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An Integrated Parcel-Based Neighborhood Interaction Model for Urban Land Use Allocation

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ABSTRACT

Objective: Land use allocation is a main component of urban and regional planning and involves strategically distributing land for various purposes. Among the approaches used, cellular automata (CA) models, particularly parcel-based CA models, have gained attention because they can more accurately represent real-world spatial interactions in calculating neighborhood effects. However, traditional parcel-based neighborhood effect models often overlook the barrier effects of road networks and the spatial heterogeneity of land parcel distributions, which both strongly influence land use interactions. To address these limitations, this study presents an integrated neighborhood effect model that incorporates road network constraints and parcel distribution to improve urban land use allocation.

Method: The proposed model integrates two key factors. First, a road weight factor that differentiates the barrier effects of primary, secondary, and local roads. Second, a gravity factor that accounts for the spatial distribution of neighboring parcels based on land use type, area, and relative position. These factors are evaluated within an 800-meter parcel-based neighborhood effect framework. The presented model was implemented in Khoramdarreh city in Zanjan Province, Iran.

Results: The results show that the integrated parcel-based neighborhood interaction model improves the average overall neighborhood effect, which reflects better suitability of land use allocation, with increases of 0.20 for the gravity factor and 0.28 for the road weight factor.

Conclusions: The model provides urban planners with a more precise and adaptive decision-support tool for spatial planning and sustainable land use management.

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1. Introduction

Land use allocation is a fundamental component of urban and regional planning, as well as environmental management. Its primary goal is to optimize the utilization of limited land resources while addressing diverse societal needs (Antrop, 2004; Maleki et al., 2017; Song & Chen, 2018; Abolhasani et al., 2016; Abolhasani, Taleai, & Lakes, 2022). This process involves strategically distributing land for various purposes, including residential, commercial, industrial, agricultural, recreational, and conservation uses (Karimi et al., 2012; Alberti, 2008; Masoomi et al., 2013; Levy et al., 2016).

Among the various approaches employed in land use allocation, cellular automata (CA) models, particularly parcel-based CA models, have gained significant attention due to their ability to more accurately represent real-world spatial interactions (Barredo et al., 2003; Abolhasani et al., 2016; Abolhasani and Taleai, 2020). Several studies have sought to refine neighborhood definitions in parcel-based CA models to enhance their realism. However, implementing parcel-based representations in CA models is challenging due to the overlooked barrier effects of road networks and the heterogeneous nature of parcels, which differ from conventional raster-based neighborhood definitions in their size, shape, and spatial distribution (O'Sullivan, 2001; Dahal and Chow, 2015; Abolhasani et al., 2016).

Stevens and Dragicevic (2007) proposed defining neighborhoods based on parcel function, highlighting the importance of classification methods tailored to different parcel types. However, achieving higher modeling precision requires incorporating additional spatial externalities, such as geometric characteristics and the structural distribution of neighboring parcels.

Crooks (2010) introduced a distance-based neighborhood approach using a buffer radius, where geographic obstacles such as rivers and roads influenced neighborhood inclusion. His study emphasized the importance of accounting for physical barriers in urban modeling, suggesting that road networks and other obstacles should be incorporated into neighborhood effect calculations rather than assuming uniform influence across all parcels. However, this approach did not regulate the influence of parcels separated by barriers; instead, these barriers were treated as absolute neighborhood boundaries.

Building on the role of transportation networks in urban growth simulations, Dahal and Chow (2015) examined irregular CA models using parcel maps with various neighborhood configurations. Their findings demonstrated that defining roads as absolute barriers produced more realistic urban expansion patterns. However, this strict exclusion overlooked the potential of incorporating a weighted influence structure to regulate interactions across barriers. Both Dahal and Chow (2015) and Crooks (2010) treated barriers as absolute boundaries, neglecting the influence of parcels located across roads and other obstacles. Consequently, their models failed to capture interactions beyond these barriers. Furthermore, neither study accounted for heterogeneous parcel characteristics or spatial distribution, both of which are essential for accurately modeling land use interactions.

Abolhasani et al. (2016) defined the neighborhood effect of parcels using an 800 m radial structure that incorporated distance, parcel area, land use type, and service level of irregular cadastral parcels, thereby covering parcel characteristics and location as influential factors. In addition, compactness, dependency, and compatibility measures were employed to assess neighborhood effects (Abolhasani and Taleai, 2020; Abolhasani et al., 2022; Maleki et al., 2020; Sadooghi et al., 2022). However, the model did not account for the spatial positioning and distribution of parcels with the same land use within the neighborhood relative to the central parcel, nor did it consider the influence of the transportation network as an interaction barrier, limiting its ability to fully represent urban spatial interactions.

According to the studies conducted, traditional neighborhood models often assume that all neighboring parcels exert equal influence on the central parcel, neglecting the role of roads as physical barriers that modify spatial connectivity and diffusion, as well as the spatial distribution of neighboring parcels. This oversimplification introduces inaccuracies in land use allocation and limits the ability of these models to fully capture the complexity of real-world urban structures. Also, recent advancements in parcel-based CA models emphasize the importance of refining neighborhood effect formulations to improve land-use allocation accuracy. Yao et al. (2021) demonstrated that incorporating interactions between neighboring parcels enhances the realism and precision of urban land-use simulations. Shi et al. (2024) highlighted the significant role of road network centrality in shaping neighborhood influence and guiding the spatial distribution of urban activities. Additionally, Song and Ling (2025) emphasized the necessity of considering spatial connectivity and parcel-level interactions to improve the prediction of urban land-use patterns. Collectively, these studies underscore the need to refine neighborhood effect definitions in CA models by integrating parcel distribution metrics and road-based barriers.

To address these limitations, this study integrates the gravity factor and the road weight factor into the parcel-based CA model to enhance the effectiveness of urban land-use allocation. The key contributions of this research are as follows:

- Unlike previous studies, this study presents a gravity factor that modifies the influence of neighboring parcels based on their spatial distribution, land use type, and the relative distance between the central parcel and the neighbors' center of gravity.
- Unlike previous studies, in this study, a road weight factor is introduced that accounts for the barrier effects of different road types, including primary, secondary, and local roads, on interactions between parcels.

The remainder of this paper is organized as follows. Section 2 introduces the proposed model. Section 3 presents the results, and Section 4 provides the discussion. Finally, conclusions are presented in Section 5.

2. Methodology

This study presents an integrated cellular automata model to improve urban land use allocation. The focus of this study is on refining the neighborhood effect, which is a key component in land use allocation. For this purpose, the 800-meter parcel-based CA (ParCA) model (Abolhasani et al., 2016; Abolhasani & Taleai, 2020; Abolhasani et al., 2022) is extended by incorporating two new factors into the conventional parcel-based CA model. The factors are 1) a road weight factor that differentiates the barrier effects of primary, secondary, and local roads, and 2) a gravity factor that accounts for the spatial distribution of neighboring parcels based on land use type, area, and relative positioning within a neighborhood (Figure 1).

The parcel-level land-use and road network datasets were provided by the Karaj Municipality, Alborz Province, Iran, for the year 2019. Both datasets were supplied as vector layers at parcel resolution, representing individual cadastral parcels with their associated land-use attributes, as well as road alignments within the study area. Prior to analysis, the datasets were preprocessed in ArcMap10.8.2 to ensure they were analysis-ready. Preprocessing steps included checking and correcting parcel geometries, cleaning and verifying attribute tables, and reprojecting all layers to a consistent coordinate system.

It should be noted that land use allocation process first involves determining the suitability factors (i.e., neighborhood effect, physical suitability, and accessibility) as well as the land use demand. Then, the allocation is performed using the suitability factors and estimated demand (Dahal & Chow, 2015). However, in this paper, to clearly highlight and compare the outcomes of this study, only the neighborhood effect and land use demand are considered for the allocation process (Dahal & Chow, 2015). This focus ensures that differences in results can be directly attributed to neighborhood interactions, without interference from physical suitability or accessibility factors. Also, note that in this study, five main land-use types, industrial, residential, commercial, park, and educational, are considered for the purpose of model implementation.

In the following, Section 2.1 describes the new factors of the presented model, Section 2.2 presents the neighborhood effect and its components, including compatibility, dependency, and compactness and Section 2.3 describes the land use allocation.

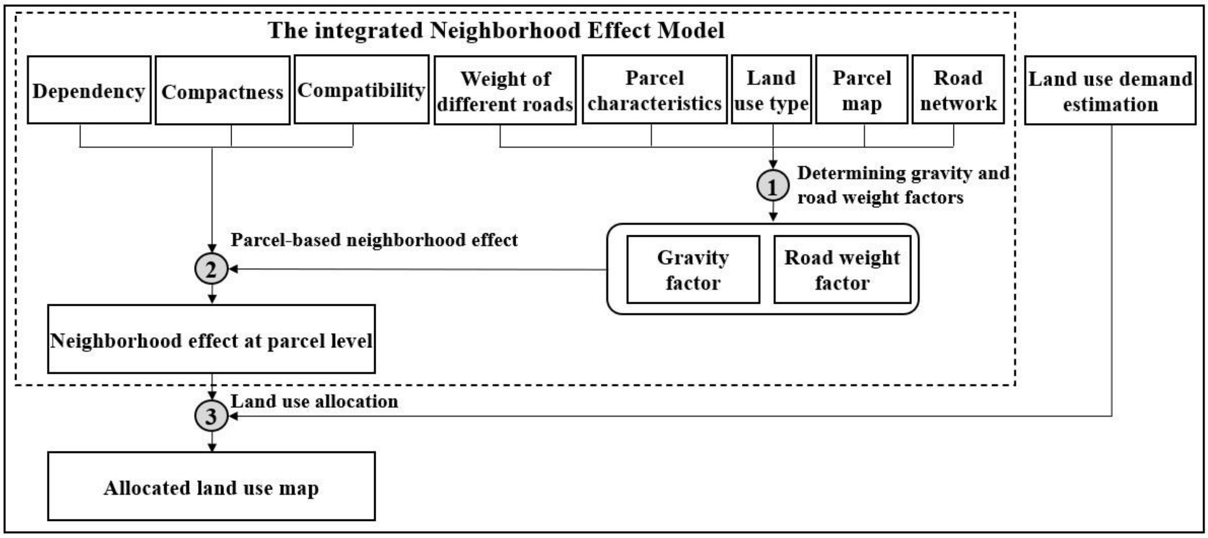

Figure 1. Flowchart of the presented model

2.1. Integrated Neighborhood Effect Model

In this paper, in order to refine the neighborhood effect calculations, the gravity factor and road weight factor are integrated into the neighborhood component calculations, which are explained in Sections 2.1.1 and 2.1.2, respectively.

2.1.1. Gravity Factor

The purpose of the gravity factor is to modify the influence of neighboring parcels based on their spatial distribution, land use type, and the relative distance between the central parcel and the neighbors' center of gravity. As illustrated in Figures 2(a) and 2(b), four residential parcels are positioned at the same distance from the central parcel; however, their center of gravity varies depending on their spatial distribution. When the center of gravity is closer to the boundary of the central parcel, the influence of these parcels is stronger. A closer center of gravity, as illustrated in Figure 2(a), indicates that the neighboring parcels more effectively surround the central parcel. In other words, the central parcel is more deeply embedded within their influence zone, thereby amplifying their effect.

In order to determine the gravity factor, Equation (1) is formulated in this paper as an exponential decay function within a given extent R:

$$\mathrm{F(DG)} = exp\left({}^{(R - DG_K)}/_{R}\right) \tag{1}$$

Where DG_K represents the distance from the central parcel to the center of gravity of grouped neighboring parcels of land use type k, and R denotes the neighborhood size. This formulation ensures that smaller values of DG_K (i.e., when the center of gravity is closer) correspond to a stronger influence, while larger values reduce the effect.

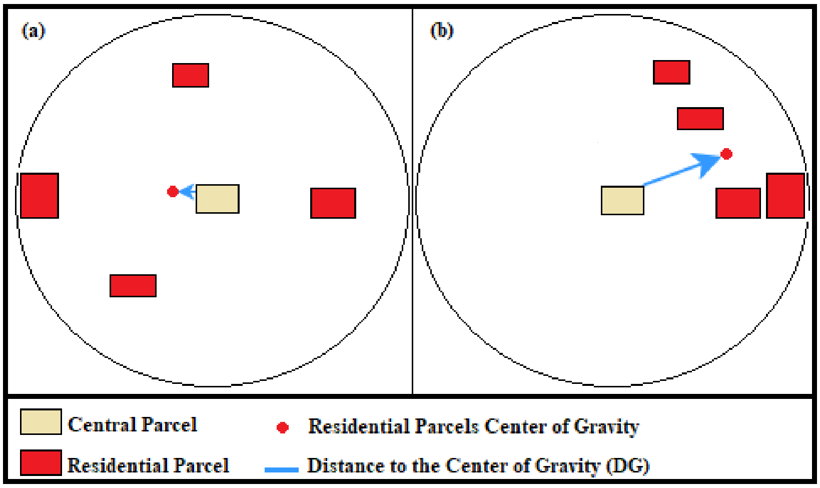

Figure 2. Comparison of neighboring residential parcel distributions and their center of gravity relative to the central parcel.

2.1.2. Road Wight Factor

The second factor introduced in this paper is the road weight factor, which accounts for the barrier effects of different road types (primary, secondary, and local) on parcel interactions, where smaller weights indicate stronger barriers. It is determined by the types of roads separating a central parcel from its neighboring parcels. In order for that, four categories are defined:

- Primary roads (WP): Represent a high-level barrier between parcels.
- Secondary roads (WS): Represent a medium-level barrier between parcels.
- Local roads (WL): Represent a low-level barrier between parcels.
- No roads (WN): Indicate areas with no roads, meaning no barrier (WN = 1).

When multiple road types exist between a central parcel and a neighboring parcel, their effects are aggregated. The aggregated road weight for a neighboring parcel, W_{road}, is computed using Equation (2).

$$W_{road} = \prod_{\{r\,\in\{P.S.L.N\}\}} exp(w_{rl}^{\{\delta_r\}}) \tag{2}$$

Where W_{rl} represents the weight assigned between parcels based on road type $\boldsymbol{r}$ and neighboring land use type (l), with $\boldsymbol{r}$ referring to primary roads (P), secondary roads (S), local roads (L), and no road (N). δ_r is an indicator variable, where δ_r= 1 if the corresponding road type r exists, and δ_r= 0 otherwise.

Figure 3 illustrates a central parcel and four selected neighboring parcels, each demonstrating different levels of road barriers in the neighborhood effect calculation. Parcel (a) is adjacent to the central parcel without any road separation, meaning there is no barrier effect (W_{rl}= 1), despite another parcel being situated between them. Parcel (b) is separated by a local road, applying a single road barrier (W_{rl}= WL). Parcel (c) is separated by both a secondary and a local road, leading to a combined barrier effect (W_{rl}= WL × WS). Parcel (d) experiences the highest barrier effect, as it is separated from the central parcel by primary, secondary, and local roads, leading to a cumulative reduction factor (W_{rl}= WP × WS × WL). This figure highlights how different road types act as barriers, influencing the neighborhood effect in the land use allocation process.

It should be noted that each road type is assigned a specific weight to reflect its influence on parcel-level interactions based on neighboring land-use types (Table 1). These weights were determined using a structured expert-based fuzzy judgment procedure (Chang, 1996; Chen and Hwang, 2000). Domain experts evaluated the expected transmission of land-use influence across each road type using five predefined linguistic terms ranging from Very Low to Very High. The qualitative assessments were subsequently transformed into triangular fuzzy numbers and defuzzified using the centroid method to obtain numerical weights for primary, secondary, and local roads. This approach ensures a consistent and interpretable hierarchy of road effects, with primary roads producing the greatest attenuation of parcel interactions and local roads the least, while also accounting for variations in land-use sensitivity to road-related barriers.

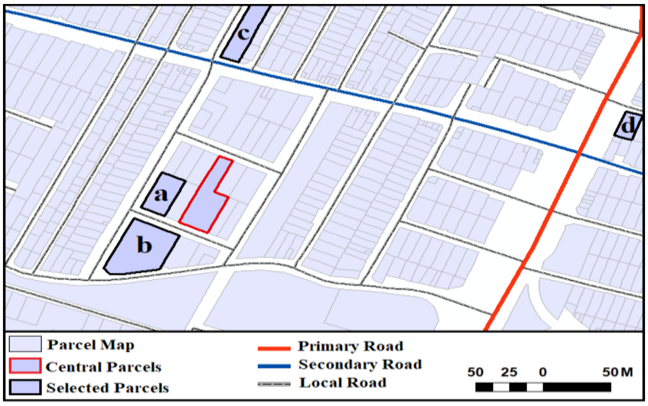

Figure 3. Central parcel and neighboring parcels with different road barriers.

Table 1. Weight assigned to the road type based on neighboring land use types

Neighbor Land Use Type	Road Type			
	Primary (P)	**Secondary (S)**	**Local (L)**	**No Road (N)**
Urban Equipment	0.6	0.8	0.9	1.0
Administrative	0.5	0.7	0.85	1.0
Urban Facilities	0.55	0.75	0.9	1.0
Undeveloped	0.4	0.6	0.8	1.0
Green Space	0.45	0.65	0.85	1.0
Educational	0.65	0.85	0.95	1.0
Commercial	0.7	0.9	1.0	1.0
Depository	0.5	0.7	0.85	1.0
Agricultural	0.4	0.6	0.75	1.0
Residential	0.65	0.85	1.0	1.0
Religious	0.55	0.75	0.9	1.0
Industrial	0.6	0.8	0.95	1.0
Medical	0.7	0.9	1.0	1.0
Cultural	0.6	0.8	0.9	1.0
Military	0.45	0.65	0.8	1.0
Sport	0.55	0.75	0.9	1.0
Park	0.5	0.7	0.85	1.0

2.2. Parcel-Based Neighborhood Effect

The neighborhood effect describes the spatial relationships between a central land unit and its surrounding land units. It is quantified by assessing the influence of a neighboring unit (b) with a given land use (k) on a central unit (a) with land use (l), as formulated in Equation (3) (Abolhasani et al., 2016; Abolhasani & Taleai, 2020; Abolhasani et al., 2022):

$$N_{ab_{lkd}} = f\left(I_{a_l b_k}.\, d_{ab}.\, A_b\right) \qquad (3)$$

The neighborhood effect is a function of distance (dab), area (Ab), and land use interaction ($\boldsymbol{I_{a_l b_k}}$), representing the attraction or repulsion between land use types. This interaction is decomposed into three components, compatibility (P_{al}), dependency (D_{al}), and compactness (C_{al}), as defined in Equation (4) (Karimi et al., 2012; Abolhasani et al., 2016). Compatibility reflects positive or negative influences between land uses, such as industrial areas negatively affecting residential zones due to pollution. Dependency represents land uses that rely on others, for instance, commercial areas depending on nearby residential neighborhoods to remain active (Masoomi et al., 2013). Compactness captures the tendency to cluster similar land uses, reducing infrastructure preparation costs and improving efficiency, as seen in the grouping of industrial zones in suburban areas (Karimi et al., 2012).

The compatibility and dependency matrices used in this study were adopted from previous land-use allocation research (Masoomi et al., 2013; Masoomi et al., 2020; Sadooghi et al., 2022). In these studies, the matrices were developed through a two-round Delphi process involving domain experts, and the resulting qualitative assessments were subsequently quantified using the Analytic Hierarchy Process (AHP).

$$\begin{Bmatrix} P_{al} \\ D_{al} \\ C_{al} \end{Bmatrix} = \sum_{L}\sum_{K} exp\sqrt{\left(\frac{\frac{A_b}{A_a}}{\frac{A_{max}}{A_{min}}}\right)} \times exp\left({}^{-d_{ab}}/_{R}\right) \times \begin{Bmatrix} I_{a_l b_k^P} \\ I_{a_l b_k^D} \\ I_{a_l b_k^C} \end{Bmatrix} \tag{4}$$

In Equation (4), $(A_b/\ A_a)/\ (A_{max}/\ A_{min})$ is the relative parcel size factor, ensuring that larger parcels exert a stronger influence while smaller parcels exert a weaker influence. Here, A_a and A_b are the areas of the central and neighboring parcels, respectively, and A_{max} and A_{min} are the maximum and minimum parcel areas in the study area. $exp(-d_{ab}/R))$ is the distance decay factor, which reduces the influence of neighboring parcels with increasing distance, where d_{ab} is the distance between parcels, and R is the neighborhood size. $I_{a_l b_k}$ represents the dependency, compatibility, and compactness interaction, derived from quantified matrices based on land-use type (Massomi et al., 2013). The overall neighborhood effect is obtained by aggregating these three components (Equation 5).

$$N_{alL} = \lambda_C \times C_{al} + \lambda_P \times P_{al} + \lambda_D \times D_{al} \tag{5}$$

Where λ_C, λ_P and λ_D are weight factors controlling the influence of each component.

It should be noted that according to Figure 1, the neighborhood effect calculation in this study is refined by integrating two new factors, which were described in Section 2.1. The equation for the neighborhood components, incorporating the relevant factors, is expressed as Equation (6). However, for the purpose of comparing the results, the proposed model is applied in three configurations: with the gravity factor only, with the road weight factor only, and with both factors integrated into the land use interaction model.

$$\begin{Bmatrix} P_{al} \\ D_{al} \\ C_{al} \end{Bmatrix} = f(I_{a_l b_k}.d_{ab}.A_b.W_{road}.\mathrm{F(DG)})$$

$$= \frac{1}{n}\sum_L \sum_K exp\sqrt{\left(\frac{\frac{A_b}{A_a}}{\frac{A_{max}}{A_{min}}}\right)} \times exp\left({}^{-d_{ab}}/_{R}\right) \times \begin{Bmatrix} I_{a_l b_k^P} \\ I_{a_l b_k^D} \\ I_{a_l b_k^C} \end{Bmatrix} \times \prod_{\{r\,\in\{P.S.L.N\}\}} exp(\omega_{rl}^{\{\delta_r\}}) \times exp\left({}^{(R\,-\,DG_K)}/_{R}\right) \tag{6}$$

In Equation (6), A_a and A_b represent the areas of the central and neighboring parcels, respectively, while A_{max} and A_{min} denote the maximum and minimum parcel areas in the study area, forming the relative parcel-size factor. The term d_{ab} refers to the distance between parcels a and b. The interaction component $I_{a_l b_k}$ represents the dependency, compatibility, and compactness interactions between the parcels based on their land-use types. W_{rl} denotes the weight associated with each road type r and neighboring land use type l, where r represents the road type between the central and neighboring parcels, including primary (P), secondary (S), local (L), and no-road (N) conditions, and δ_r indicates the presence of each road type between the parcels. The variable DG_K denotes the distance from the central parcel to the center of gravity of the grouped neighboring parcels belonging to land-use class k, and R represents the neighborhood size.

2.3. Land Use Allocation Process

For the purpose of land use allocation, firstly, land-use demand is estimated. In this study, land use demand is estimated by treating the region as a unified demand unit to determine the required area for each land-use type. The baseline land-use map is used as the starting point, and future demand is projected over a 10-year time step. An assumed annual increase of 1–2% per LUT is applied, corresponding to a total increase of 10–20% over the period. To ensure that the allocation process adequately represents all categories, particularly land uses with limited current coverage, such as parks or educational areas, demand was adjusted within a range of 15–70% of the baseline area. This approach follows established practices in cellular automata-based urban land-use modeling (Verburg et al., 2002; Koomen et al., 2011) and allows for meaningful evaluation of spatial allocation patterns while reflecting general urban growth pressures.

After determining the suitability factors (which are considered equivalent to the neighborhood effect in this study) and land use demand, land-use allocation is performed. It generally involves either prioritizing specific land use types or assessing parcel suitability for different uses (Verburg and Overmars, 2009; Pilehforooshha et al., 2014). In this study, allocation is performed exclusively for residential, commercial, industrial, educational, and park land uses, where each undeveloped parcel is assigned to the land use for which it has the highest neighborhood effect score. When multiple land uses have the same value for a given parcel, a priority-based approach is applied to determine the final assignment. The priority order is commercial, followed by industrial, residential, educational, and park uses (Abolhasani et al., 2016; Abolhasani et al., 2022).

3. Results

The study was implemented in Khorramdarreh city in Zanjan Province, Iran. The study area covers approximately 12 km² and contains around 20,500 cadastral parcels with average parcel size of approximately 448 m², providing a detailed parcel-level landscape suitable for testing urban land-use allocation. With a variety of land-use types represented in the parcel map (Figure 4a) and a diverse road network (Figure 4b), it offers an appropriate context for evaluating neighborhood effects and road barrier interactions. In this study, five main land-use types, industrial, residential, commercial, park, and educational, are considered for the purpose of model implementation.

It should be noted that the reported neighborhood suitability values are derived from deterministic parcel-based spatial modeling using complete datasets covering the entire study area; therefore, conventional statistical measures of variability such as standard deviation or confidence intervals are not applicable.

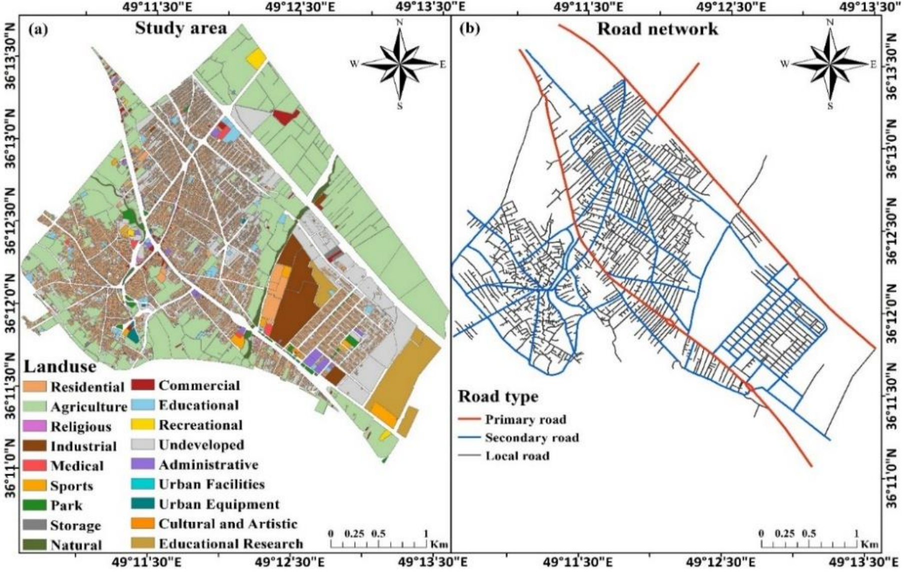

Figure 4. Land use map of the study area (a) and the road network categorized by type (b).

The first step of the proposed model involves determining gravity factor and road weight factor according to the procedure described in Section 2.1. The second step involves determining the neighborhood components, including compatibility, dependency, and compactness, as described in Section 2.2. The compatibility and dependency matrices used in this study are defined using a five-level scale ranging from highly compatible (HC) to highly incompatible (HI). These levels were originally established through a two-round Delphi process involving domain experts, and the resulting qualitative assessments were subsequently quantified using the AHP method on a scale from 0 to 1 (Masoomi et al., 2013; Masoumi et al., 2020; Sadooghi et al., 2022).

The analysis is then extended by incorporating the gravity factor (DG) and road weight factors separately, as well as by combining both factors (Equation 6). The DG results for industrial and park land uses are presented in Figure 5, while the dependency scores for industrial land use across all models are shown in Figure 6. These components are then aggregated to form the neighborhood effect, as represented in Equation (5). The parameters λ_C, λ_P and λ_D representing compatibility, dependency, and compactness, respectively, are set to 0.542, 0.34, and 0.118 for residential, commercial, and industrial land-use types, as compatibility is the most important factor for these types. These values were adopted from established parcel-based land-use modeling studies, where the relative importance of compatibility, dependency, and compactness for different land-use types was determined through expert-based evaluations (Karimi et al., 2012; Abolhasani et al., 2016). For park and educational land-use types, the parameters are set to λ_D= 0.7, λ_P= 0.3, reflecting the greater importance of dependency (Abolhasani et al., 2016; Karimi et al., 2012).

Finally, land use allocation is carried out as described in Section 2.3, where the neighborhood effect represents overall suitability. The procedure is applied to the 800-meter parcel-based CA model under four configurations: (a) the ParCA model, (b) with the DG factor, (c) with the Wroad factor, and (d) with both DG and Wroad factors combined (WDG). Only undeveloped parcels are allocated to the five designated land uses. The results for all configurations are presented in Figure 7.

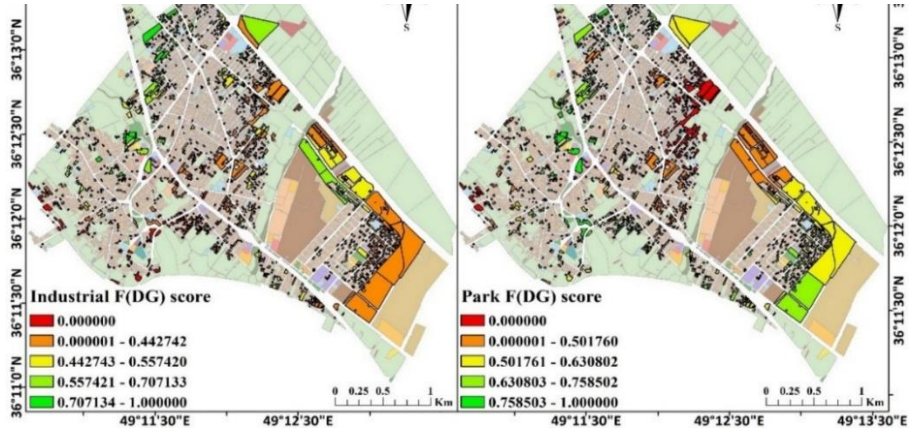

Figure 5. The Gravity factor values for (a) industrial land use and (b) park land use.

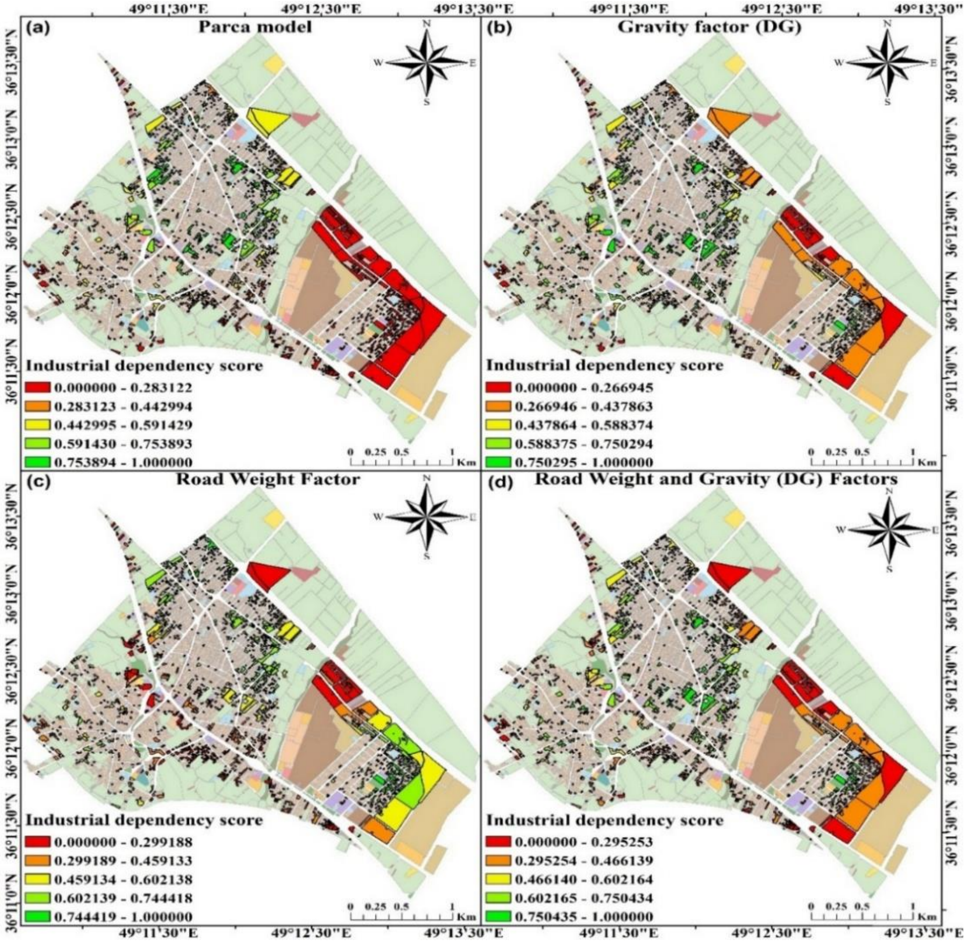

Figure 6. Dependency scores for (a) the ParCA model, (b) the ParCA model considering the gravity factor (DG), (c) the ParCA model considering the road weight factor (W_{road}), and (d) the ParCA model considering both the DG and the W_{road} factors

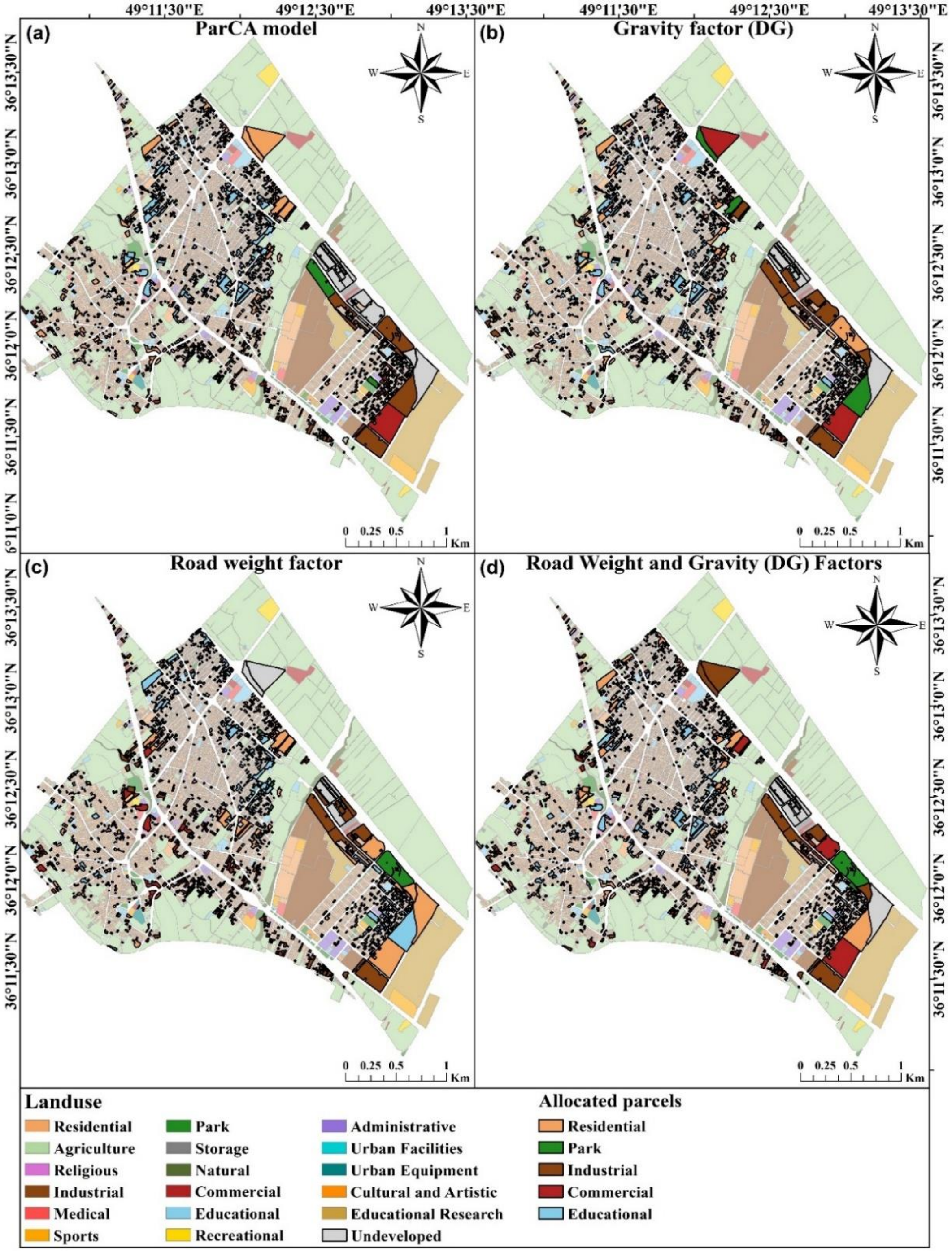

Figure 7. Allocation results for (a) the ParCA model, (b) the ParCA model with gravity factor (GD), (c) the ParCA model with road weight factor (W_{road}), and (d) the proposed model with both factors

4. Evaluation

For the purpose of model evaluation, this study focuses on assessing the effectiveness of land-use allocation rather than reproducing historical land-use change. The parcel-based cellular automata (CA) framework is intended to allocate land uses based on spatial suitability, neighborhood compatibility, and parcel-level interactions, rather than to simulate observed temporal transitions. Accordingly, model performance was evaluated using a comparative quantitative assessment in which the proposed models were benchmarked against a standard parcel-based CA model (ParCA). The evaluation metric is based on neighborhood suitability scores, which quantify how well the allocated land uses conform to their associated suitability and neighborhood interaction criteria.

The impacts of incorporating the gravity factor, the road weight factor, and their integrated effect were assessed by comparing the mean overall neighborhood values for each land-use type, as well as the average across all land uses. Higher mean neighborhood scores indicate improved allocation performance in terms of spatial compatibility and neighborhood coherence. Table 2 summarizes the mean overall neighborhood suitability values for each land-use type, as well as the average across all five land uses, for the four evaluated models: the baseline ParCA model, the ParCA model incorporating the gravity (distance-decay) factor, the ParCA model incorporating the road weight factor, and the proposed integrated neighborhood effect model.

Compared to the baseline ParCA model, all three enhanced models show substantial improvements in mean neighborhood suitability across all land-use types. The average suitability across the five land uses increases from 0.307 in the baseline model to 0.508, 0.592, and 0.500 in the gravity-based, road-weight-based, and integrated models, respectively.

The model incorporating the road weight factor achieves the highest overall average improvement, highlighting the strong influence of road-related barriers on parcel-level land-use interactions. The integrated model, while slightly lower in overall average, maintains consistently higher suitability values across all land-use types compared to the baseline model, indicating a balanced representation of both distance-based and road-induced neighborhood effects.

It should be noted that unlike cell-based urban growth models such as SLEUTH or regional allocation frameworks such as CLUE-S, which primarily operate at coarser spatial resolutions, the proposed model emphasizes parcel-level neighborhood interactions and road-induced barriers. This allows the model to capture fine-scale spatial compatibility that is often generalized or implicitly represented in existing approaches.

Table 2. Mean neighborhood effect of allocated parcels across different models.

Model	Land use type					Average
	Residential	Commercial	Industrial	Park	Education	
ParCA model	0.425	0.117	0.025	0.245	0.722	0.307
ParCA model + gravity factor	0.670	0.335	0.087	0.601	0.851	0.508
ParCA model + road weight factor	0.763	0.415	0.110	0.798	0.873	0.592
The proposed model	0.666	0.330	0.0827	0.588	0.836	0.500

*For each land-use type, the mean neighborhood effect represents the average neighborhood effect value of all parcels allocated to that specific land use. The "Average" column reports the overall mean calculated across the five land-use–specific values and is used to compare model performance

5. Discussion

To directly assess the effect of factor modifications, Figure 5 illustrates the gravity factor values for industrial and park land uses across the study area. This factor plays a crucial role in adjusting the neighborhood effect based on the distance of each parcel from the center of gravity of its land-use agglomeration. A clear pattern emerges, with parcels closer to the center of gravity exhibiting higher factor values, while those farther away show lower values, reflecting reduced influence from neighboring parcels. This behavior indicates that the gravity factor effectively captures the spatial cohesion of land-use clusters, allowing the model to differentiate between central and peripheral parcels in a way that the standard model could not.

In the standard 800 m ParCA model, parcels at the periphery were treated similarly to those near the center of gravity, leading to overestimated neighborhood component values. By incorporating the gravity factor, the modified model ensures a more accurate representation of the actual neighborhood structure based on parcel distribution, resulting in a more meaningful neighborhood score distribution. Similarly, other land uses, such as commercial, residential, and educational parcels, exhibited the same pattern. This trend was also observed in compatibility and compactness values, where neighborhood component values have been effectively adjusted in the modified model. This pattern was also reflected in the second analysis, where the spatial distribution pattern remained consistent across land-use types, demonstrating that the gravity factor provides a systematic improvement rather than a land-use-specific enhancement.

In addition to addressing the spatial distribution of neighboring parcels, the road weight factor plays a fundamental role in refining the neighborhood effect by incorporating road network constraints. Roads act as barriers that influence land-use interactions, with different road types introducing varying degrees of separation between neighboring parcels. The inclusion of the road weight factor ensures that a neighboring parcel's influence is adjusted according to road barriers rather than being determined solely by distance or land-use type. In the ParCA model, parcels were assumed to exert equal influence on the central parcel, regardless of whether they were separated by a primary, secondary, or local road. The modified model, however, accounts for these differences by applying weight reductions based on road classifications. Consequently, parcels separated by primary roads exert significantly lower influence than those separated by local roads or no roads at all. This refinement demonstrates that urban form, particularly road hierarchy, plays a stronger role in shaping local interactions than distance alone, emphasizing the importance of explicitly representing road-induced barriers in parcel-based CA models.

A thorough examination of the results, particularly regarding the neighborhood components, encompasses the standard ParCA model and the modified models incorporating the gravity and road weight factors separately and in combination. Evaluation reveals a significant shift in the outcomes of the three neighborhood components. Specifically, some values increase at the periphery of the study area, while differences between parcels in the central area become more meaningful as the effect of parcels in large neighborhoods is balanced. This balancing is particularly evident for parcels close to a specific land-use type, where neighboring component scores are equalized by increasing the effect for parcels within a concentrated distribution or experiencing low road barrier effects, and decreasing the effect for more distant parcels.

As shown in Figure 6, the industrial dependency scores across all models indicate that parcels in the southeast consistently score higher in the gravity factor, road weight factor, and the integrated model compared with the standard ParCA model. This pattern is attributed to the high presence of nearby preferred parcels, such as depository and industrial parcels, and the low barrier effect due to the absence of multiple road types. These results demonstrate that the modified framework captures localized industrial clustering more realistically, allowing dependency effects to reflect functional relationships rather than geometric proximity alone.

The visual comparison of allocation patterns in the modified models demonstrates more regulated and coherent land-use distributions, particularly in the southern region, where large industrial and educational parcels dominate the landscape and provide a clear basis for comparison (Figure 8). In the ParCA model (Figure 8(a)), a park was allocated adjacent to the largest industrial area, an outcome that is spatially incompatible, while new industrial land use was extensively allocated in the southern region near educational and research parcels. In contrast, the three modified models produced more consistent outcomes: industrial land use was allocated in closer proximity to existing industrial parcels, and park land use was arranged in a more balanced manner alongside both industrial and residential areas. Among them, the model incorporating the road weight factor (Figure 8(c)) yielded the most refined allocation, with industrial parcels more accurately aligned with existing industrial areas, parks positioned adjacent to residential neighborhoods, and educational uses appropriately allocated within established educational zones. These outcomes illustrate that adjusting neighborhood influence improves not only numerical scores but also the spatial coherence and policy relevance of allocation results.

The overall results in Table 2 further confirm the improved performance of the modified models. All three tested models outperformed the baseline ParCA model, showing increases of approximately 0.20, 0.28, and 0.19 in the average mean neighborhood effect across the five land-use types. Here, the mean neighborhood effect refers to the value computed for parcels allocated to each specific land-use type, and the reported average represents the combined value across all five types.

The road weight factor tends to have a stronger impact than the gravity factor because it accounts for the barrier effects of different road types on neighborhood interactions, assigning specific weights to primary, secondary, and local roads that reduce the influence of neighboring parcels on the central parcel. When multiple road types separate a central parcel from its neighbors, their effects are aggregated, producing a cumulative reduction in influence, so parcels farther away, especially those separated by multiple roads, exert much lower impact. In contrast, the gravity factor modifies neighborhood influence more uniformly based on the distance from the center of gravity of grouped parcels, gradually reducing the effect with increasing distance. As a result, the road weight factor produces more pronounced and variable adjustments in neighborhood effect values, particularly in areas with dense or hierarchical road networks, while the gravity factor mainly fine-tunes influence based on spatial distribution. This difference explains why the road weight factor often generates stronger and more noticeable impacts on allocation patterns compared with the gravity factor.

Conceptually, the gravity function captures parcel distribution patterns through neighborhood agglomeration, simultaneously mitigating edge effects, while the road weight factor refines neighborhood influence by considering transportation barriers. Together, these adjustments offer a more realistic representation of urban spatial dynamics, improving the spatial distribution of land uses and the accuracy of suitability assessments, and providing a more robust framework for parcel-based CA modeling. Overall, they offer a more robust framework for parcel-based CA modeling by aligning neighborhood calculations with both morphological and functional structures observed in real urban systems.

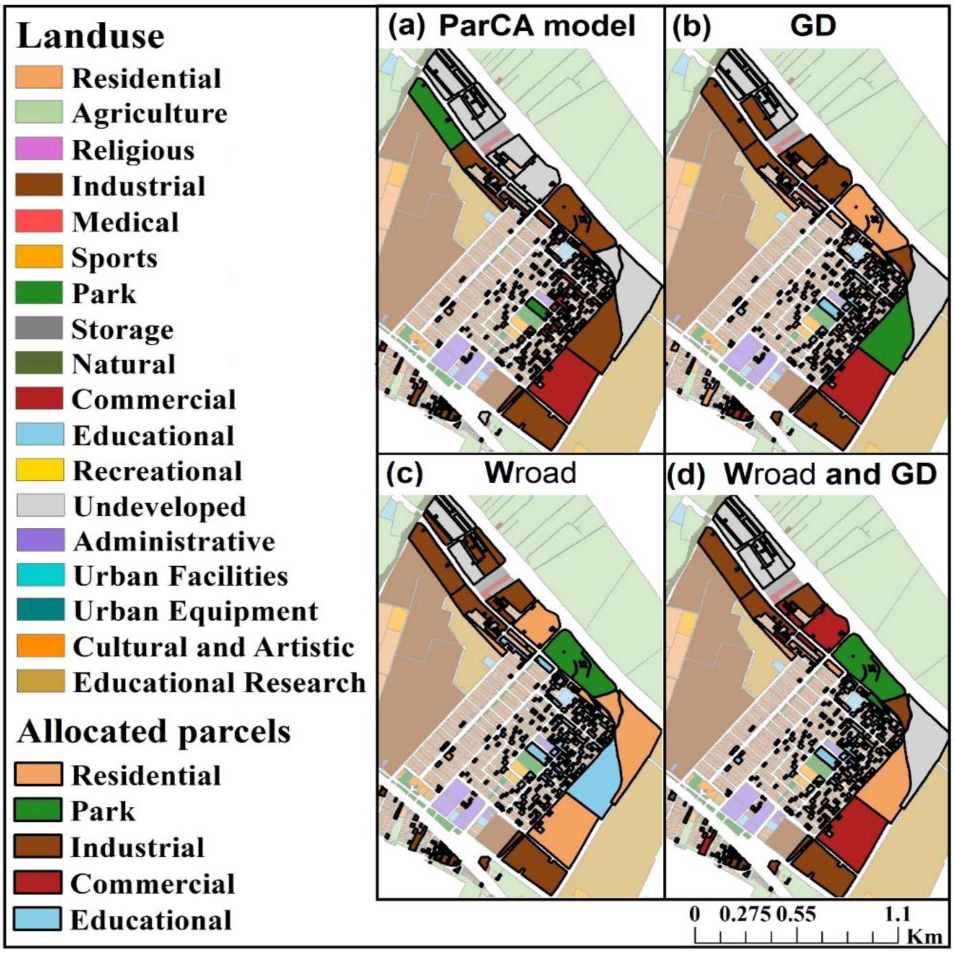

Figure 8. A close-up view of the land use allocation for parcels in the southeastern region across various models.

6. Conclusion

This study addresses key challenges in parcel-based CA models, including the non-linear and asymmetric distribution of neighborhoods, the impact of parcel arrangement relative to the central parcel, and the influence of transportation networks. While previous research has examined some of these issues, the combined effect of parcel distribution and road-induced barriers on neighborhood interactions has remained largely unexplored, particularly in large neighborhoods where parcels can belong to multiple neighborhoods with different spatial arrangements.

To address these limitations, this study presents an integrated neighborhood effect model that incorporates road network constraints and parcel distribution to improve urban land use allocation. The results of the proposed model showed that incorporating a gravity factor based on parcel distribution and a road weight factor significantly improves land-use allocation. The gravity factor adjusts neighborhood influence according to the distance from the center of gravity of neighboring parcels, while the road weight factor reduces influence based on road barriers. Together, these factors capture the positive and negative effects of surrounding land uses more realistically, producing coherent and spatially consistent allocation patterns.

Although each factor independently enhances performance, their combined application yields slightly less than the sum of individual effects due to overlapping influences. Nonetheless, all modified models consistently outperform the baseline, demonstrating practical value for urban planners by guiding new development placement and supporting land-use layouts that minimize conflicts between adjacent parcels.

Future research will explore the application of the proposed parcel-based CA model to large metropolitan areas. Such extensions are expected to introduce computational challenges due to substantially higher numbers of parcels, more complex neighborhood interactions, and dense road networks, which increase data-handling demands and computational time.

To enhance scalability, future work will investigate hierarchical parcel generalization strategies, in which parcels are aggregated or processed at multiple spatial levels while preserving essential neighborhood relationships. In addition, spatial indexing and parallel processing techniques will be examined to improve computational efficiency. Model robustness will also be evaluated through sensitivity analyses across metropolitan areas with varying sizes, densities, and urban morphologies.

Overall, integrating parcel distribution and road barrier effects provides a more realistic and effective framework for urban land-use planning, ensuring neighborhood interactions are accurately represented and supporting allocation decisions that optimize land-use arrangements, promote functional urban development, and reduce conflicts between adjacent parcels. The proposed model provides planners with a parcel-level decision-support tool for evaluating land-use allocation alternatives that account for neighborhood compatibility and road-induced spatial effects.

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