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Research Paper

Unveiling land competition through interaction networks: A consistency-based mining and simulation model that integrates inhibiting effects of land uses

Xun Liang [a,b], Jun-Long Huang [c], Qingfeng Guan [a,b,*]

[a] School of Geography and Information Engineering, China University of Geosciences, Wuhan, Hubei 430078, China
[b] National Engineering Research Center of GIS, China University of Geosciences, Wuhan 430078 Hubei Province, China
[c] Department of Ecology and Evolutionary Biology, University of Toronto, Toronto, ON, Canada

HIGHLIGHTS

- An intPLUS model is proposed to visualize and simulate land competition.
- A consistency-based mining method, enhanced by logarithmic transformation, is integrated into the Cellular Automata model.
- A novel land competition analysis framework can mine the interaction network of land uses.
- This framework can quantify the driving and inhibiting effects between land uses.

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ABSTRACT

Exploration of the competition among multiple land uses can reveal the fundamental mechanism of the evolution process of land system. However, quantification of the competition among land uses remains a challenge. Because most land use simulation studies do not consider the amplitude differences resulting from the influences of the spatial suitability map, neighborhood aggregation effect, and stochastic effect of multiple land uses, the driving and inhibiting effects among land uses have not yet been thoroughly discovered. To address this problem, we propose an interaction network discovery model via consistency-based simulation, called intPLUS (available for download at https://github.com/HPSCIL/intPLUS), to find the interaction relationships among land uses and to improve the projections of future land use changes. This model uses the logarithm transformation to embed weights into multiple effects, including the inter-land use inhibiting effects, which drive the evolution of land use. The correctly projected land use change (i.e., consistency) is analyzed with a random forest (RF) model to explore the weights of the driving and inhibiting effects between land uses. This model is applied to Wuhan, China. The results showed that 'cultivated field' was greatly restrained and was restrained by other land uses. The application of the interaction network obtained accuracy enhancements of 30% and 13% in the calibration and future allocation processes, respectively. This model takes full advantage of the consistency information of the process of spatial simulation; the interaction network among land uses derived by the proposed model provides an insightful means to advance our understanding of spatial competition.

1. Introduction

Socioeconomic development has resulted in substantial changes in land use over decades and had dramatic impacts on the regional environment (van Vliet, 2019; Yang et al., 2020). Land use change reflects the interplay between deterministic processes (e.g., land use suitability and competition among land uses) and stochastic processes, such as neighborhood effects and wildfires. Among them, competition stems from the allocation issue of limited resources, and is crucial to maintaining the balance of ecosystems and human well-being. With the increasing number of land uses regulations and stakeholders under climate change, potential land use competition is expected to be

* Corresponding author at: School of Geography and Information Engineering, China University of Geosciences, Wuhan, Hubei 430078, China.
E-mail address: guanqf@cug.edu.cn (Q. Guan).

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exacerbated in the future (Haberl et al., 2014).

It is a longstanding consensus that competition plays a central role in determining the structure and functioning of land uses (Lawlor, 1979), and this is especially true when land-use decision makers face the challenge of balancing the growing needs for urban development, and the responsibility to safeguard future food and ecological security. In this regard, the simulation modelling approaches that incorporate both deterministic and stochastic processes of land use dynamics are promising to guide decision makers on land resources allocation and spatial policy formulation (Newbold et al., 2015; Verburg et al., 2019). Due to the inherent structural problems of existing simulation models, for example, cellular automaton (CA) model (elaborated in Section 2), most studies have implicitly assumed that the neighborhood effect and land use suitability have equal influences on land use transitions (Wu, 2002), including widely used models such as CLUE-S, FLUS, etc (Liu et al., 2017; Verburg et al., 2002). This assumption is, however, rarely met in the realistic world. For example, in the case of urban sprawl, the neighborhood effect might be dominant in driving land use transitions, yet in the case of leapfrogging development, land use suitability or competition advantages due to the cheaper land cost might override neighborhood effects (Yang et al., 2020). Moreover, the effects of these processes may also vary between land uses. For instance, the agricultural land adjacent to urban areas is likely to be converted to impervious surface, whereas agricultural land surrounded by forests may not necessarily experience the transition (van Vliet et al., 2017). To address this issue, some scholars have attempted to assign different weights to reflect different influences of these two factors (Feng et al., 2020; van Asselen and Verburg, 2013), yet those weights were most often assigned subjectively based on expert knowledge, such that they may fail to capture the true mechanism of land use dynamics, leading to an increase in simulation errors (Yeh and Li, 2006) and a decrease in the consistency of the simulation results with the actual land use. To date, there is still a lack of the structured framework to characterize and quantify interactions among land uses.

Furthermore, the simulation consistency/error compared to the realistic land use can include important information of land use interaction (Clarke and Gaydos, 1998; Huang et al., 2016), such as how multiple land uses interact and compete with each other. To solve the aforementioned problems, an interaction network mining approach via consistency-based dynamic simulation, namely intPLUS, was proposed to unveil the interactions of regional land use change. The design principles of the intPLUS model are illustrated in Fig. 1. We aimed to explore: 1) how to incorporate effects from other land uses in the simulation model; 2) the challenge of embedding weights for the corresponding effect factors; and 3) the method for mining and applying these weights. It also includes a corresponding design for solving these issues, serving as a guide for understanding the overall structure of this study. The intPLUS model has been implemented in Wuhan, located in central China, where there is intense competition among food security, economic development, and ecosystem conservation. Between 1990 and 2013, Wuhan lost 28 km^2 of wetland, including 77 % of Shahu Lake and 52 % of Nanhu Lake. Therefore, exploring land use competition in Wuhan is essential for effective ecological management and sustainable development (Yang et al., 2024; Zhang et al., 2020).

2. Literature review

2.1. Inherent structural problems of existing simulation models

Models of the dynamics of land use changes and projections of future changes (e.g., cellular automata) are commonly based on neighborhood aggregation effects (NAE, the influences of surrounding land uses on the central land use type) and spatial suitability maps (SAM, reflecting the influences of multiple human-environmental driving factors on land use changes) (Omrani et al., 2017; Yang et al., 2019), for example, the Dyna-CLUE model and the PLUS model (Liang et al., 2021a; Liang et al., 2021b; Verburg and Overmars, 2009). Stochastic effects (i.e., the unanticipated changes resulting from incidental factors in land use changes) are also considered because they also largely influence realistic landscape dynamics (Wu, 2002). Some spatial simulation models also consider the feedback factors from land use quantities in the land use simulation. Given that not all spatial simulation models incorporate feedbacks from the quantity of land use (Feng and Tong, 2020) and that the feedback from quantity is not spatially heterogeneous in some spatial simulation models (Liu et al., 2017; Verburg et al., 2002), we do not consider quantity feedback as an indispensable factor in this study.

In most studies, the three effects (neighborhood aggregation effects, spatial suitability maps and stochastic effects) are regarded as probability components or quasi-probability components with values ranging from 0 to 1, and are combined by adding or multiplying them (Schaldach et al., 2011; Yang et al., 2023) to construct total probabilities for different land uses. The summation method is very convenient for embedding weights into each effect factor by multiplying weights with corresponding effects (van Asselen and Verburg, 2013). However, it is not applicable if we consider these effects as probabilities. According to the addition theorem of probability[1], probability can only be added when they are mutually exclusive. Clearly, the three effects are not mutually exclusive in real geographic space. Therefore, researchers tend to assume that the three effects are independent of each other and use multiplication to combine them (Liang et al., 2021a; Liang et al., 2021b; Newland et al., 2020; Sohl and Sayler, 2008). The product of the effects represents the probability of the three events occurring simultaneously, which is based on the multiplication theorem of probability[2].However, the weights of these effects are difficult to embed in such a model structure. According to the commutative law of multiplication, if we still multiply weights with the corresponding effect, which eventually makes assigning a weight for each effect meaningless. Therefore, most researchers assume that the magnitude of each effect on the total probability is the same in such simulation models (Chen et al., 2023; Sohl and Sayler, 2008; Wu et al., 2019), resulting in failure of the current spatial simulation models to objectively capture the underlying mechanism of land use dynamics, and reducing the reliability of future land use predictions.

2.2. The potential of consistency analysis in exploring land use competition

An analysis of the simulation consistency (Hits) can help the model builders comprehend how various probability components interact and influence the generation of future patterns, thus potentially providing critical guidance to improve the simulation results (Clarke and Gaydos, 1998; Huang et al., 2016). By analyzing and interpreting the consistency information, we can further identify the interactions in simulation mechanisms and models, providing a basis for model improvement and correction, as well as important clues for exploring the underlying mechanisms of the model. The interactions among different land uses can also represent land use competition (Newland et al., 2018). For each land use, a set of interaction rules determines the degree to which it is attracted to or repelled by other land uses present in its surroundings (Newland et al., 2018; van Delden and Hurkens, 2011).

However, simulation consistency is commonly used by scholars to evaluate simulation accuracy (Lei et al., 2020; Pontius and Schneider, 2001), and few studies have taken full advantage of the information embedded in simulation consistency to mine the mechanism of land uses

[1] Addition theorem of probability: If events A and B are mutually exclusive, then: $P(A \cup B) = P(A) + P(B)$.

[2] Multiplication theorem of probability: $P(A \cap B \cap C) = P(A) * P(B) * P(C)$ when events A, B, and C are independent, a general formula for finding the probability of simultaneous occurrence of multiple events in a randomized experiment.

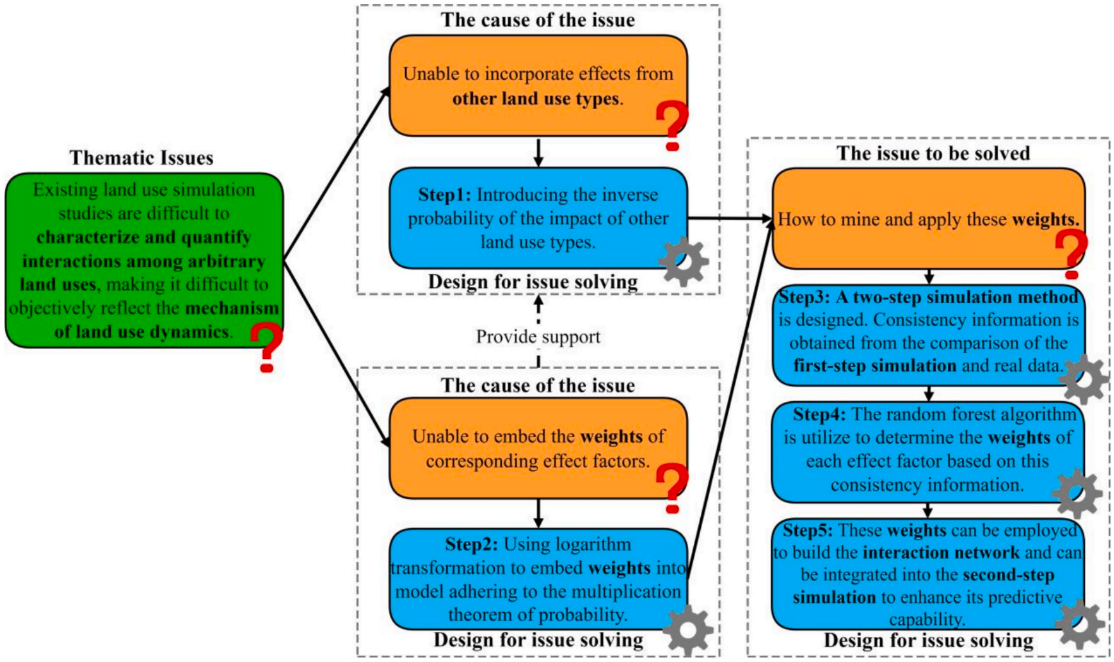

Fig. 1. The train of thought to solve the thematic issues in this study.

interactions and further promote the reliability of simulation results (Liu et al., 2017; Verburg et al., 2002). Therefore, we opted to perform a consistency analysis in this study to address this gap.

Although agent-based model is widely used in modeling the competition between different agent, using such software as NetLogo, Gama platform or HexSim (Schumaker and Brookes, 2018; Taillandier et al., 2019; Wilensky, 1999), deep reinforcement learning is also used to model the land use change, which are useful tools for modelling the change of complex social ecological systems and processes (Strannegård et al., 2024). however, the main object of this study is to unveiling land competition through a visible and measurable manner directly between land uses, not between agents. This study is complementary to the agent-based model research rather than substitutive.

3. Methods

The intPLUS model can be divided into five steps: 1) Introduce the inverse probabilities of the conventional factors as the inhibiting effects of the other types of land use on certain land use types (section 3.1); 2) A logarithmic transformation is used to realize weight embedding for every probability factor (section 3.2). 3) A two-step simulation model is adopted in the modeling process (Fig. 2). The weights of all effects are set to 1.0 by default to obtain the initial simulation results in the first step, which overlap with true land use data to obtain its consistent part with reality[3]. 4) Then, the random forest (RF) model is used to obtain the contribution values of each effect factor to the consistent part. These contribution values can be used to construct the interaction networks among land uses and provide new insights into land use change (section 3.3). 5) Finally, the contribution values are converted to corresponding parameters of the effect factors (section 3.4) to apply to the second step of the simulation and achieve the final simulation results.

[3] Consistent part with reality (Hits): the land use parcels that change during the simulation and are accurately simulated when the simulation results are compared against actual land use data.

3.1. Embedding inhibiting effects into the simulation model

In the framework of intPLUS, different land uses can be seen as mutually exclusive. The higher the proportion of the neighborhood aggregation effect and spatial suitability of a certain land use in a cell are, the lower the proportions of other types. Therefore, a given land use inhibits other land uses through its own neighborhood aggregation effect and spatial suitability map.

Based on this assumption, we give the equation of the intPLUS model:

$$OP_{i,k}^{t} = P_{i,k}^{1} \times \Omega_{i,k}^{t} \times (R_i^t \times C_{i,k}^t) \times D_k^t \quad (1)$$

where $P_{i,k}^{1}$ is the suitability that land use k will occur in cell i, which is calculated as follows:

$$P_{i,k}^{d}(x) = \frac{\sum_{n=1}^{M} I(h_n(x) = d)}{M} \quad (2)$$

The proposed model uses binary-classification-RF to obtain the suitability maps; thus, the value of d is either 0 or 1. $P_{i,k}^{1}(x)$ is the spatial suitability of other land uses converting to land uses and represents the spatial suitability of land use k; $P_{i,k}^{0}(x)$ represents the spatial suitability map of other land use not converting to land use, which does not participate in the calculation of subsequent simulation; x represents the vector constructed by multiple driven factors (e.g., traffic network, location, terrain, climate, etc.); $h_n(x)$ is the nth decision tree's prediction type for vector x; is the decision tree set's indicative function, and M is the total count of decision trees.

$\Omega_{i,k}^{t}$ represents the neighborhood aggregation effect, which is the cover proportion of land use k within the neighborhood:

$$\Omega_{i,k}^{t} = \begin{cases} \dfrac{con(c_i^{t-1} = k)}{n \times n - 1} \times w_k & if\ con(c_i^{t-1} = k) > 0 \\ r \times \mu_k \times w_k & if\ con(c_i^{t-1} = k) = 0\ and\ r < P_{i,k}^{1} \end{cases} \quad (3)$$

$con(c_i^{t-1} = k)$ reflects the quantity of land use k within the $n \times n$ window; w_k is the relative weight of the various land uses, ranging from 0 to 1. When $con(c_i^{t-1} = k)$ is equal to *0* and a random value r is lower than $P_{i,k}^{1}$,

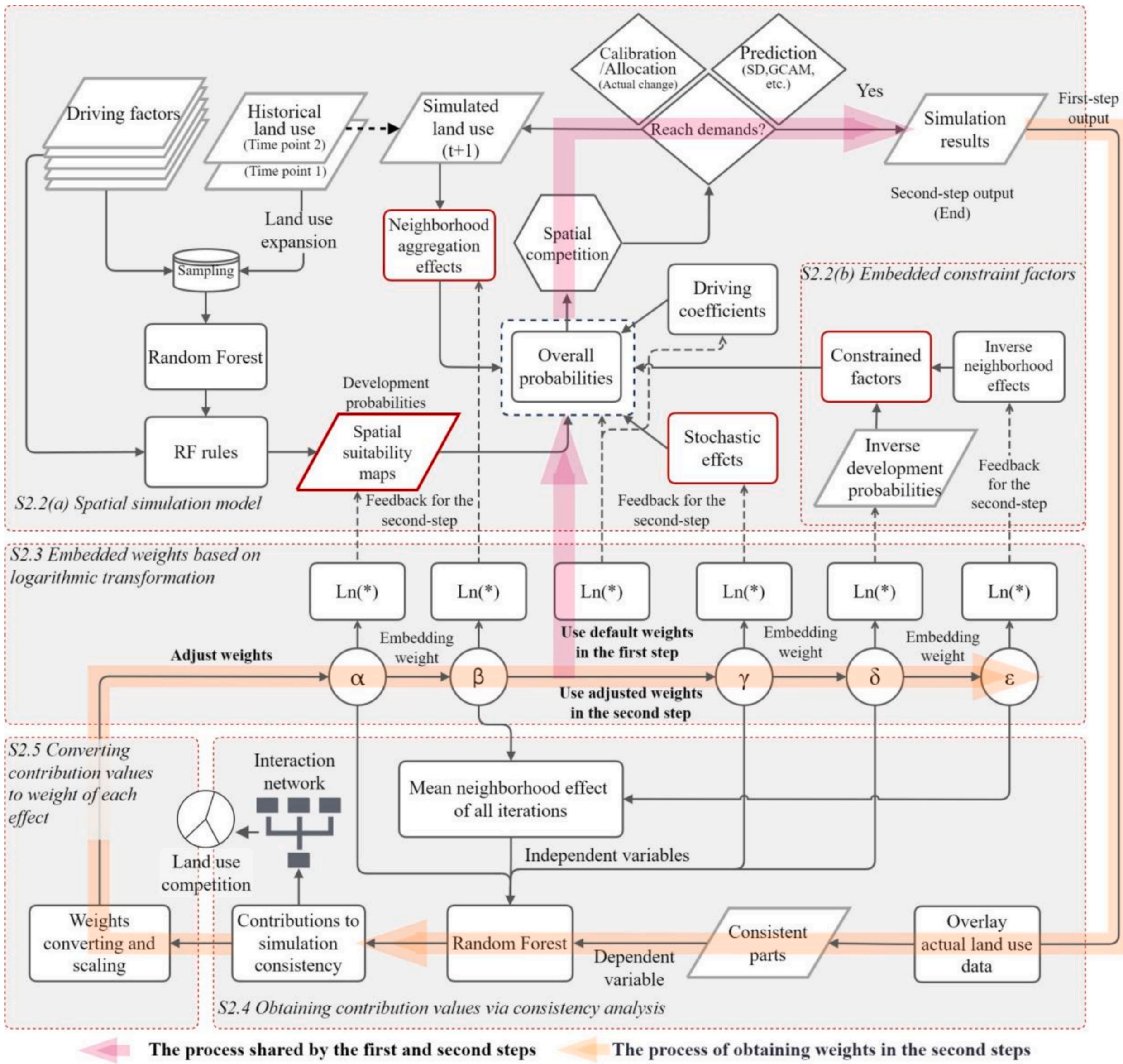

Fig. 2. Flowchart of the intPLUS model to mine the interaction network among land uses to interpret land use competition. This study involved only the calibration and allocation process; the prediction process was not carried out.

a 'seed' is planted, and a random probability constrained by $P_{i,k}^1$ is given to land use k to allow the creation of enclaves of land use k. μ_k is the cutoff value for producing new land use patches. D_k^t is the driving coefficient, which gradually drives the amounts of all land uses to close to their demands (Liang et al., 2021a; Liang et al., 2021b; Liang et al., 2024; Yang et al., 2024). It is calculated by the following equations:

$$D_k^{\prime t} = \begin{cases} D_k^{t-1} if |G_k^{t-1}| \leq |G_k^{t-2}| \\ D_k^{t-1} \times \dfrac{G_k^{t-2}+1}{G_k^{t-1}+1} if 0 > G_k^{t-2} > G_k^{t-1} \\ D_k^{t-1} \times \dfrac{G_k^{t-1}+1}{G_k^{t-2}+1} if G_k^{t-1} > G_k^{t-2} > 0 \end{cases} \tag{4}$$

$D_k^t = D_k^{\prime t}/Max(D_k^{\prime t})$

G_k^{t-1} and G_k^{t-2} are the gaps between current land use k and its future demand at iterations $t-1$ and $t-2$; Max(*) is a function to find the maximum.

The constraint factor is used to consider the inhibiting effect of the other types of land use on land use k. It consists of the inverse probabilities (product of 1.0 subtracted by the spatial suitability maps and the neighborhood aggregation effects) of other land uses, and its equation is:

$$C_{i,k}^t = \prod_{o=1}^{K} \left(1 - P_{i,o}^1\right) \times \left(1 - \Omega'^t_{i,o}\right) \qquad o \neq k \tag{5}$$

$$\Omega'^t_{i,o} = \Omega_{i,o}^t \bullet \left(1 - \Omega_{i,k}^t\right) \qquad if\ con\left(c_i^{t-1} = k\right) = 0\ and\ r < P_{i,k}^1 \tag{6}$$

K denotes the area of land use. Equation (6) means that when a random probability is given to land use k, other neighborhood aggregation effect of land use o should decrease proportionally to ensure that the sum of all neighborhood aggregation effect is equal to *1.0*. $C_{i,k}^t$ does not directly represent the inhibiting effects of other land uses. It acts as a conduction value of the inhibiting effects of and of other land uses o. The greater $P_{i,o}^1$ or $\Omega_{i,o}^t$ is, the smaller $C_{i,k}^t$ is, which results in a decrease in $OP_{i,k}^t$. Through this conductive process, the proposed model can simulate the inhibiting effect of other types of land use o on land use k.

3.2. Embedded weights based on logarithmic transformation

To embed weights into equation (1), we applied the logarithmic transformation in base e to equation (1) to unfold it as the sum of several effect factors:

$$ln(OP_{i,k}^{t}) = ln(P_{i,k}^{1} \times \Omega_{i,k}^{t} \times R_{i}^{t} \times C_{i,k}^{t} \times D_{k}^{t}) \tag{7}$$

$$ln(OP_{i,k}^{t}) = ln\left(P_{i,k}^{1}\right) + ln\left(\Omega_{i,k}^{t}\right) + ln\left(R_{i,k}^{t}\right) + ln(C_{i,k}^{t}) + ln(D_{k}^{t}) \tag{8}$$

$$ln\left(OP_{i,k}^{t}\right) = ln\left(P_{i,k}^{1}\right) + ln\left(\Omega_{i,k}^{t}\right) + ln\left(R_{i,k}^{t}\right) + \sum_{o=1}^{K} ln\left(1 - P_{i,o}^{1}\right) + \sum_{o=1}^{K} ln\left(1 - \Omega_{i,o}^{t}\right) + ln(D_{k}^{t}) \quad o \neq k \tag{9}$$

Now, equation (1) can be regarded as a simulation model where all effect factors have the same weight of 1.0. The use of logarithmic transformation merely presents another expression of the original model. Thus the proposed model adheres to the probabilistic principles of original land use modeling. However, in the actual process of land use change, the weights of the influences of the effect factors might differ. Thus, we give each effect factor a different weight to improve the model (except D_k^t because it is a global variable):

$$ln\left(OP_{i,k}^{t}\right) = \alpha_k ln\left(P_{i,k}^{1}\right) + \beta_k ln\left(\Omega_{i,k}^{t}\right) + \gamma_k ln\left(R_{i,k}^{t}\right) + \sum_{o=1}^{K} \delta_{o\to k} ln\left(1 - P_{i,o}^{1}\right) + \varepsilon_{o\to k}\sum_{o=1}^{K} ln\left(1 - \Omega_{i,o}^{t}\right) + ln(D_{k}^{t}) \quad o \neq k \tag{10}$$

α_k, β_k, and γ_k denote the weights of the conventional effect factors of land use k (spatial suitability map, neighborhood aggregation effect, and stochastic effect, respectively); $\delta_{o\to k}$, $\varepsilon_{o\to k}$ represent the weights of the inverse spatial suitability map and inverse neighborhood aggregation effect of other land use o. If the new simulation model is converted to the original multiplication form, equation (10) can be expressed as:

$$OP_{i,k}^{t} = {P_{i,k}^{1}}^{\alpha_k} \times {\Omega_{i,k}^{t}}^{\beta_k} \times {R_{i,k}^{t}}^{\gamma_k} \times \prod_{o=1}^{K}\left(1 - P_{i,o}^{1}\right)^{\delta_{o\to k}} \times \prod_{o=1}^{K}\left(1 - \Omega_{i,o}^{t}\right)^{\varepsilon_{o\to k}} \times D_{k}^{t} \quad o \neq k \tag{11}$$

Therefore, the mathematical meaning of the weight of each effect factor is the power of the effect factors. The spatial simulation process of the weight embedding intPLUS model is shown in Fig. 3. The proposed model employs the "Multitype Random Seeds based on a Descending Threshold" in the simulation process, which is elaborated in Liang et al. (2021a,b).

3.3. Obtaining contribution values and interaction networks via consistency analysis

To obtain the weights of each effect factor, a two-step simulation procedure is carried out in the modeling process. In the first step, we initialize all effect factor weights of the proposed model (α_k, β_k, γ_k, $\delta_{o\to k}$, $\varepsilon_{o\to k}$) to 1.0 to generate the first simulation results. Then, the simulation results and the actual land use data are overlaid, and the parts that change during the simulation and are correctly simulated are extracted to obtain the consistent part of the first simulation for analysis. The equations for consistency extraction are:

$$Consistency_k = ((L_{sim} = L_{true}) \text{ and } (L_{sim} \neq L_{start})) \tag{12}$$

$Consistency_k$ represents the correct parts of land use k in the simulation; L_{sim} is the simulation result; L_{true} is the actual land use data used to verify the simulation result; and L_{start} is the initial land use data.

Then, we regard $Consistency_k$ as the dependent variable and the

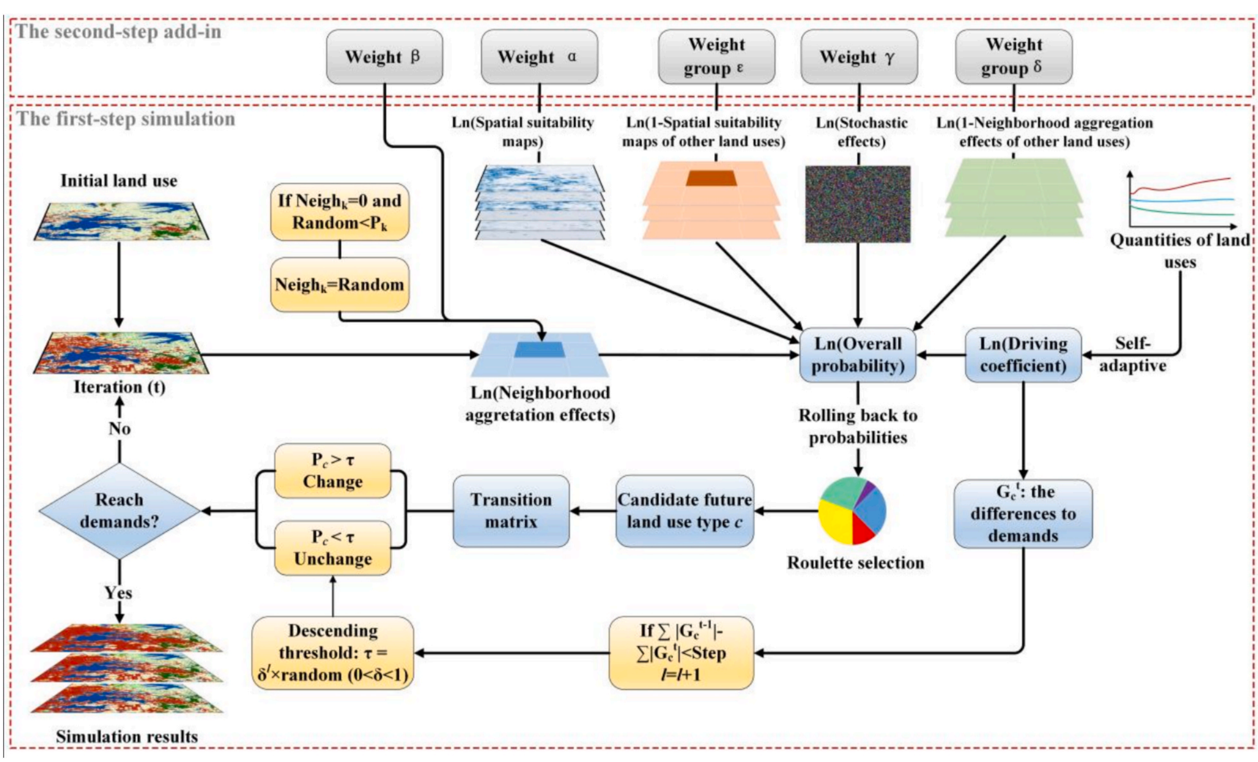

Fig. 3. The spatial simulation process of the intPLUS model.

neighborhood aggregation effect $m\Omega_{i,k}^t$, spatial suitability $P_{i,k}^1$, stochastic effects R_i^t (means the stochastic effects in cell i at time t, ranging from 0 to 1), and the inverse probability group ($C_{i,o}^t$) as the independent variables. Considering that the neighborhood aggregation effect $\Omega_{i,k}^t$ is a dynamic variable that changes with each iteration, we accumulate the neighborhood aggregation effect of every iteration and calculate the mean neighborhood aggregation effect as the overall neighborhood aggregation effect of the proposed spatial simulation model:

$$m\Omega_{i,k}^t = \frac{\sum_{t=1}^{T}\Omega_{i,k}^t}{T} = \frac{\sum_{t=1}^{T}\frac{con(c_i^{t-1}=k)}{n\times n-1}}{T} \tag{13}$$

T denotes the number of iterations. Then, we use a RF model to obtain the weights of the contribution of independent variables on the dependent variable:

$$Consistency_k = RF\left(P_{i,k}^1, m\Omega_{i,k}^t, R_{i,k}^t, C_{i,o}^t\right) \qquad o \neq k \tag{14}$$

The RF model offers benefits for assessing the contribution of predictor variables to the change in induced variables, which can be computed based on the change in the out-of-bag (OOB) error brought on by erratic noise (Zhang et al., 2019). Specifically, by using the bootstrapping method, the RF model divides the training dataset into several batches. Approximately 2/3 of the samples in each batch are used to train the classifier, and the remaining samples are referred to as the OOB dataset. The OOB dataset is employed to test the accuracy of the RF classifier and to generate the OOB error ($errOOB_l^1$) for each decision tree. Then, stochastic noise is added to all the auxiliary spatial variables l and generates a larger OOB error ($errOOB_l^2$). Thus, the importance of driving factor l for the growth of land use k (i.e., contribution values) is as follows:

$$Imp_{l,k} = \frac{\sum_{n=1}^{M}(errOOB_l^2 - errOOB_l^1)}{M} \tag{15}$$

The principle of this method is that the accuracy of RF will decrease due to the addition of stochastic noise for driving factor l, l=1, 2, 3,…, K. The more accurate the loss is, the more important a factor is. $Imp_{l,k}$ ranges from 0 to 1.0.

$Imp_{l,k}$ can be used to construct the interaction network in this study, which is a generation of “Measuring the inhibiting effects of spatial suitability maps and neighborhood aggregation effects of other land uses on a given land use while also measuring the promoting effects of spatial suitability maps, neighborhood aggregation effects, and stochastic effects of a land use on itself.” intPLUS applies the RF model to each given land use. Thus, a series of contribution values describing the inhibiting and promoting effects between the three effect factors across all land uses are obtained. By taking the three effect factors for all land uses as nodes, the inhibiting and promoting effects as directions, and the contribution values as weights, we can construct a directed graph to depict this interaction network.

Note that intPLUS uses the RF model to maintain consistency with the caculation process of land suitability maps and its predecessor, the PLUS model. Other machine learning models capable of calculating the importance weights of each factor, such as XGBoost and LightGBM, are also applicable.

3.4. Converting contribution values to weights of each effect for the second step simulation

All the effect factors of the spatial simulation model range from 0 to 1, and the values of the logarithmic function (base e) are monotonically increasing functions ranging from infinitesimal to 0 in the interval of 0 to 1. The smaller the weights are, the higher the probability value. However, when building a spatial simulation model based on simulation consistency, a greater importance means that the corresponding effect factor is more likely to contribute to a simulation pattern with greater consistency with actual land use. Therefore, we need to make the weights of high-importance effect factors as small as possible:

$$\varnothing_{l,k} = \left(Max\left(Imp_{l,k}\right) - Imp_{l,k} + \tau\right) \times S \qquad Imp_{l,k} = \alpha_k, \beta_k, \gamma_k, \delta_{o\rightarrow k}, \varepsilon_{o\rightarrow k} \tag{16}$$

$\varnothing_{l,k}$ is the weight of each effect factor; S denotes the scale factor defined by users. τ is a very small positive number, which is used to prevent the weights from equaling 0. We define τ as 1×10^{-7} in this study, other sufficiently small-enough values may also be used depending on implementation requirements (Weisz and Rgy, 2020). The weights of each effect factors can be adopted to the second-step simulation to improve the model reliability.

4. Study region and datasets

4.1. Study region

Wuhan, China, is used to illustrate the proposed model in this study. It has an area of 8,494.41 km^2 and serves as the capital of Hubei Province. The study region is situated at the confluence of two great rivers (the Yangtze and Han Rivers). A quarter of Wuhan’s spatial extent is covered by water, which includes lakes, rivers, and harbors. The location of Wuhan is shown in Fig. 4. Wuhan is a main metropolis in central China. The population of Wuhan city reached 12.265 million in 2020. Wuhan’s urban area expanded from 65,864 to 153,748 ha in the period from 2000 to 2015, resulting in an 8 % decrease in ecological area (Wang et al., 2018). This study utilized the China land uses Dataset (CLUD) to illustrate the proposed model (Kuang et al., 2016). The classification system in CLUD covers common and important land use types in the study region. The net observed change in land use in Wuhan was 7.72 % in 1980–2005 and 13.50 % in 2000–2015 (Fig. 4).

4.2. Datasets

The CLUD, which has a spatial resolution of 30 m × 30 m and contains land use data for the years 1980, 2000, and 2015, was used in this study; it included forest, cultivated field, grass, water body, urban area, rural settlement, and unused area (Kuang et al., 2016). We also collected 18 driving factors and aligned them to the same extent; they included climatic factors, environmental factors and socioeconomic factors. The spatial datasets utilized in this study are listed in Table 1.

5. Results

We obtained the first step simulation results from 1980 to 2000 and 2000 to 2015. By conducting a consistency analysis, we were able to derive the contribution values of the interaction networks in the two periods. A 3 × 3 Moore neighborhood is used for the dynamic simulation model. We set the number of RF trees to 20 and the sampling rate to 0.1 in the weight mining process. Fig. 5 shows the consistency maps (Hits) of the simulation of the intPLUS model in the two periods. Most of the hits during 1980–2000 were associated with the gain of water body because the observed dominant land use change was the expansion of water body (Fig. 4(a)).

We compared the contribution weights of the spatial suitability map, neighborhood aggregation effect, and stochastic effect of all land uses with the consistent parts (Hits) of the simulation results in the two periods extracted by the intPLUS model. Since growth of unused area was not found in these periods (only encroachment by other land uses), we do not discuss the contribution of other land uses to the expansion of the unused area. The contribution of other land uses to the growth of unused area was set to 0.5 by default in the simulation process of the intPLUS model.

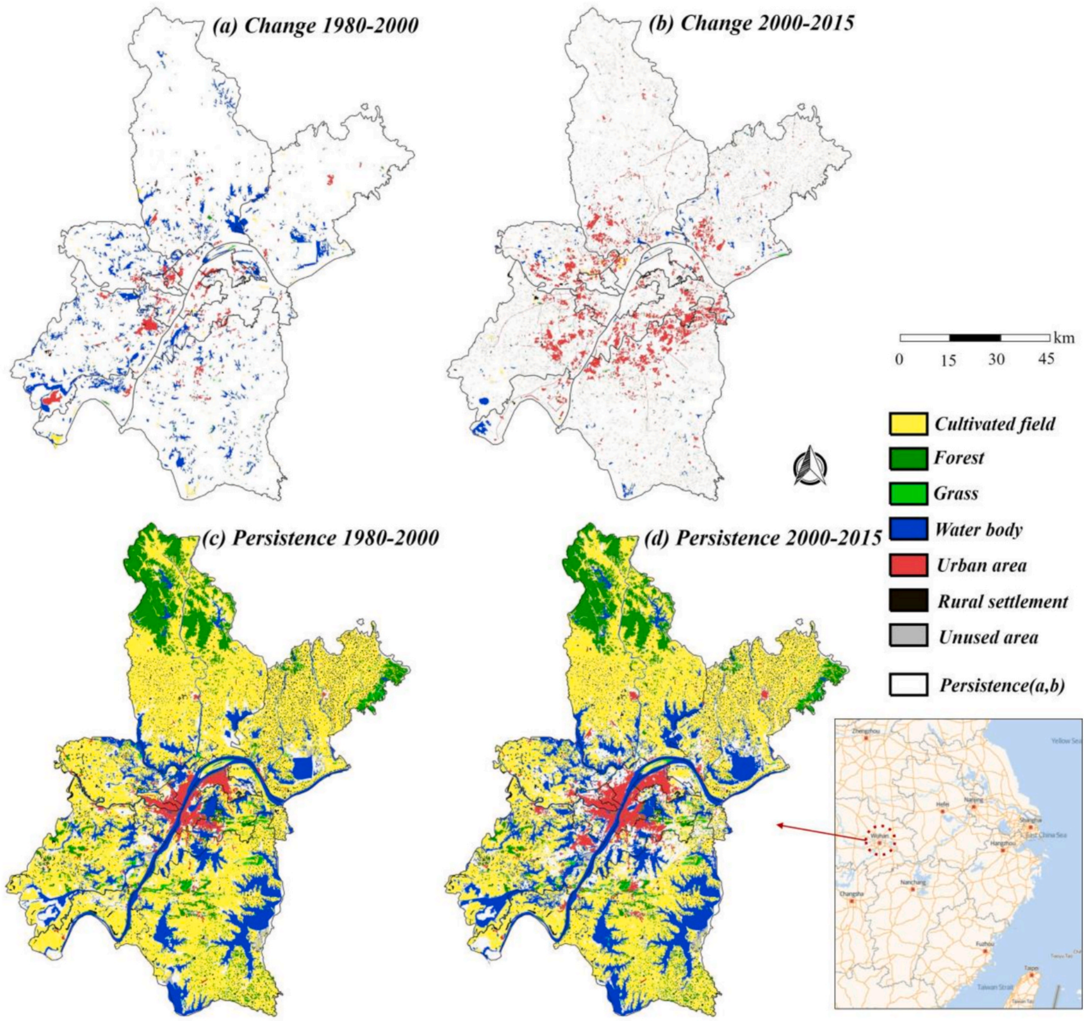

Fig. 4. Case study area: Wuhan. Panels (a) and (b) show the gaining categories during the time interval.

Table 1
Land uses and driving factors utilized by the intPLUS model. We edited the OpenStreetMap data according to historical electronic maps to obtain the historical road network.

Land uses and driving factors	Layers	Spatial resolution	Temporal interval	Reference
land use and land cover change (LULC)	land use data	30 m	*1980, 2000, 2015*	CLUD datasets
Society and economy data	Population GDP	1000 m	*1990, 2010*	Global Change Research Data Publishing & Repository
	Distance to highway entrance Distance to governments	30 m	*2000, 2015*	http://lbsyun.baidu.com
	Distance to tertiary road Distance to secondary road Distance to primary road Distance to highway Distance to railway Distance to arterial road	30 m	*2000, 2015*	https://www.openstreetmap.org/#map = 5/39.232/123.135
	Distance to high-speed railway stations	30 m	*2000, 2015*	https://lbs.amap.com/
Environmental and climatic data	DEM Slope	30 m	*2000*	SRTM1 (https://www.earthdata.nasa.gov/)
	Type of soil	1000 m	*1995*	HWSD v 1.2 (https://daac.ornl.gov/SOILS/guides/HWSD.html)
	Distance to open water	30 m	*1980, 2000, 2015*	CLUD datasets
	Evapotranspiration	1000 m	*1990, 2010*	https://data.tpdc.ac.cn/zh-hans/data/8b11da09-1a40-4014-bd3d-2b86e6dccad4/
	Annual Mean Temperature Annual Precipitation	1000 m	*1970–2000*	https://www.worldclim.org/

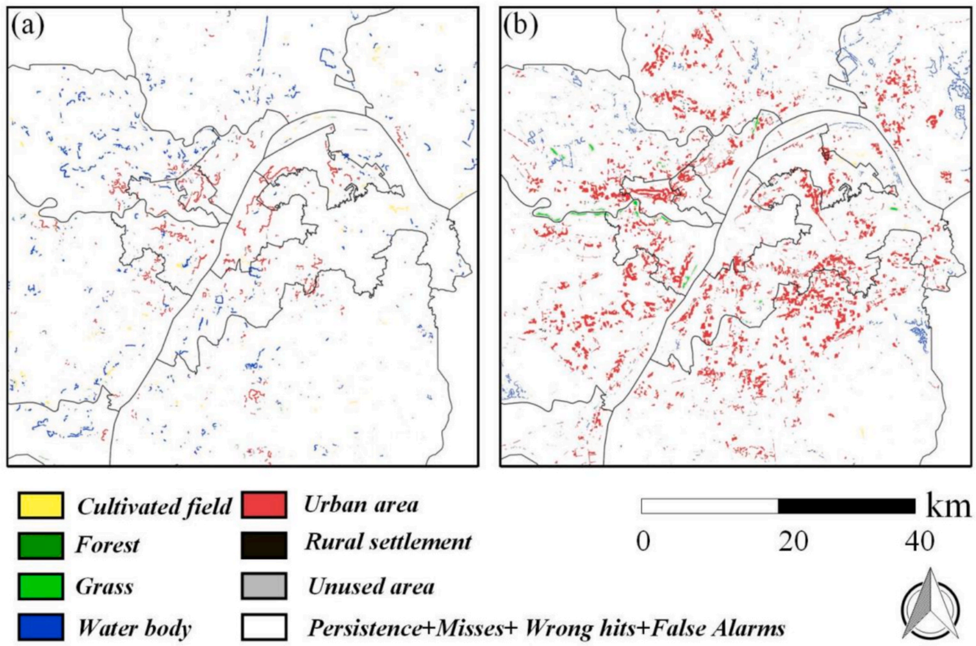

Fig. 5. The simulation consistency map (Hits) in 1980–2000 (a) and 2000–2015 (b).

5.1. Contribution value mining by the intPLUS model

Fig. 6 shows the contributions of the abovementioned effect factors of all land uses to the hits of the simulation results in the two periods. The positive values indicate the weights of those effect factors that drove the growth of a land use. SAM denotes the spatial suitability map of the land use ($P^1_{i,k}$ in equation (1)). Similarly, NAE is the overall neighborhood aggregation effect of land use ($m\Omega^t_{i,k}$ in equation (13)), and 'Stochastic factor' denotes the stochastic effect ($R^t_{i,k}$ in equation (1)). Negative values indicate the weights of effect factors that restrain the growth of a land use, which correspond to $C^t_{i,k}$ in equation (5). Because all the weights of the RF model are originally positive. We added a - negative sign to the contribution values of the spatial suitability and neighborhood aggregation effect of other land uses to represent the inhibiting effect of the other types of land use on land use k (Fig. 6).

In both the period from 1980 to 2000 and the period from 2000 to 2015, the absolute values of the driving effects were generally greater than those of the inhibiting effects. The consideration of stochastic effects had a very limited contribution to simulating the change in all land uses. For different land uses, the contribution values of the spatial suitability map and neighborhood aggregation effect were different and varied widely. For example, for cultivated field, the contribution weight of spatial suitability map in the two periods (SAM of cultivated field: 0.73 and 0.57) was substantially greater than the weight of the neighborhood aggregation effect (NAE of cultivated field: 0.29 and 0.23) (Fig. 6(a)), indicating that the occurrence of a new cultivated field does not substantially depend on its proximity to an existing cultivated field, and spatial suitability is much more important than proximity. Conversely, the contribution weight of spatial suitability map (SAM of urban area: 0.47 and 0.27) was much less than the weight of the neighborhood aggregation effect (NAE of urban area: 0.71 and 0.49) for urban areas (Fig. 6(e)), demonstrating that new urban areas are highly dependent on their proximity to existing urban areas rather than environmental suitability. These results also indicated that the traditional urban simulation models that assume that all the weights of the effect factors are the same do not accurately reflect the actual process of land use change.

5.2. The interaction network constructed by the contribution values

These contribution values also revealed the law of interactions between different land uses. The variability of inhibiting effects also showed that the influences of other land uses on one land use were heterogeneous. We constructed an interaction network according to the contribution values (Fig. 7) derived from the simulation period from 1980 to 2000, which clearly shows the driving or inhibiting effects of various effect factors on the expansion of different types of land use. We discovered that forest growth was primarily restrained by water suitability (−0.16), cultivated field suitability (−0.13), and rural neighborhoods (−0.08) from 1980 to 2000. The growth of water bodies and rural settlements was also restrained by cultivated field suitability (−0.25 and −0.29) and cultivated field neighborhoods (−0.09 and −0.17). Rural suitability also partly restrained the growth of water (−0.10). Urban growth was mainly restrained by cultivated field suitability (−0.24) and cultivated field neighborhood (−0.11).

Fig. 7 shows that the growth of forest and water bodies was restrained by most of the effect factors with an in-degree of 3, followed by the growth of urban areas, rural settlements and cultivated fields, with an in-degree of 2. The last is the growth of grass, which was constrained only by the cultivated field neighborhood. The spatial suitability map and neighborhood aggregation effect of cultivated fields restrained the expansion of most land uses. This conclusion is also supported by the out-degree of the nodes of cultivated field suitability (4) and cultivated field neighborhood (3), which were the highest among all nodes in the diagram.

The interaction network for the period from 2000 to 2015 was different from that for the period from 1980 to 2000 (Fig. 8), and forest growth was mainly constrained by cultivated field suitability (−0.06) and cultivated field neighborhood (−0.10). The growth of water bodies and rural settlements was also restrained by cultivated field suitability (−0.06 and −0.05) and cultivated field neighborhoods (−0.12 and −0.09). Forest suitability restrained cultivated field growth (−0.10) in addition to water suitability (−0.05) and water neighborhood (−0.09). Grass growth was also constrained by the cultivated field suitability (−0.06) and cultivated field neighborhood (−0.10).

This interaction network from 2000 to 2015 shows that the growth of cultivated fields and water bodies was restrained by most effect factors

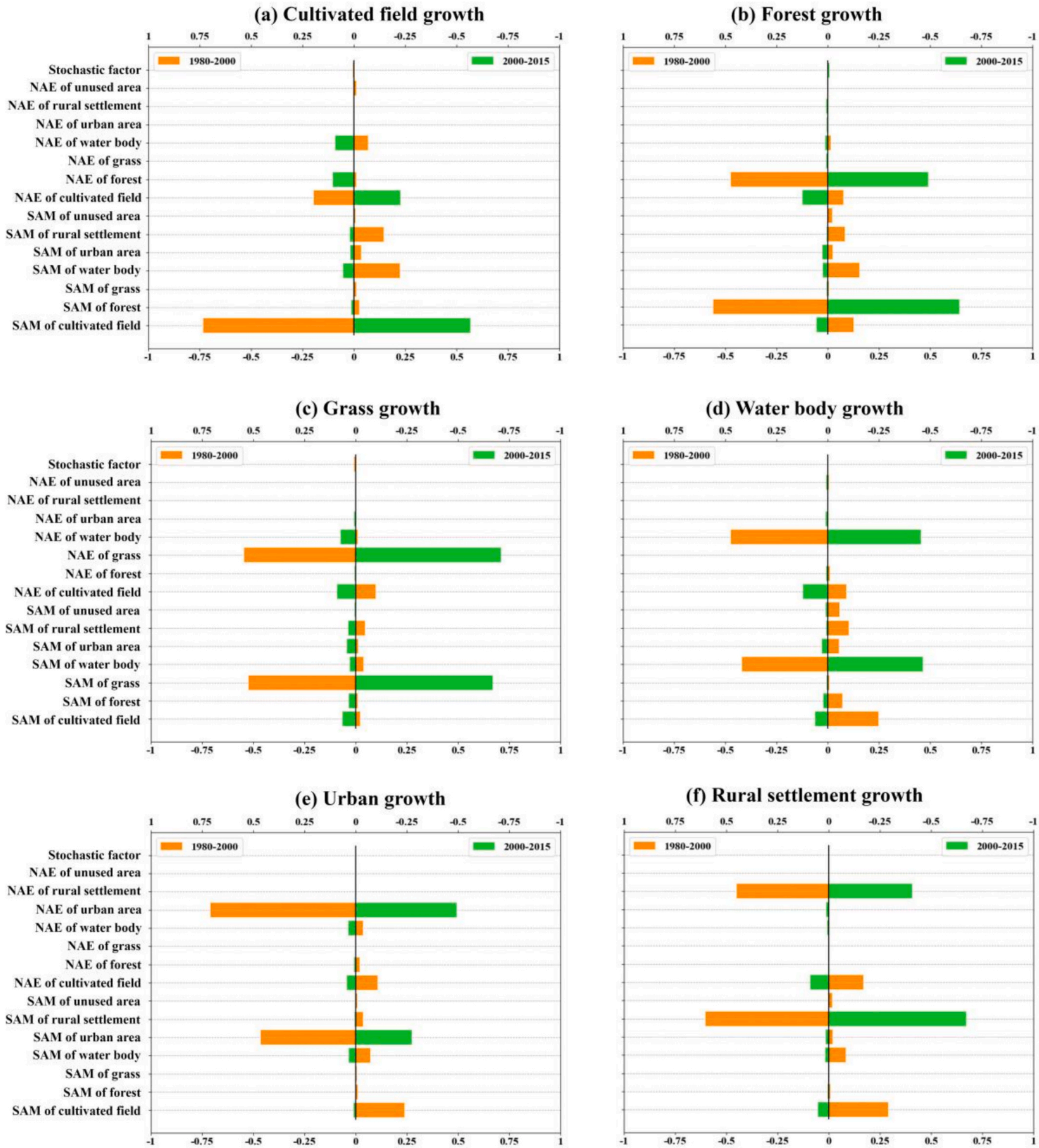

Fig. 6. Contribution values of different effect factors (no units) for the development of corresponding land uses extracted by the intPLUS model. Positive values indicate driving effects, while negative values indicate inhibiting effects. NAE denotes the neighborhood aggregation effect, SAM means the spatial suitability map.

with an in-degree of 3, followed by the growth of rural settlements, grass and forest, with an in-degree of 2. The last is the growth of urban growth, which was not constrained by any of the effect factors in the period from 2000 to 2015. The spatial suitability map and neighborhood aggregation effect of cultivated fields also restrained the expansion of most land uses, with an out-degree of 4 nodes for both cultivated field suitability and cultivated field neighborhood. This may be due to the relatively flat terrain of the study area, and the abundance of cultivated land. However, the ability of cultivated land to expand amidst competition for land use is relatively weak, which leads to the expansion of various types of land use primarily at the expense of the opportunities and distribution of cultivated land. This quantitatively illustrates to policymakers that arable land is more likely to be sacrificed as a cost of land use changes. Surprisingly, the urban suitability and urban

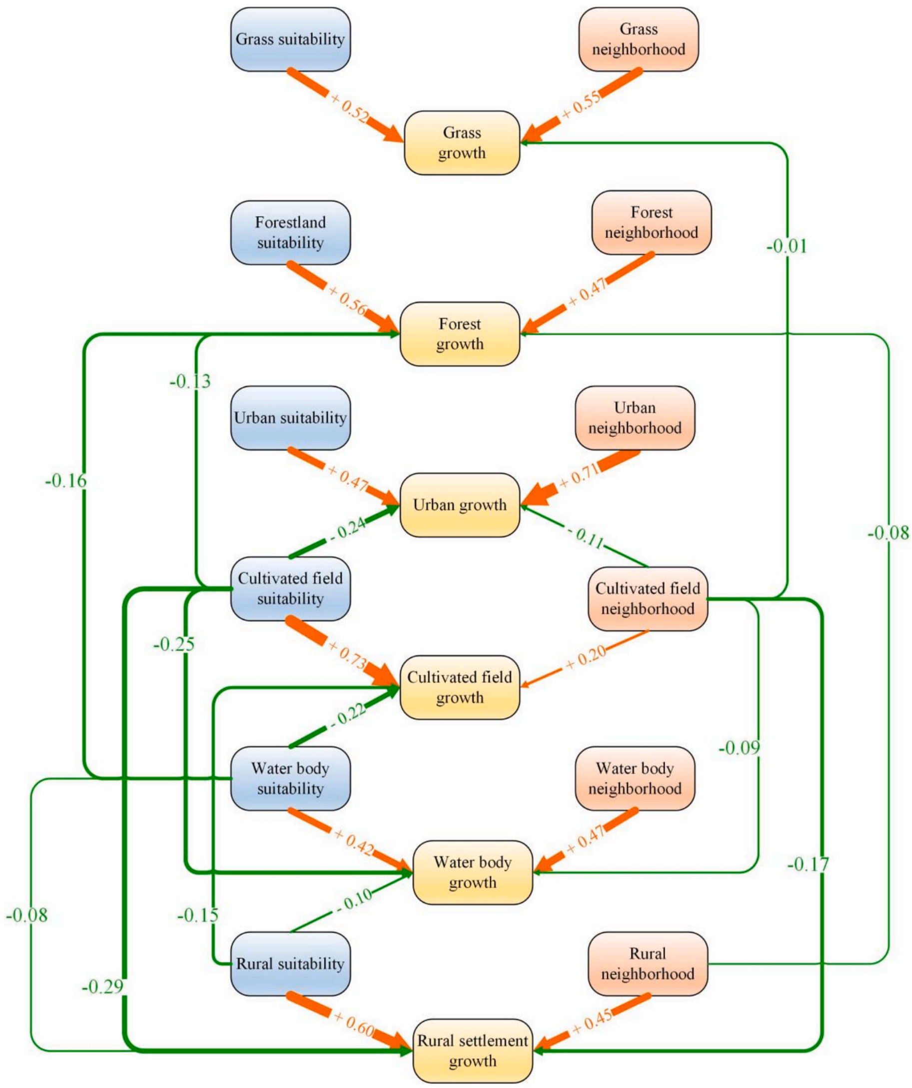

Fig. 7. Interaction network in the period from 1980 to 2000 mined by the intPLUS model (values less than 0.08 are not shown in the network). The blue box denotes SAM, and the carnatio box denotes NAE. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

neighborhood aggregation effects did not show high restraint values (lower than 0.05) for the growth of other land uses in either the period from 1980 to 2000 or that from 2000 to 2015, which means the growth of other land use types does not face strong competition from the growth of urban area. Similarly, urban growth was restrained by cultivated field suitability and cultivated field neighborhood in the period from 1980 to 2000, but in the period from 2000 to 2015, with the rapid development of urban areas, the constraining effect of other land uses on urban growth became increasingly weaker.

5.3. Stability of interaction networks between different stages

To measure the stability of interaction networks between the periods from 1980 to 2000 and 2000 to 2015, we constructed a scatter plot with all contribution values of six land uses in different stages (1980–2000, 2000–2015) in Fig. 9. The overall stability of contribution values between the period from 1980 to 2000 and the period from 2000 to 2015 was moderately high (with an R^2 of 0.89 and a gradient of 0.88). In particular, the driving effects of spatial suitability map, the neighborhood aggregation effect and stochastic effects on the growth of different land uses in different stages were stable (the first quadrant of Fig. 9, the points are mainly distributed around the fitting line). The slope of 0.88 for the least squares line suggests that the contribution values from the 1980–2000 data are high compared to those from the 2000–2015 data.

Correspondingly, a part of the inhibiting effects of other land uses had relatively low stability with respect to the contribution values between different stages (the third quadrant of Fig. 9). For example, the inhibiting effects of cultivated field suitability on the growth of water, urban, and rural settlements from 2000 to 2015 were lower than those from 1980 to 2000 (Fig. 6(d), (e), and (f)). The change in inhibiting effects may affect the simulation accuracy of future simulations. However, the absolute values of the inhibiting effects were generally far lower than those of the driving effects, which decreases the negative effects of the change in the inhibiting effects on the future simulation. Although some of the inhibiting effects of other land uses changed between stages, the relative stability of the driving effects and other inhibiting effects maintained the overall stability of the contribution values between the two periods (with an R^2 of 0.89). Therefore, we believe that even when applied to other regions, this stability will ensure that the R^2 values of the weights between different time periods remain highly consistent.

5.4. Validation and application of the interaction networks

We adopted interaction networks to the second step simulation and examined whether the application of the interaction networks can

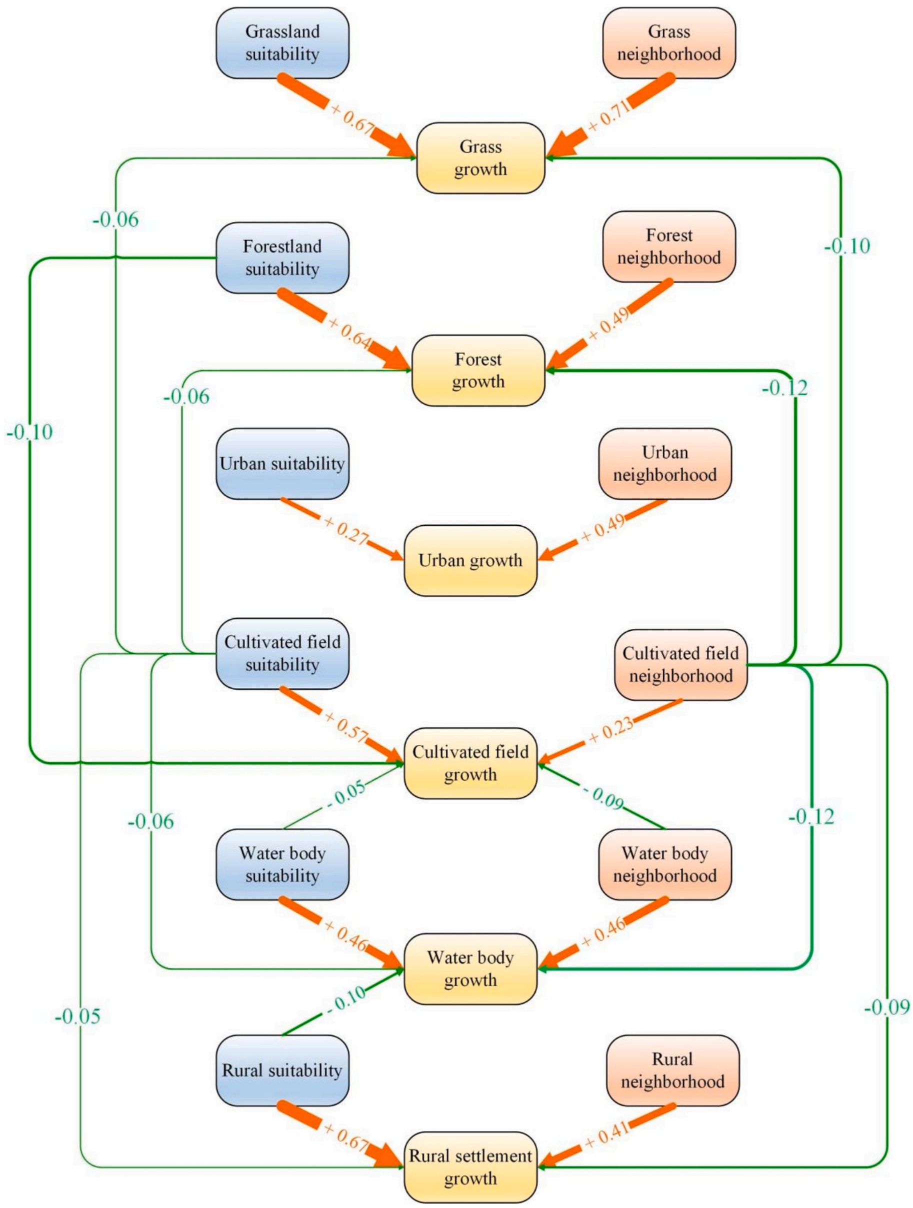

Fig. 8. Interaction network in the period from 2000 to 2015 mined by the intPLUS model (values less than 0.05 are not shown in the network).The blue box denotes SAM, and the carnatio box denotes NAE. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

improve the reliability of the simulation of future spatial simulation dynamics. This process acts as a kind of rationality and usability validation of the mining interaction networks. We compared the simulation accuracy and simulated pattern of the intPLUS-default-parameters (all the values of the interaction network are default to 1.0) and intPLUS-interaction-network (values of the interaction network are mined by the proposed model of this study) in the calibration stage (1980–2000). Afterward, we assumed that there was no information after 2000, projected the land use change from 2000 to 2015 with the two models and compared the results with actual 2015 land use. This procedure separates the evaluation procedure of the calibration time interval (1980–2000) from the validation time interval (i.e., the simulation from 2000 to 2015).

The experimental flow chart is shown in Fig. 10. Figure of merit (FOM), a widely used indicator proposed by (Pontius et al., 2008; Pontius et al., 2011), was used to compare the simulation accuracy of different models (FOM=Hits/(Misses + Hits + Wrong Hits + False Alarms)). When simulating land use change from 1980–2000 and 2000–2015, we directly used the actual quantities of land use demands from 2000 and 2015. We allow the model to not fully meet the demands, reflecting potential scenarios that may arise in real-world applications, especially in large-scale, fine-resolution simulations.

The results revealed that the intPLUS model with the interaction network can enhance the simulation accuracy compared to that of the one without the mining interaction network (from 0.10 to 0.13, an improvement of 30 %) in the calibration period (1980–2000). In the allocation period, the use of the mining interaction network from the calibration step improved the simulation result to some extent (from 0.16 to 0.18, an improvement of 13 %). The value falls within a range reported in some previous studies (1–59) (Pontius et al., 2008).

The comparison of the accuracy between the two models showed that the proposed intPLUS model can apply mining knowledge of the interactions between land uses to increase the simulation accuracy of both the calibration and allocation stages. Although the accuracy improvement of the allocation stages was less than that of the calibration stage, it was still apparent, which indicates that the interaction network can improve the projected results of the spatial simulation model. We also analyzed the variation in the four elements of FOM in

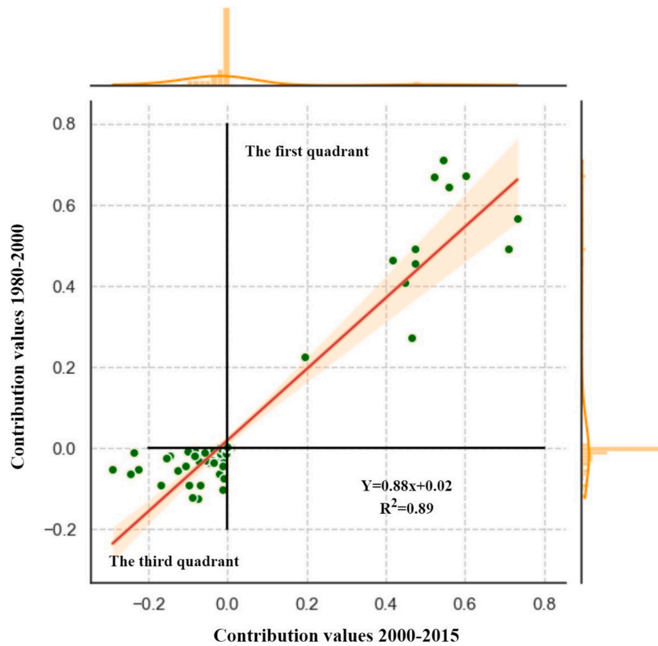

Fig. 9. Scatter plot of the interaction network between the period from 1980 to 2000 and the period from 2000 to 2015. The 2000–2015 data are the horizontal coordinates and the contribution values from 1980 to 2000 are the vertical coordinates. The dots represent the intersection of the x-axis (contribution values 2000–2015) and y-axis (contribution values 1980–2000).

each simulation: misses, hits, wrong hits, and false alarms (Chen and Pontius, 2010; Pontius et al., 2018). Considering the mining weights for effect factors makes the simulation more aggressive and introduces more change (the sum of the four elements is larger, and closer to the pre-defined demands). This produces more wrong hits and false alarms. However, the much larger reduction in misses still improves the overall value of the FOM in both the calibration and allocation processes.

Fig. 11 shows the simulation results and zoomed-in example areas of the intPLUS-default-parameters and intPLUS-interaction-network from 1980 to 2000 and 2000 to 2015. We found that by using the interaction network (Fig. 11, Panel (c vs. f,c1 vs. f1)), the simulated urban pattern of the intPLUS-interaction network became more compact and more similar to the actual land use in 2015 than those simulated by the intPLUS-default parameters (Fig. 11, Panel (b vs. e, b1 vs.e1)). By visualizing the spatial distribution of the simulation misses, hits, wrong hits, and false alarms, we found that considering the interaction network concentrates the hits more around urban areas in the allocation process (2000–2015) (Fig. 11, f vs. e, f1 vs. e1). Furthermore, it improves the simulation accuracy of the calibration process by facilitating the expansion of water bodies onto other land uses (Fig. 11, Panel (b1 vs. c1)).

6. Discussion

Spatial competition is difficult to parameterize and visualize. In past studies, there was a lack of structured frameworks to quantify and characterize competition among land uses. We proposed an intPLUS model that can discover the interaction network of land use competition, and we used this network to improve future land use projections. This model could be a useful tool for revealing and explaining the complex competition mechanism of land use change. It provides a structural framework for visualizing and analyzing the competition and interaction behind land use change with arbitrary classification systems.

By introducing weights based on a logarithmic transformation, constraint factors from other land uses, and the automatic parameter mining process based on consistency analysis, we have developed not only a mining tool for exploring the intricate interactions inherent in land use competition but also a spatial simulation model with higher projecting accuracy and reliability.

Methodological innovations are reflected in the following aspects. First, in previous spatial simulation studies, weights could not be embedded while adhering to the multiplication theorem of probability. To address this issue, we proposed a weight embedding technique based on logarithmic transformation. Second, we proposed a new spatial simulation framework that integrates constraint factors and embedded weights, enabling the spatial simulation model to simulate the influence of other land uses on a given land use. To derive the weights of all effect factors, we devised a model to extract information from consistency analysis and leveraged this information to determine the weight of each effect factor. Each of these processes is indispensable and has not been proposed by past studies.

The proposed model has the potential to support regional planning from three aspects. First, a clear visualization of the land use competition mechanism (i.e., interaction network) can help planners identify conflicting land uses that impede the growth of a given land use (Wang et al., 2023) and determine whether the growth of a certain land use is driven primarily by the presence of surrounding the same land use or by its spatial suitability map. This approach provides guidance for planners in planning new parcel types and the space they will occupy and further identifying the stakeholders behind land use parcels, which is beneficial for adjusting urban growth boundaries and protecting ecological redlines from illegal land use. Second, higher simulation accuracy and reliability can provide planners with a more reliable tool for examining the possible trends or futures of land use change. Finally, the intPLUS model can visualize the complex competition among land uses, largely improving the transparency of the model structure and communication interface (all the interactions within the interaction network are editable) for model users and stakeholders. Stakeholders can model the impacts of different competition policies on future land use by adjusting the interaction network, which conventional models do not have such functionality to accommodate (Ke et al., 2018; Verburg et al., 2002).

Furthermore, the introduction of the interaction network allows the intPLUS model to autonomously uncover diverse settings for land use simulation. This capability enables the model to be effectively applied to regions with distinct land use systems and complex environmental and socio-economic contexts, such as arid regions and megacities, without requiring users to rely on their own experiential settings. This characteristic not only broadens the method's applicability but also offers greater potential for expanded application.

6.1. Why the mining weights take effect

In the intPLUS model, the contribution values exported by the RF model are not directly input into the simulation process. According to equation (11), we convert the contribution values into the powers of different effect factors to explain why the mining weights take effect (Fig. 12). Because all the values of the effect factors range from 0 to 1 (the orange curves when $a < 1$), for a given X (original value of an effect factor), the lower a is, the higher Y (weighted value of an effect factor). Therefore, to improve the value (Y) with a high contribution weight, we must give it a lower power for the corresponding effect factor. Conversely, we assign a higher power for effect factors with low contribution values that may be larger than 1 to reduce the influence of corresponding effect factors on the simulation process (the green curves when $a > 1$). The contribution values range from 0 to 1, but the weights of the effect factors range from 0 to infinity. We used equation (16) with a scale factor (S) to implement the reverse conversion of the contribution values.

6.2. Sensitivity analysis

However, a very high or very low scale factor results in most of the

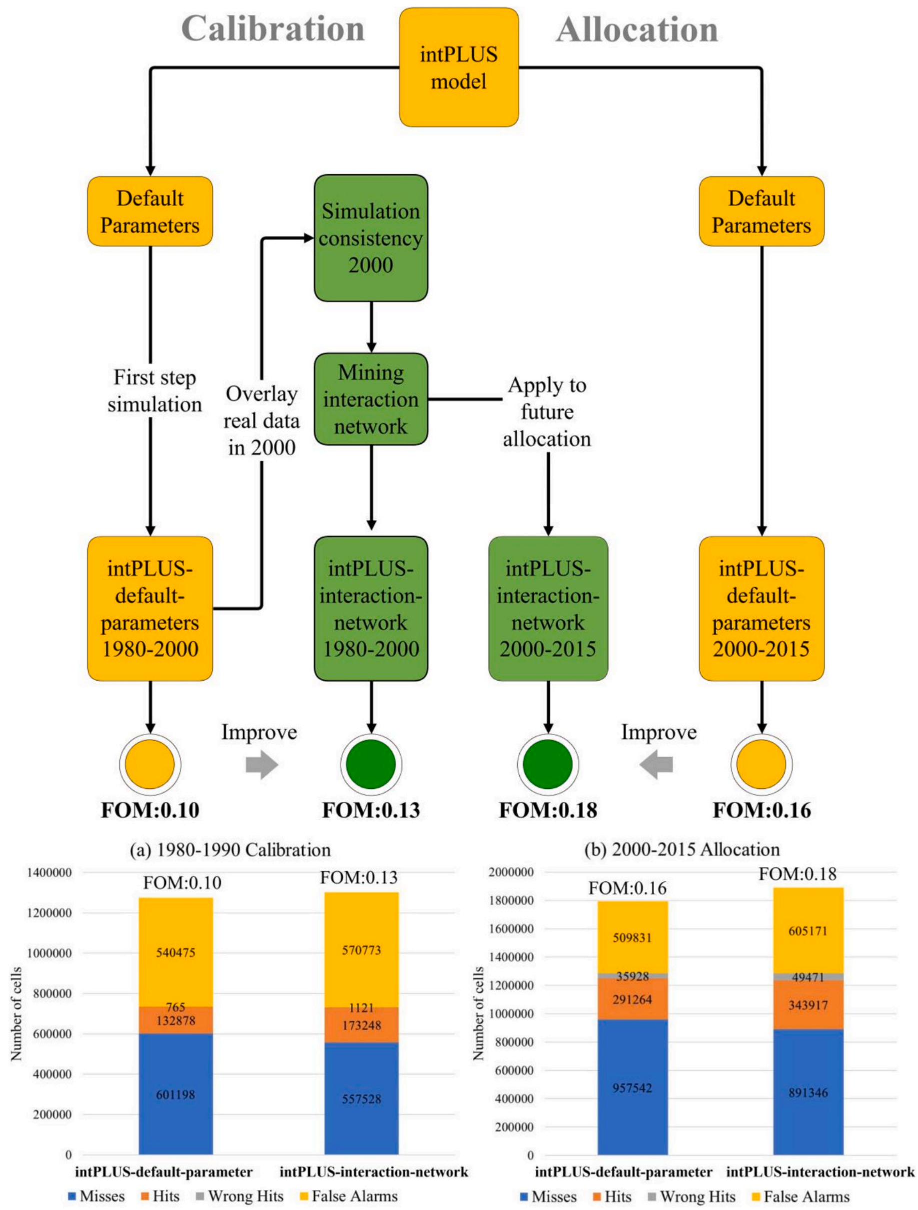

Fig. 10. Flow chart of the accuracy comparison between the intPLUS-default-parameters and intPLUS-interaction-network.

values of Y (i.e., the effect factors via exponential transformation) infinitely approaching 1 or 0 and eventually results in the loss of spatial heterogeneity for the simulation process. Therefore, the scale factor is an important parameter. To validate the sensitivity of the intPLUS model to scale factors, we tested the model performance from 2000 to 2015 with different values of scale factors. Fig. 13 shows the accuracy change with the growth of the scale factors. The intPLUS model obtained the highest FOM when the scale factor was 200. The variation in FOM exhibited an increasing trend with the scale factors. There was a sudden decrease in FOM when the scale factor was 250 because the intPLUS model could not reach the final land use demands due to the loss of spatial heterogeneity (most of the cell probability values are close to 1). This experiment revealed that although the scale factor had a large impact on the simulation, the simulation results under different scale factor values were still higher than those of the intPLUS-default-parameters (0.16).

Although the improvement in simulation accuracy from 2000 to 2015 is modest (up to 13 %), we argue that this improvement is still meaningful. This is particularly true because the allocation process was performed for a complex, large-scale city with high resolution and seven distinct land uses, relying primarily on historical data from 1980 to 2000 without calibration from more recent 2000–2015 data. The steady improvement in simulation accuracy shown in Fig. 13 demonstrates that the increase in FOM is stable and not merely a result of stochastic effects. The results in Fig. 6 also reveal that the stochastic effect has a very limited contribution to hits, with contribution values close to 0 for all land uses. When the proposed model is applied to regions where the actual land use of a region demonstrates stationary patterns over time, it may offer greater potential for enhanced accuracy.

6.3. Future work

In this study, we simply analyzed the contribution driving and inhibiting effects in two long periods (1980–2000 and 2000–2015). The interaction networks between the effect factors of different land uses in the two periods exhibited high stability (R^2 = 0.89). However, differences were still observed, such as the inhibiting effects of cultivated fields on other land uses showing a decreasing trend, which may limit the accuracy improvement of future simulations.

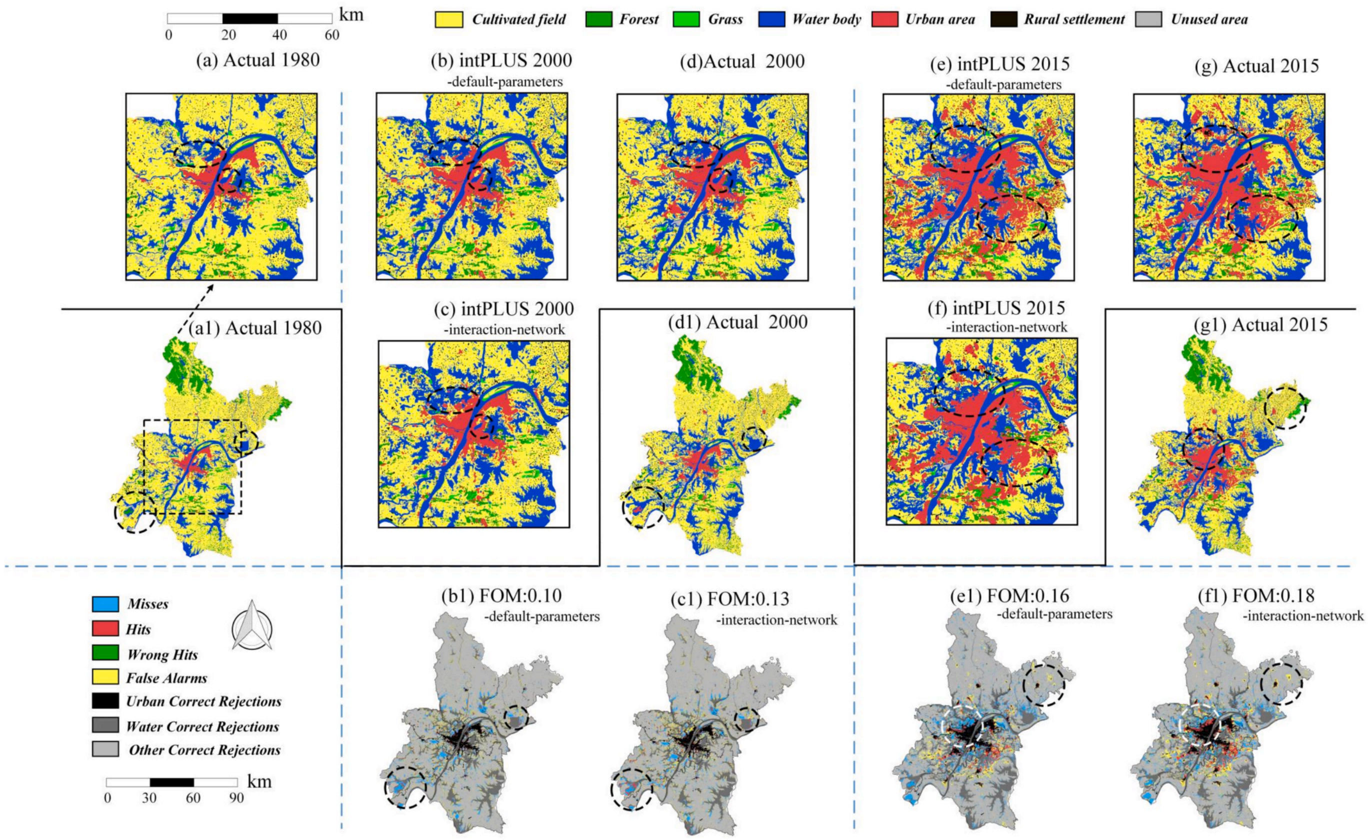

Fig. 11. The simulation results and zoomed-in example areas of the intPLUS-default-parameters and intPLUS-interaction-network from 1980 to 2000 and 2000 to 2015.

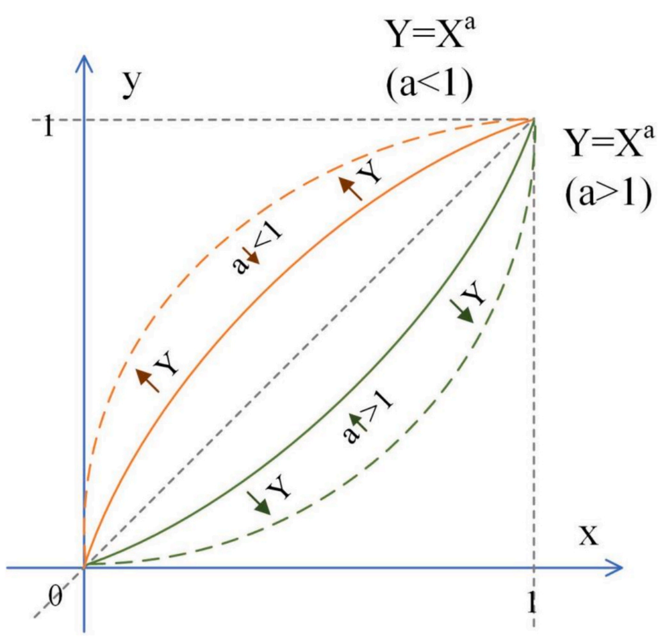

Fig. 12. Schematic diagram of the weights affecting the probability values.

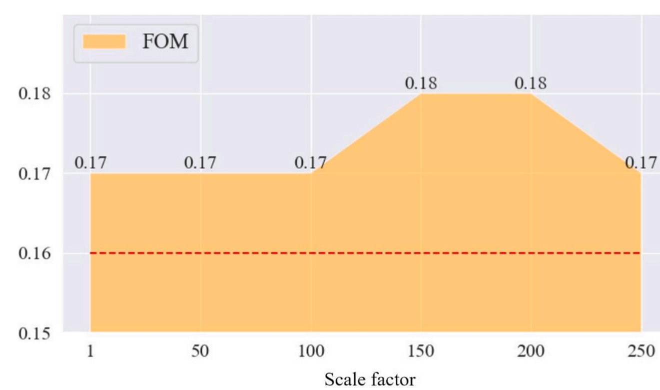

Fig. 13. The sensitivity of the intPLUS-interaction-network model to the scale factors of weights. The red line is the simulation accuracy of the intPLUS-default-parameters. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Therefore, many valuable subjects can be studied in future work. For example, it would be interesting to determine whether any rules exist regarding the change in driving and inhibiting effects with time or space, whether the interactions between land uses still work at other spatial resolutions and whether the inhibiting effects between land uses exist in other spatial classification systems (e.g., commercial space, residential space, industrial space). We can also examine whether inhibiting effects exist between different vegetation forms. To facilitate the study of the above problems, we released intPLUS software, which is freely available for download at https://github.com/HPSCIL/intPLUS. This study contributes significantly to the long-term impact of using intPLUS software in diverse regions, across different study periods, and with various land use classification systems in the future. Researchers can collect the results of these studies to implement a *meta*-analysis to answer these questions and obtain deeper insights about land use dynamics. Knowledge of the change rule of driving and inhibiting effects with time or space can help the model adopt changing contribution values, which will enable it to better characterize the trajectory of future land use change in our future studies.

The comparison of interaction networks across different time periods and cities may offer further policy insights for urban decision-makers. This represents a potential next step in the development of the intPLUS model. In addition, one limitation of our study is that we did not extract information from errors, which may help explain the reasons for the errors. In our future study, we plan to incorporate error information into the spatial simulation model to enhance its accuracy and interpretability. We also plan to analyze which method is superior in the future, comparing the summation method and the multiplication method.

Moreover, the contribution values generated by the RF model can be viewed as a comprehensive representation of all the social and ecological factors across various spatial and temporal scales. These values can be correlated with the importance weights produced by the binary-classification-RF during the calculation of spatial suitability maps (Liang et al., 2021a; Liang et al., 2021b). In our next phase study, we will integrate them to construct an interaction network knowledge graph that interprets the mechanisms by which multiple driving factors influence the evolution of land use and ultimately shape its final form. However, the intPLUS model primarily analyzes local land use changes and then aggregates them at the regional level. To incorporate macro-scale social and ecological factors, one approach could be to down-scale these macro-scale variables to the spatial level and then include them as factors within the CA model.

The modest simulation accuracy in this study is related to the low net observed change shown in Fig. 5. From a statistical perspective, simulation models tend not to achieve very high FOM when the net observed change is small; for example, referring to the study proposed by (Zhang et al., 2023), all the FOM values of the compared models in Shenzhen, China (2005–2015) are lower than 11 %. The ratio of net observed change to FOM in this study is consistent with the findings of Pontius et al. (2008). We believe that applying the proposed model to an area with higher net observed change may have had a greater possibility of yielding higher simulation accuracy. However, when the real landscape exhibits nonstationary patterns over time, accuracy improvement may not always be possible in some scenarios (Varga et al., 2019), and the proposed model can still provide the possibility of increasing simulation reliability and the maximum potential of the model compared to the previous model. Moreover, the extracted interaction network can still aid researchers in understanding historical land use dynamics and competition.

7. Conclusion

In this study, we proposed a novel interaction network discovery model that can generate interaction networks to characterize and visualize land use competition. A logarithmic transformation was used to realize weight embedding for every effect factor. A two-step simulation framework was designed in the simulation process. The first simulation was used to obtain the consistency of the simulation data with the real land use data. Then, the RF model was applied to mine the contribution values of multiple effect factors to construct the interaction network. Finally, the contribution values were applied to the second step simulation, and the final simulation results were obtained.

The proposed intPLUS model can uncover the competition mechanisms of land use change using any arbitrary spatial classification system based on the interactions among land uses. Compared to other existing models, the intPLUS model not only improves simulation accuracy and reliability but also generates new insights into the competition between land uses by examining the mutual driving and inhibiting effects, which previous models (including reinforcement learning and digital twin support simulation models) could not address. Furthermore, it enhances the transparency of the model structure, making it a significant contribution to land use simulation theory. This model provides valuable support for geography researchers and policymakers while establishing a new research paradigm for geographical analysis.

CRediT authorship contribution statement

Xun Liang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jun-Long Huang:** Writing – original draft. **Qingfeng Guan:** Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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