development (Chen et al., 2019). A cellular automaton typically consists of a grid of cells, each in a specific state and influenced by a defined set of neighboring cells. However, traditional grid-based models have inherent limitations, such as fixed cell sizes and an inability to accurately represent the irregular shapes of real-world land parcels (Chen et al., 2017). Most early research in urban development relied on these grid-based approaches, which, while practical, often lacked precision when applied to complex urban landscapes. To address these shortcomings, vector-based CA models have been introduced (He et al., 2023). Unlike grid-based models, vector-based approaches simulate irregular land parcels more effectively, offering a more realistic representation of the urban environment (Abolhasani et al., 2016; Nikbayan & Karimi, 2017). These advancements enhance the accuracy of urban studies by incorporating the diverse geometries of urban landscapes, which are critical for understanding development patterns and spatial dynamics (Abolhasani et al., 2016; Chen et al., 2020; Chen et al., 2017). In research (Koziatek & Dragićević, 2017), irregular parcels were developed using vector-based GIS data and CA methods to simulate land use change. This approach addresses the limitations of simulation models that use square cells to represent cadastral parcels, which often fail to accurately represent urban fabrics. Additionally, Chen Li's research (Chen et al., 2017) highlights that vector models define parcels using polygons or shapes that precisely reflect the actual land surface. By bridging the gap between simplicity and precision, vector parcel-based models mark a significant evolution in urban modeling, providing researchers with robust tools for analyzing and predicting urban growth with greater accuracy and detail.

To address the limitations of traditional CA models in capturing the complexity of urban systems, researchers have integrated them with various advanced techniques. Standard CA models often struggle with accurately simulating multifaceted urban processes, such as land-use change, urban sprawl, and building height estimation, due to their simplistic rule-based structure and limited ability to process diverse influencing factors. To enhance their efficiency and predictive capability, CA models have been combined with methods like artificial neural networks (ANNs)(He et al., 2017; Shafizadeh-Moghadam, 2019), random forests (Zhao et al., 2022), logistic regression (Huang & Stouffs, 2024; Li et al., 2017; Rienow & Goetzke, 2015), weighted linear combinations (Nikbayan & Karimi, 2017), multi-criteria decision making (Koziatek & Dragićević, 2017; Liang et al., 2021; Bakhtiarifar et al., 2010), if-then rules (Lin et al., 2014), ant colony optimization (Huang & Stouffs, 2024; Ma et al., 2017), genetic algorithms (Huang & Stouffs, 2024; Zarei et al., 2012), and fuzzy models (Sheikhi and Roshanas,2015). In Shenzhen, a densely built city, (Zhao et al., 2022) developed a 3D[1] simulation model combining ANNs and random forests. The model predicted horizontal development probabilities and vertical building heights based on 17 driving factors, encompassing natural, ecological, socio-economic, and transportation variables. Similarly, in Wuhan, China, (He et al., 2017), employed a hybrid approach combining Backpropagation ANNs (BPANN) with case-based reasoning and organized CA (CBRSortCA). This model prioritized non-urban cells based on development potential and used neural networks to estimate building heights, updating predictions iteratively to ensure accuracy. By overcoming the limitations of traditional CA frameworks, these models effectively simulate both horizontal and vertical urban development, accommodating diverse influencing factors and dynamic spatial interactions. This integration not only improves the

[1] Three-dimensional

accuracy of urban growth predictions but also expands the applicability of CA models to multifaceted urban planning and decision-making scenarios.

While integrating advanced methods such as ANN with CA has improved urban growth modeling, existing approaches often focus on either horizontal or vertical development separately, failing to comprehensively capture both. Most models apply ANNs to predict building heights independently or use CA frameworks for horizontal expansion, rarely integrating these methodologies into a cohesive framework addressing both dimensions of urban development. Moreover, some studies have incorporated factors like land use, economic considerations, and accessibility, but often overlook their simultaneous influence on horizontal and vertical growth or lack the spatial detail needed for real-world urban dynamics. The complexity and irregularity of urban land parcels challenge traditional grid-based CA models. Although vector-based CA approaches have improved simulations of irregular land shapes, many do not combine these advancements with predictive tools like ANN for vertical growth estimation.

This study aims to address the limitations in current urban development modeling by proposing a comprehensive framework that models both horizontal and vertical urban development using a vector-based CA approach combined with ANNs. The main contribution is the integration of physical, economic, and accessibility factors to assess urban suitability, along with ANN-based methods for predicting vertical development (building heights). This approach improves the accuracy of urban growth modeling and provides valuable insights for urban planning, as demonstrated through a case study in Karaj.

The paper is structured as follows: Section 2 outlines the methodology, Section 3 implements and results, Section 4 discusses the results and findings, and Section 5 concludes with the model's practical implications for urban planning, key challenges, and future research directions.

2. Methodology

The framework for modeling both horizontal and vertical urban development, as proposed in this study, is illustrated in Figure 1.

The methodology comprises several stages: First, horizontal development potential is calculated using a weighted linear combination model and an artificial neural network, considering physical suitability, neighborhood effects, accessibility, and economic factors. Next, vertical development potential is determined based on 20 sub-criteria from building characteristics, accessibility, population, and economic factors. The third stage evaluates overall urban parcel suitability through both simultaneous and non-simultaneous development approaches, incorporating both horizontal and vertical potentials. The fourth stage calculates regional demand using growth data from 2011 to 2021. Finally, parcel allocation is performed based on demand levels, overall suitability, and the number of floors indicated in the vertical potential map.

The mathematical formulations and equations used in the methodology are provided in Appendix A for clarity and reference.

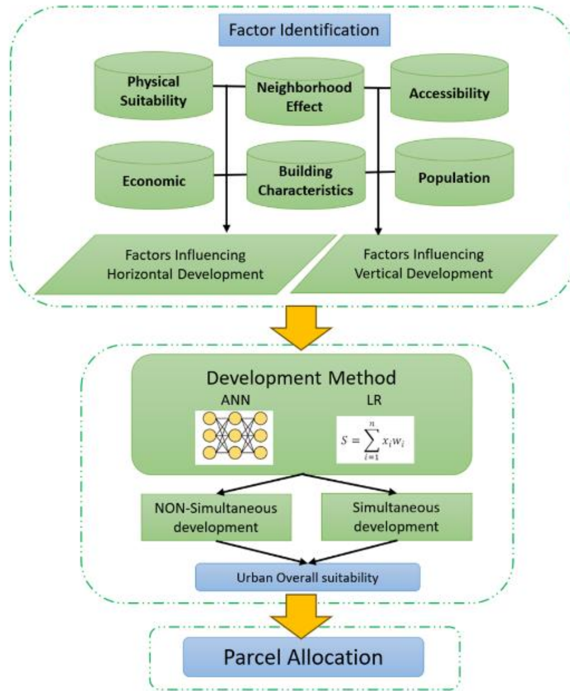


Figure 1. Methodology Workflow

2.1. Factors Influencing Urban Development

Numerous studies have explored horizontal and vertical urban development, identifying six key criteria influencing urban growth:

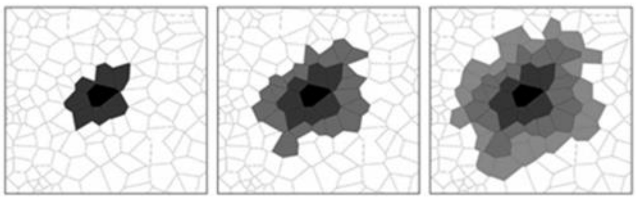
2.1.1. Physical Suitability

Physical suitability is determined by inherent land conditions such as regional elevation, steep slopes, and flood hazards, which restrict growth in certain locations (Koziatek & Dragićević, 2017). The physical suitability of each parcel is calculated based on its average slope, which is classified to indicate suitability for urban development (Abolhasani et al., 2016).

2.1.2. Neighborhood

Neighborhood effects are typically calculated using CA models, which consider the various land use types surrounding each parcel (Liang et al., 2021). The future status of a parcel is influenced by its neighboring parcels; a factor developers consider [22 In vector CA models, neighborhoods are defined similarly to non-vector CA, with a range specified as adjacent to or at a specific distance from the central parcel. A common definition of neighbors includes topologically adjacent parcels, as illustrated in

Figure 2, showing the first, second, and third neighborhoods (Chen et al., 2017).



(a) First radius (b) Second radius (c) Third radius

Figure 2. A representation of the effect of the first, second, and third neighborhoods (Chen et al., 2017).

To calculate the neighbourhood effect map for the desired parcel, consider the external outcomes (both positive and negative) of all parcels within the neighbourhood radius as detailed in Equation A1 (Appendix A), and integrate them (Nikbayan & Karimi, 2017).

The magnitude of the external outcome is calculated based on three parameters: area, distance, and the positive or negative effects of the land uses (Abolhasani et al., 2016). The magnitude of the external outcome in Equation A2, examined in three categories: *concentration*, *compatibility*, and *dependency* (Abolhasani et al., 2016).

The neighborhood effect of each urban parcel is calculated as the sum of the effects of neighboring parcels across the three categories of concentration, compatibility, and dependency. The external outcomes are analyzed separately in Equations A3, A4, and A5 (Nikbayan & Karimi, 2017).

This research utilizes the compatibility and dependency matrices of residential use from Table 1 and Table 2, respectively, as in the study (Ebrahimi et al., 2021). To calculate concentration, plots with residential use within the neighborhood distance are selected, and the effects of area and distance are combined (Nikbayan & Karimi, 2017). The weights for compatibility, dependence, and centralization are calculated based on expert knowledge (Ebrahimi et al., 2021).

Table 1. Residential Use Compatibility Matrix

Land Use	Residential	Commercial	Industrial	Educational
Residential	0.42	0.42	0.04	0.42
Land Use	Health	Religious	Sports	Facilities
Residential	0.42	0.42	0.08	0.42

Table 2. Residential Use Dependency Matrix

Land Use	Residential	Commercial	Industrial	Educational
Residential	0.42	0.42	0.04	0.42
Land Use	Health	Religious	Sports	Facilities
Residential	0.42	0.28	0.18	0.04

2.1.3. Accessibility

Accessibility is considered in terms of Euclidean or network distance. According to research (Rienow & Goetzke, 2015), accessibility is weighted based on road network speed limits, with distances determined as the shortest path lengths (Equation A6). This method allows calculating the distance between each parcel and other points. To calculate the accessibility of each parcel, the network distance and an importance factor are used. Accessibility is categorized into three types: access to roads, transportation hubs, and city centers, such as economic, industrial, educational, or recreational hubs, each playing a crucial role in urban development (He et al., 2017).

2.1.4. Economic Factors

Economic factors, such as housing prices, play a crucial role in shaping urban development, often reflecting the level of economic growth in a region. Land prices, typically collected at a regional scale, may be available for specific parcels, while others are estimated through interpolation.

2.1.5. Building Characteristics

The vertical characteristics of buildings are crucial in modeling urban vertical development. Building height (number of floors), building density, and land geometry are interrelated. The geometric characteristics of parcels, significantly influenced by the land shape, are measured by Equations A7 (Chen et al., 2017).

Building height, a key density variable, is crucial for organizing the urban landscape and must be developed considering neighboring buildings (Koziatek & Dragićević, 2017; Lin et al., 2014; Munshi et al., 2014; Nikbayan & Karimi, 2017; Taleai et al., 2007; Shamai, and Jahani, 2011). In vertical urban modeling, buildings are classified by the number of floors, and the height of the plot is calculated using the neighboring buildings' floor counts, with the neighborhood radius being particularly important (Koziatek & Dragićević, 2017).

2.1.6. Population

Population is a key factor in vertical urban development, reflecting social dispersion and population density (Koziatek & Dragićević, 2017). Larger populations drive higher building heights and vertical development (Kuru & Yüzer, 2021). Urban development often involves high-density vertical growth, and increasing population density (Chen, 2022).

2.2. Weighted Linear Combination Model

The weighted linear combination (WLC) model is a straightforward approach, determined by summing influencing factors with specified weights. In the study, this model provided alternative solutions for the development potential (Ma et al., 2017). The criteria weights were derived through statistical analysis of the relationships between current values and the criteria. These weights were evaluated using the WLC method, and the model's resulting values were calculated accordingly. Ultimately, the potential of each piece was determined using the WLC method (Kuru & Yüzer, 2021), where influencing factors were combined as illustrated by Equation A8. The weights have been chosen such that their sum equals one ($\sum_{i=1}^{n} w_i = 1$).

2.3. Artificial Neural Network Model

ANNs are a computational method that predicts output responses from complex systems, inspired by biological nervous systems. While many ANNs can determine urban potential (Shafizadeh-Moghadam et al., 2017; Tayyebi & Pijanowski, 2014; Xu et al., 2024), few have been presented, with urban CA models' calibration relying more on theory than real-world applications. ANNs, a common architecture, consist of an input layer, one or more hidden layers, and an output layer. In this study, the input layer connects to the output layer through the hidden layer, with nodes equal to the influencing factors on urban development. The output layer indicates the developed parcels or the number of floors. Figure 3 illustrates this study's ANN. The model features four input neurons, one hundred hidden neurons, and one output neuron, with weights adjusted at a learning rate of 0.05.

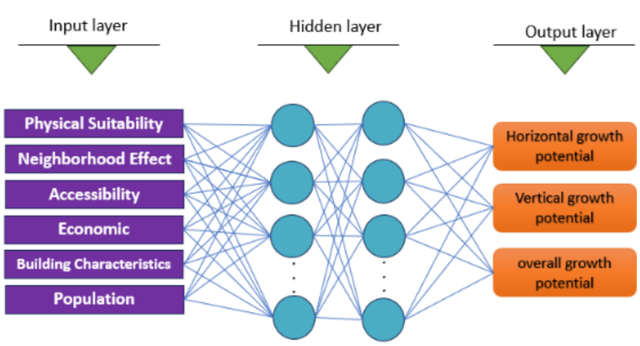


Figure 3. Structure of Artificial Neural Network

2.2. Potential for Horizontal Urban Development

Research on horizontal urban development has identified four key factors influencing development: physical suitability, neighborhood, accessibility, and economic factors. Various models, notably the weighted linear combination (WLC) model, simulate horizontal urban development by determining the potential of each urban parcel based on these criteria. The weights of the criteria are derived through statistical analysis (Kuru & Yüzer, 2021), evaluated, and combined as per Equation A9 (Nikbayan & Karimi, 2017).

2.3. Potential for Urban Vertical Development

This research uses the weighted linear combination model and the ANN model to determine vertical development potential. In the WLC model, influencing factors are combined with weights to accurately determine building heights, while sub-criteria are combined according to specified weights to assess vertical development potential for non-urban plots (Equation A10).

In this research, 20 specified sub-criteria (Appendix. B) are input into the artificial neural network model, which predicts the number of building floors based on defined weights. The weights are adjusted each time a plot is selected to improve the model's accuracy. This artificial neural network model features a hidden layer with 100 neurons and a learning rate of 0.05, optimized through trial and error to enhance accuracy.

2.4. Overall Suitability of Urban Plots

After determining horizontal and vertical urban potential, establishing the overall suitability of urban plots is crucial, as it determines the development likelihood for each plot (Zhao et al., 2022). Most studies have used non-simultaneous development, focusing on horizontal potential and using vertical potential only for building height calculation (Chen, 2022). This means plots with the highest horizontal potential are chosen, with building height based on vertical potential (Nikbayan & Karimi, 2017). However, research indicates that horizontal and vertical expansion are interconnected, leading to a need for simultaneous development assessment. This approach combines horizontal and vertical potential using a weighted linear combination, specifying parcel development likelihood and determining building height, prioritizing high-rise buildings, and preventing low-rise development. Simultaneous vertical and horizontal urban development addresses the weaknesses of traditional CA models. The model in this research can predict urban growth in both dimensions simultaneously, though it is a simple combination.

2.5. Allocation

Allocation is a crucial stage in urban development modeling. In this study, four urban parcel allocation maps are created using the weighted linear combination (WLC) model and the artificial neural network (ANN) model, based on simultaneous and non-simultaneous development methods. The process involves calculating horizontal and vertical urban potential using either the WLC model or ANNs, determining overall suitability using simultaneous or non-simultaneous methods, selecting the plot with the highest overall suitability, calculating its height based on vertical development potential, and subtracting the developed plot's area from the demand. This process repeats until the current year's demand is met. Developed plots from the previous year are converted into urban plots for the next year, affecting several factors. Studies show that land use alters the neighborhood effect of adjacent plots, and building height impacts the vertical development potential of neighboring plots. Therefore, the neighborhood effect and adjacent building heights must be recalculated annually. This process continues for ten years, with model outputs compared.

2.6. Model Accuracy Assessment

CA models are evaluated using data from different periods, making them valuable for analyzing the spatiotemporal dynamics of urban expansion. The overall urban suitability from the WLC model and the ANN model is assessed over *ten years* using both simultaneous and non-simultaneous methods. A cross matrix is formed between the reference and simulated maps in the final year to calculate overall accuracy. Urban development changes based on differences between future land use demand and current land use.

3. Implementation and Results

The implementation of the urban horizontal and vertical development model involves examining the study area, calculating factors influencing urban development, assessing horizontal and vertical urban development potential using WLC and ANN, determining overall potential, allocating non-urban plots, and evaluating the model. Further details will be explained.

3.1. Study Area

Karaj, the capital of Alborz Province, is the twenty-second most populous city in the Middle East. Formerly part of Tehran Province until 2010, Karaj benefits from its strategic location, industrial towns, economic position, and proximity to Tehran, making it the second most immigrant-receiving city in Iran. It spans approximately 220 square kilometers. The 2016 census recorded its population at 1,592,492, with a density of 7,500 people per square kilometer. Additionally, Karaj has one of the highest population growth rates among Iranian metropolises at 4.7 percent annually (Figure 4).

This research focuses on the 400-Dastgah neighbourhood in region 9 of Karaj, covering 1.15 square kilometres with an average elevation of 1300 meters. The area includes residential, commercial, industrial, educational, health, religious, and sports land uses. A highway divides it into two halves, with additional highways to the north and south for better access. The main street runs east-west, and the tallest buildings, at 13 stories, are located adjacent to this main street.

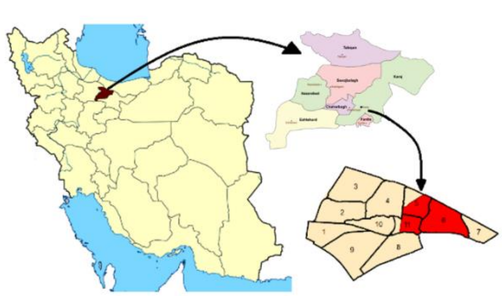


Figure 4. Study area

3.2. Calculation of Factors Influencing Urban Development

This section will address the calculation of factors influencing horizontal and vertical urban development based on the six main criteria, with data sourced from the Municipality.

3.2.1. Physical Suitability

The elevation map of the study area was derived from elevation points and the DEM of the region, showing an elevation range from 1320 to 1342 meters above sea level. According to management regulations, this range does not restrict horizontal development (Abolhasani et al., 2016)Thus, the area is assessed only for slope. The slope map, derived from the elevation map, indicates variations from 0 to 13 degrees. Most of the area has a slope close to zero degrees, with a small portion exceeding 10 degrees. To determine physical suitability, the slope map is standardized. Following the approach in (Abolhasani et al., 2016). Different slope degrees are ranked according to Table 3**.**

Table 3. Ranking different degrees of (Abolhasani et al., 2016)

Slope (Degree)	Rank
0-5	4
5-10	3
10-15	1

After standardizing the slope map, a physical suitability map is created to combine with other influencing factors. Figure 5-a illustrates the physical suitability of each urban parcel, indicated on a scale from 0 to 1.

3.2.2. Neighborhood

This factor, determined based on land use type, area, and the distance between parcels, is categorized into three groups: compatibility, dependency, and concentration, as defined by Equations (3), (4), and (5). The weights for these categories, 0.306, 0.118, and 0.567 respectively, are based on expert knowledge to calculate the neighborhood effect (Ebrahimi et al., 2021). Figure 5-b illustrates the neighborhood map for urban parcels, where the concentration of this effect is observed in the center of the area.

3.2.3. Accessibility

The accessibility of each land parcel is determined by its distance to roads, stations, and centers. Roads are classified into three categories: highways, main roads, and secondary roads, each weighted as per Table 4. The accessibility maps are then calculated using the weighted linear combination method based on these weights.

Studies indicate that access to metro stations, taxis, buses, and terminals promotes both horizontal and vertical urban development, particularly in commercial, industrial, healthcare, and recreational centers. Accessibility to roads, stations, and centers is calculated separately and then combined into a final accessibility measure using a weighted linear combination model. Figure 5-c displays the final accessibility map of the urban parcel.

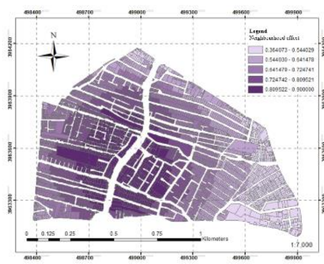
Table 4. Weight of road access surfaces (Lin et al., 2014).

Category	weight
Highway Access	4
Main Road Access	3
Secondary Road Access	1

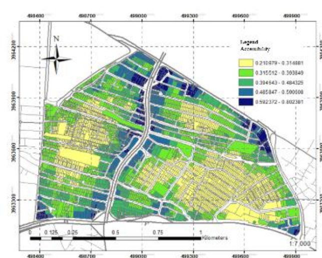
3.2.5. Building Characteristics

The geometric shape of a parcel, influenced by its environment and area, significantly affects its suitability for vertical urban development (Huang, 2023; Kwinta & Gniadek, 2017). Parcels that are too large, too small, or irregularly shaped are unsuitable for such development. Figure 5-e shows that most parcels in the area have geometric shapes between 0.2 and 0.6, making them suitable for vertical development. Building density is another crucial

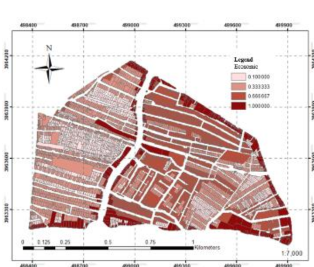
(a) physical suitability map



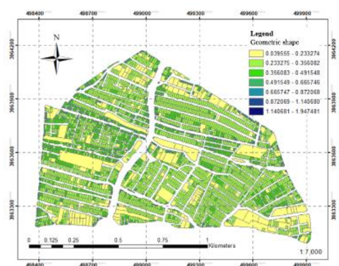
(b) Neighborhood effect map



(c) Accessibility map

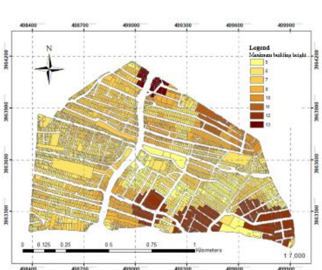


(d) Economic map

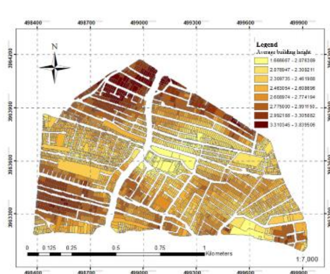


(e) Geometric shape map

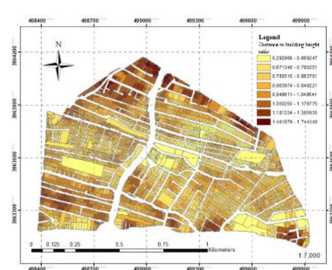
(f) Population map



(g) Maximum building height map



(h) Average building height map



(i) Distance to building height ratio map

Figure 5. Maps of factors influencing horizontal and vertical urban development

3.2.4. Economic Factors

Land price is another influential factor in modeling urban development. Figure 5-d shows the economic value of urban parcels, classified into four categories from 0 to 1. Parcels in the eastern section, indicated by darker colors, have a higher economic value.

factor, with high-density areas featuring small parcels suitable for taller buildings. The height of adjacent buildings also impacts the height of construction sites.

This study uses three height categories within a 100-meter radius for modeling. The first category calculates the maximum building height in the vicinity, highlighting northern and southern sites within 100 meters of the tallest buildings in Figure 5-g, indicating potential for high-rise development. The second category calculates the average building height within a 100-meter radius by summing the heights of urban parcels and dividing by their number, ensuring equal impact. Figure 5-h shows the average building height, with significant height values in southwestern parcels due to the prevalence of 5-story buildings. The third category calculates the ratio of distance to the height of adjacent buildings, using distance to distinguish between parcels near or far from tall buildings. Figure 5-i illustrates the distance-to-height ratio of adjacent buildings.

3.2.6. Population

In this study, regional population data are generalized for each parcel of land. Population density, calculated as the ratio of population to area, shows that small areas with large populations have high density. Ultimately, both population and population density for each parcel are determined. Figure 5-f displays the population data.

3.3. Calculation of Urban Horizontal Development Potential

The WLC model combines factors influencing horizontal development with specific coefficients: 0.1 for physical suitability, 0.5 for neighborhood, 0.3 for accessibility, and 0.1 for economic factors, as shown in Figure 7-a. The model's accuracy, evaluated from the cross matrix of predicted and actual maps, is 60%. The ANN model inputs four factors: physical suitability, neighborhood, accessibility, and economic factors, using systematic random sampling for training (70%) and evaluation (30%). Weights are adjusted with a backpropagation algorithm at a learning rate of 0.05 until stabilization. Figure 7-b shows the potential horizontal development map from the ANN model, which correctly developed 67% of the parcels. This model was tested multiple times with consistent results, and its accuracy was determined using the cross matrix from predicted and actual maps. Figure 6 compares the degree of conformity of developed horizontal parcels from both models and the actual amounts. The red represents the WLC model, the blue is the ANN model, and the green is the actual parcels. The ANN model demonstrates higher credibility and accuracy in determining parcel potential. Both models are used to evaluate overall suitability and final results in this study.

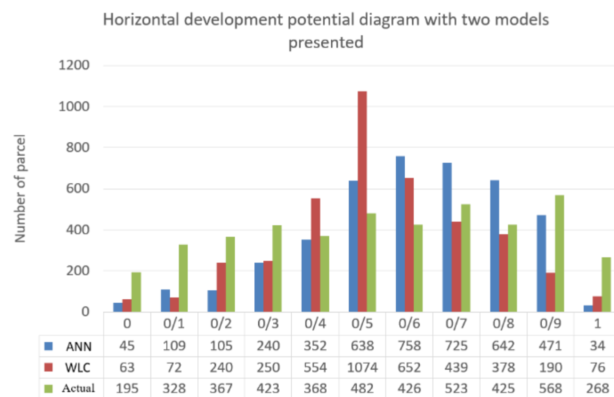
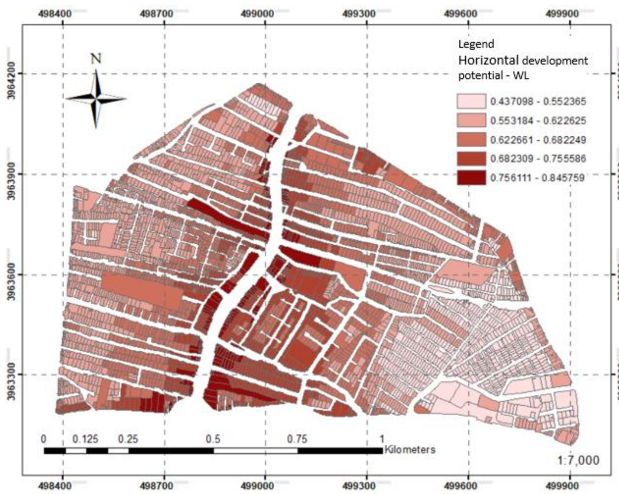


Figure 6. Comparison chart of horizontal development potential models

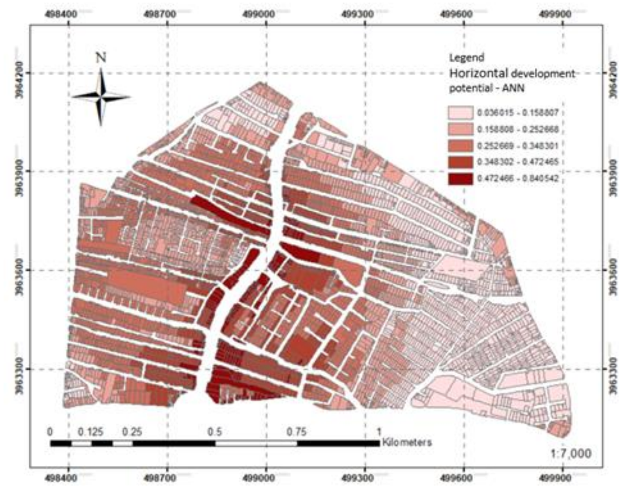
3.4. Calculation of Urban Vertical Development Potential

The study area contains buildings ranging from one to eight stories, with two 13-story buildings in the northern part. In the WLC model, sub-criteria are combined with assigned weights, determined through trial and error for optimal accuracy in predicting building heights. The output is a map showing the predicted number of floors for each urban plot (Figure 7-c), with heights ranging from 1 to 5 stories. The model's accuracy is evaluated by comparing predicted and actual heights using a cross matrix, achieving 30% accuracy in exact predictions and 60% with a maximum error of one floor, demonstrating its reliability in determining vertical development potential. For the ANN model, 20 sub-criteria from each plot are input. The model calculates plot heights based on initial weights, compares them with actual heights, and adjusts the weights using a backpropagation algorithm with a learning rate of 0.05 until stabilization. Using systematic random sampling, 70% of the data is for training and 30% for evaluation. Figure 7-d shows the number of floors obtained from the ANN model. The evaluation, derived from the confusion matrix comparing predicted and actual heights, indicates 65% accuracy for exact building heights and 84% accuracy with a one-floor error. Comparing the simulated floor number maps from the WLC and ANN models with actual floor numbers reveals that the ANN model has greater capability in modeling building heights. Figure 8 shows this comparison, with the blue and red lines representing the WLC and ANN models, respectively, and the green line indicating actual floor numbers.

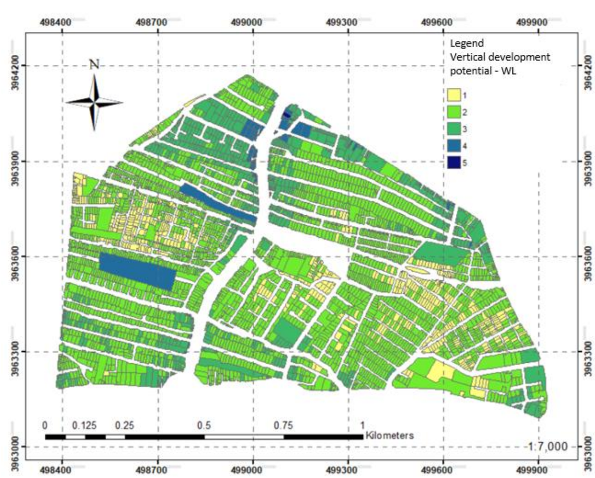
In the region, there are more plots with similar floor numbers (e.g., 1253 one-story plots) than others. ANN can



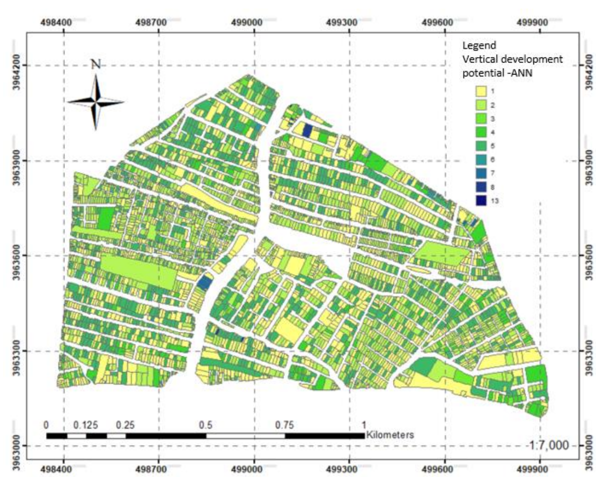
(a) Map of horizontal development potential obtained from the weighted linear combination model



(b) Map of horizontal development potential obtained from the artificial neural network model



(c) Map of vertical development potential obtained from the weighted linear combination model



(d) Map of vertical development potential obtained from the artificial neural network model

Figure 7. Maps of horizontal and vertical potential

More accurately predict these types of plots, but becomes less reliable in modeling plots with fewer numbers, particularly those with more than five floors.

3.5. Calculation of Overall Suitability of Urban Plots

Overall suitability determines the likelihood of developing each vacant plot. This study uses a weighted linear combination (WLC) model and an artificial neural network (ANN) model to calculate urban overall suitability annually, creating a ten-year urban development map. In non-simultaneous development, overall suitability is based on the horizontal potential of each plot, with vertical potential determining the building height. This approach does not require specific calculations for overall suitability, as horizontal and vertical potentials are used directly. Simultaneous development calculates overall suitability by combining horizontal and vertical potentials, allowing for a synergistic simulation of three-dimensional urban expansion. The combined potentials, with specific coefficients, determine the overall suitability of each plot. As development progresses annually, these potentials change, necessitating yearly recalculations of overall suitability. In this study, horizontal and vertical potentials are combined in the WLC model with weights of 0.66 and 0.33, respectively, to create the overall suitability map for simultaneous development.

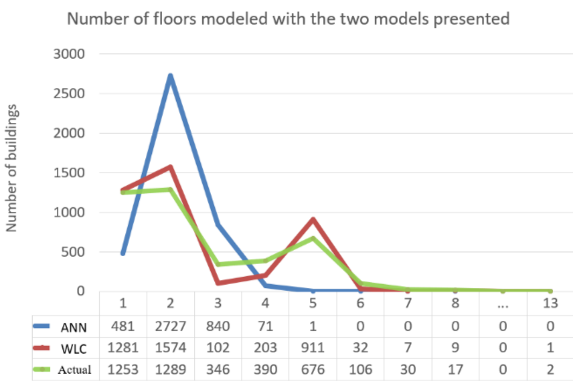


Figure 8. Comparison chart of the number of floors modeled with actual height

3.6. Calculation of Allocation

After determining the overall ratio, the allocation for each vacant plot is calculated based on the estimated demand in the area. This demand, derived from urban growth over the past five years, showed a 7% increase from 2006 to 2011. The calculated percentage is used to estimate the demand for the next ten years, which is 20,000 square meters from 2011 to 2021, averaging 2,000 square meters per year.

The allocation process occurs in four stages based on demand. First the overall urban ratio is determined for vacant plots using simultaneous or non-simultaneous development methods, and they are sorted by the highest ratio. Second, plots with the highest ratios are selected, and their number of floors is determined based on vertical development potential. Third, the developed plot area is multiplied by the number of floors and subtracted from the demand. If demand remains, the stages are repeated for other vacant plots until the annual demand is met. Finally, the potential for horizontal development, vertical development, and the overall ratio are adjusted, and the stages are executed for the following year.

Figure 9 shows allocation maps of urban plots using both development methods in the WLC and ANN models. The yellow plots represent residential plots constructed before 2011, green plots for the first five years, blue for the second five years, and red for undeveloped plots. Figure 9-a illustrates non-simultaneous development using the WLC model, showing developed plots adjacent to highways, compensating for 20,000 square meters of demand with 45 plots. Figure 9-b shows simultaneous development using the WLC model, with 41 plots meeting the demand, leaving some vacant plots undeveloped in residential areas. Figure 9-c depicts non-simultaneous development using the ANN model, with 43 allocated plots in eastern and western residential areas. Figure 9-d displays simultaneous development using the ANN model, prioritizing taller plots, meeting the demand with 36 plots.

4. Discussion

The horizontal sprawl of urban development and the lack of management in high-rise construction necessitate modeling urban development in both horizontal and vertical dimensions. Vertical development, both within and outside the city, positively impacts the area by preventing excessive horizontal expansion and conserving valuable land.

The objective of this research was to develop a comprehensive model capable of accurately predicting both horizontal and vertical urban development using a combination of weighted linear combination (WLC) and artificial neural network (ANN) models. The contribution lies in the novel approach of integrating simultaneous and non-simultaneous development methods within these models to enhance the accuracy and reliability of urban development predictions.

The results of this research are divided into two categories. The first category examines the simultaneous and non-simultaneous development of urban parcels using the WLC and ANN models. Both models show significant similarity in the developed parcels, indicating that most parcels developed using the simultaneous method were also developed in the non-simultaneous method. However, in the simultaneous development method, taller parcels develop earlier than others with the same horizontal potential, a phenomenon not seen in the non-simultaneous method. If urban development had only occurred in the first five years, there would have been a significant difference between the two methods. Additionally, fewer developed parcels were observed in the simultaneous method compared to the non-simultaneous method, indicating that using the simultaneous method yields better results in determining parcel suitability (Figure 10).

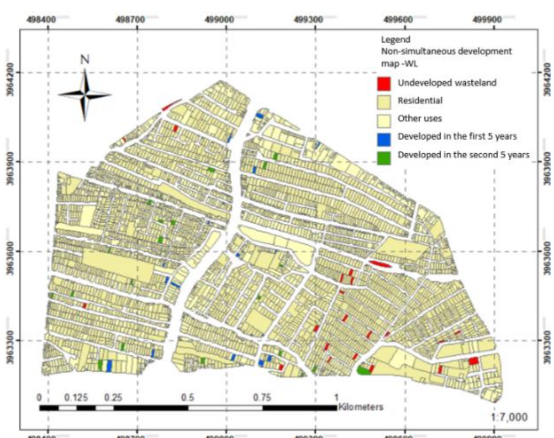
The second category involves conclusions from the WLC and ANN models. The WLC model achieved 60% accuracy in determining horizontal development potential and 30% in determining vertical development potential, with an overall urban suitability accuracy of 50% using the simultaneous method. In contrast, the ANN model demonstrated 67% accuracy in determining horizontal development potential, 65% in vertical development potential, and 66.3% in overall urban suitability using the simultaneous method. Therefore, the ANN model and the simultaneous development method demonstrate better results in determining urban development potential.

5. Conclusion

The uncontrolled horizontal sprawl of urban development and the lack of management in high-rise construction, both inside and outside cities, highlight the need for an integrated modeling approach to urban development that addresses both horizontal and vertical dimensions. This research identifies the necessity to optimize land use and prevent the excessive conversion of valuable land into urban space.

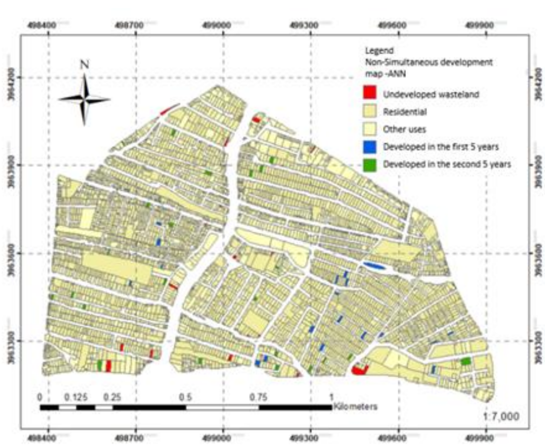
To address this issue, a comprehensive model was developed, capable of accurately predicting horizontal and vertical urban development. This model combines a weighted linear combination (WLC) and artificial neural network (ANN) models, integrating simultaneous and non-simultaneous development methods to enhance prediction accuracy and reliability. The research findings indicated that the WLC model provided moderate accuracy in estimating urban development potential. It effectively captured the horizontal development patterns and offered insights into vertical growth trends. However, the ANN model exhibited superior performance, delivering more precise and reliable predictions for urban development. Its findings support policymakers in anticipating growth, optimizing resource allocation, and mitigating the environmental and economic impacts of urban expansion. The model identifies areas for sustainable vertical development, limiting sprawl and preserving land, while informing targeted infrastructure improvements to ensure balanced growth.

Future studies should consider incorporating older parcels with long construction histories to minimize the conversion of vacant lots into urban areas. By focusing on constructing taller buildings instead of replacing old, low-rise parcels, vertical urban development can be modeled more effectively, optimizing land use and accommodating urban growth sustainably. Additionally, future research should evaluate the neighborhood radius for determining horizontal development potential and the height radius for vertical development with varying distances. The impact coefficients of each factor should range between -1 and 1 to account for factors with both positive and negative impacts. It is also recommended to use the random forest model for determining horizontal and vertical potential and compare its performance with the WLC and ANN models.

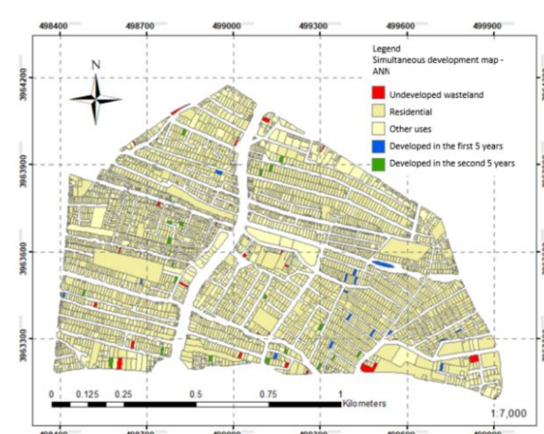


(a) Non-Simultaneous development map with weighted linear combination model

(b)Simultaneous development map with weighted linear combination model



(c) Non-Simultaneous development map with artificial neural network model



(d) Simultaneous development map with an artificial neural network model

Figure 9. Urban parcel allocation

Appendix A. Equations

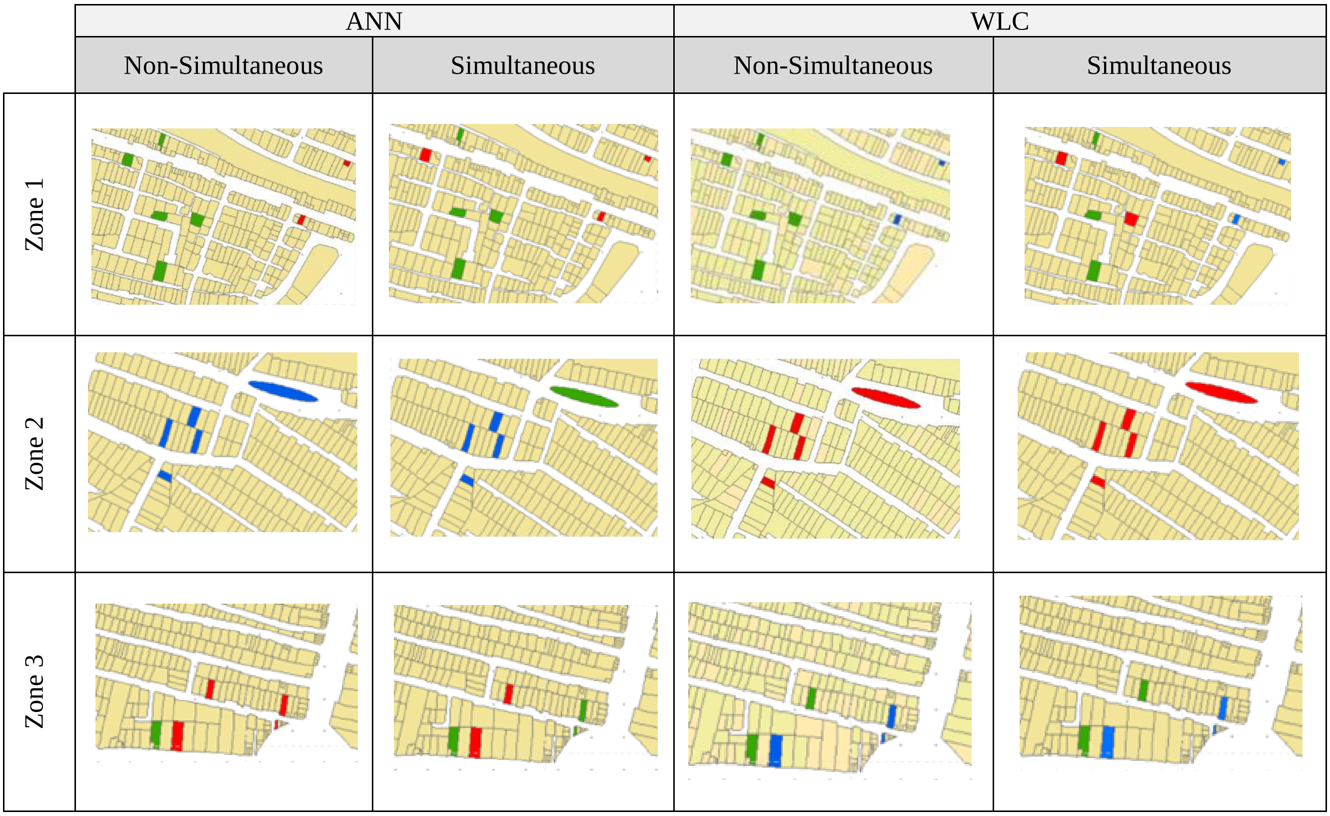


Figure 10. Comparison of Simultaneous and Non-Simultaneous Urban Spatial Suitability Modeling

(A1)	$N_{al} = \sum_{k} N_{ablkd}$
N_{al}	The neighbourhood effect on the target parcel.
N_{ablkd}	Indicates the magnitude of the external spatial outcome of parcel *b* with land use *k*, located at distance *d* from the target parcel *a* with land use *l*.

(A2)	$N_{ablkd} = \left(\exp\left(\frac{\frac{A_b}{A_a}}{\frac{A_{max}}{A_{min}}} \right) + \exp\left(\frac{-d_{ba}}{1000} \right) \right) \times I_{ablk}$
N_{ablkd}	The magnitude of the external outcome.
A_a	The area of the target parcel.
A_b	The area of the neighbouring parcel.
A_{max}	The largest parcel areas in the study area.
A_{min}	The smallest parcel areas in the study area.

d_{ba}	The distance between the target and neighbouring parcels.
exp	The normalized exponential function.
I_{ablk}	The degree of attraction or repulsion of parcel *b* with land use *k* on target parcel *a* with land use *i*.

(A3)	$C_{al} = \sum_{k}^{c} Nab_{lkd}$
C_{al}	The dependence target parcel "a" with the user "l."
N_{ablkd}	The magnitude of the external outcome.

(A4)	$D_{al} = \sum_{K}^{D} N_{ablkd}$

D_{al}	The centralization target parcel "a" with the user "l."
N_{ablkd}	The magnitude of the external outcome.

(A5)	$P_{al} = \sum_{k}^{p} Nab_{lkd}$
P_{al}	The compatibility target parcel "a" with the user "l."
N_{ablkd}	The magnitude of the external outcome.

(A6)	$A_{aj} = \frac{1}{1+\frac{D}{\sigma_j}}$
A_{aj}	The accessibility of parcel a for user j.
D	Denotes the network distance from each property parcel to the nearest desired point.
σ_j	Indicates the importance of user j.

(A7)	$c_i = \frac{l_i}{a_i}$
c_i	Indicates the plot's shape.
l_i	The perimeter of the plot.
a_i	The area of the plot.

(A8)	$S = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{n} W_i}$
S	The output value of the model.
x_i	The influencing factors on the model's output.
w_i	The weights affecting the model's output.
n	The number of influencing factors.

(A9)	$TP_{ij} = W_S S_{ij} + W_N N_{ij} + W_A A_{ij} + W_P P_{ij}$
TP_{ij}	The potential for horizontal urban development for property parcel i with usage j.

S_{ij}	The physical suitability for property parcel i with usage j.
N_{ij}	The neighborhood effect for property parcel i with usage j.
A_{ij}	The accessibility for property parcel i with usage j.
P_{ij}	The land price for property parcel i with usage j.
W_S	The relative importance of physical suitability.
W_N	The relative importance of neighborhood effect.
W_A	The relative importance of accessibility.
W_P	The relative importance of price.

(A10)	$S = \sum_{i=1}^{n} X_i W_i$
S	The potential for vertical development.
x_i	The influencing factors.
w_i	The weight factors.

Appendix B. List of Sub-Criteria

Row	criteria	Sub-criteria
1	Building Features	Parcel Perimeter
2		Parcel Area
3		Persian Shape
4		Existing Building Density
5		Maximum Height of Adjacent Building
6		Average Height of Adjacent Building
7		Ratio of Distance to Height of Adjacent Building
8	Accessibility	Subway
9		Main Road
10		Highway
11		Industrial Centres
12		Medical Centres
13		Recreation Centres
14		Metro Station
15		Taxi Station
16		Bus Station
17		Terminal
18	Population	Population
19		Population Density
20	Economic	Land Price

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