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Simulating urban expansion and its impact on functional connectivity in the Three Gorges Reservoir Area

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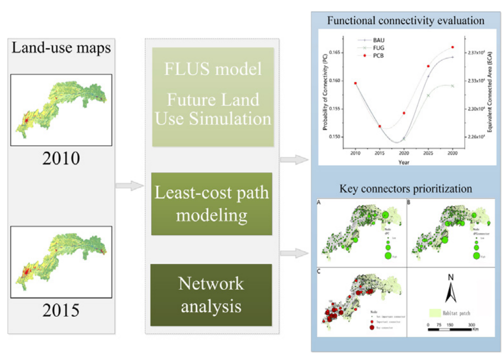
HIGHLIGHTS

- We studied the impact of urban expansion on functional connectivity.
- Urban expansion simulation and network analysis is coupled.
- Population-change-based urban expansion is an ideal development mode.
- Grain-for-Green Project is helpful to improve connectivity against urban expansion.
- Key connecting nodes were identified to provide guide for conservation.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the impact of urban expansion on functional connectivity is significant to biodiversity conservation. Particularly, in the Three Gorges Reservoir Area (TGRA, Southwest China), the urban land has rapidly expanded to provide settlements for an enormous population of TGRA migrants. However, the consequence of future land-use changes to the functional connectivity of the local habitat network has rarely been studied. To extend this knowledge, this paper proposes a framework that integrates a novel cellular automata (CA) simulation model and ecological network analysis, taking the TGRA as the study area, to predict how different urban expansion scenarios might affect functional connectivity for a nationally protected species, the leopard. The least-cost path modeling is used, and a set of connectivity indicators are adopted to evaluate functional connectivity. The results show that, the population-growth-based urban expansion maintains a higher connectivity than the business-as-usual and fast-urban-growth scenarios. In addition, the connectivity loss due to urban expansion can be offset by the reforestation efforts of the Green-for-Grain Project. Finally, we identify habitat patches that act as key connectivity providers, and suggest that those patches be prioritized for protection to avoid significant connectivity loss.

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1. Introduction

In developing countries, urban land is expanding at an unprecedented rate, and by 2030, urban land is projected to be triple the size it was in 2000 (Seto et al., 2012). Rapid urban expansion has increasingly caused serious habitat loss and a decline in landscape connectivity (Beninde et al., 2015; Thompson et al., 2017), which is the degree that a landscape facilitates or impedes animals from reaching new suitable habitats (Taylor et al., 1993; Theobald et al., 2006; McRae and Beier, 2007; Kukkala and Moilanen, 2017). Therefore, connectivity evaluation in an urbanizing landscape is of paramount importance to biodiversity conservation, and can be useful to urban planners in answering questions such as the following: (1) How well are habitats connected? (2) Which urban expansion rate helps to balance socio-economic development and habitat conservation? (3) Where is the right place to develop new urban land? (4) What areas should be prioritized for protection?

Generally, studies about the relationship between urban expansion and landscape connectivity can be separated into two parts: (1) the urban expansion simulation and projection, and (2) the connectivity assessment. The first part is generally achieved by applying a variety of land-use change (LUCC) simulation models. However, some of them (Baker et al., 2004) fail to account for the neighborhood effect that is crucial in landscape dynamics (Batty and Xie, 1994), some can only simulate the LUCC between two components of land-use types (Pontius et al., 2001), and some have high data requirements, which can hardly be met in many situations (Daniel et al., 2018). In this aspect, the cellular automata (CA) model seems appealing as it can overcome the first two problems with readily accessible data (Batty and Xie, 1994; Li and Yeh, 2000).

For the connectivity assessment, connectivity models based on graph theory have been widely used (Urban and Keitt, 2001; Thompson et al., 2017; Alvarez-Romero et al., 2018). Early connectivity assessments have mainly investigated structural connectivity, which only considers the spatial arrangements of habitats while ignoring realistic animal movements (Urban and Keitt, 2001; Bierwagen, 2006). However, all landscape graphs should represent functional connectivity, as it would be meaningless without representing some actual target species (Urban et al., 2009). More importantly, urban expansion might lead to variations in network connectivity through: (1) loss of nodes (i.e. habitat shrinkage or loss due to the encroachment of urban land), or (2) even without node losses, the increase of the barrier effect in the landscape matrix that hampers animal movements. The second mechanism is, however, unable to be delineated from the perspective of structural connectivity. For these reasons, the least-cost modeling (Adriaensen et al., 2003) has gained increasing attention (Rayfield et al., 2010; Gurrutxaga et al., 2011; Huang et al., 2018) because the distances between pairs of nodes are weighted by the cost of movement, to denote the friction of an intervening landscape matrix. However, there are only a few studies with insight into the impact of urban expansion on functional connectivity. This knowledge must be extended if our aim is to balance the trade-offs between urban development and biodiversity conservation.

Our primary objective is to investigate the impact of potential urban expansion on the functional connectivity of forested land. The additional objective is to prioritize the key connecting elements for protection. We propose an integrating framework of a novel CA model – the Future Land Use Simulation (FLUS) model – and ecological network analysis. We assume that land-use changes are driven by (1) proximity factors (e.g. the distance to the core city), (2) socio-economic factors (e.g., GDP and population), (3) biophysical factors (e.g., the soil quality) and (4) the neighborhood effect. We also assume that an individual can always find the path with the least cumulative cost in an intervening landscape. To demonstrate the performance of our framework, we select Three Gorges Reservoir Area (TGRA, SW China) as the study area, and the leopard (*Panthera pardus*) as the target species.

2. Materials and methods

2.1. Study area, target species and data collection

The TGRA is located in the middle catchment of the Yangtze River in China (Fig. 1), covers *circa.* 55,000 km^2 and includes 20 county-level

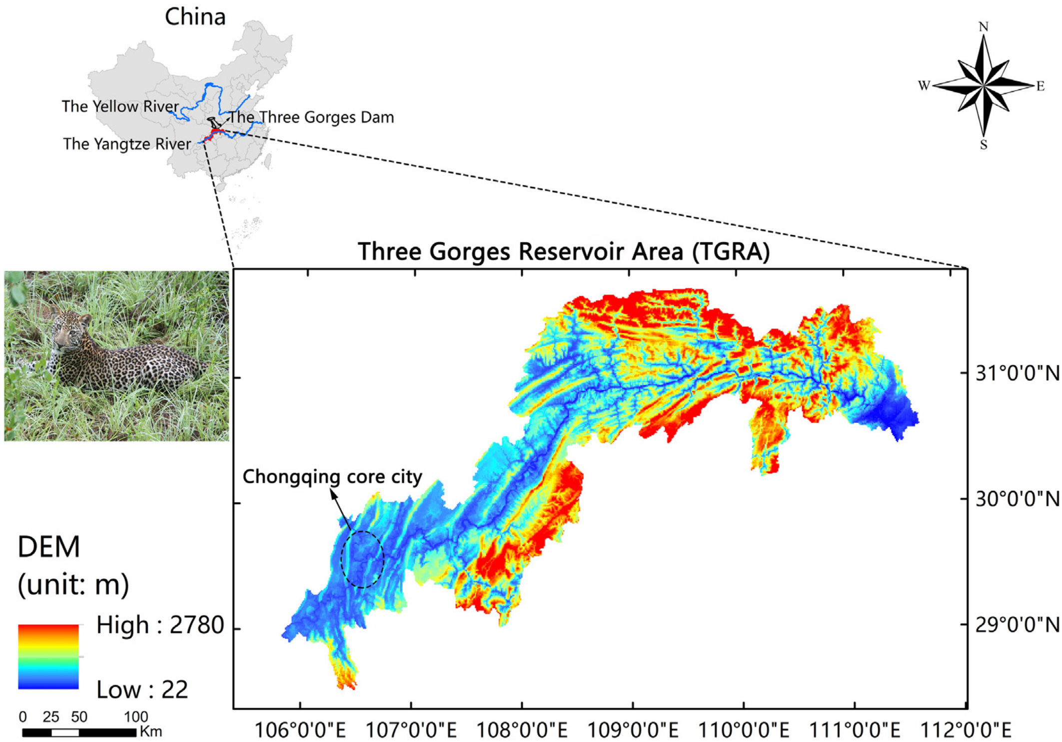

Fig. 1. The study area. Leopard's photograph credit: Donald H. Gudehus.

administrative districts. The forest takes up the largest proportion (*c.* 48%), and this region is one of the richest areas in terms of biodiversity in China (Wu et al., 2003). Rapid urban expansion has occurred in TGRA since the planning of the Three Gorges Dam Project, due to the expansion in residential land that provides settlements for migrants. Thus, studying the impact of urban expansion on landscape connectivity is significant for regional biodiversity conservation and is informative for local decision makers.

Our target species, the leopard (*Panthera pardus*), is a Grade I nationally protected animal (the highest conservation level) in China and is classified as "vulnerable" according to the International Union for Conservation of Nature (IUCN) Red List (Stein et al., 2016). The primary habitat type of the leopard is forest, and generally the home range area is between 8 and 15 km^2 (Stein et al., 2016). The primary threats to species persistence are habitat loss and habitat fragmentation that are caused by anthropogenic activities (Stein et al., 2016). In addition, the natal dispersal distance of the leopard is 11.0 ± 2.5 km for males and 2.7 ± 0.4 km for females, and the dispersal behavior is often male-biased (Fattebert et al., 2015). Multitype data are collected from diverse sources, as listed in Table 1.

2.2. The FLUS model

The transition rule is considered the primary issue in CA simulations. Over the last two decades, a variety of transition rules have been developed, including logistic regression (Verburg et al., 2002; Wu, 2002), agent-based model (Li and Liu, 2008), artificial neural network (Li and Yeh, 2002) and many others. Among them, the artificial neural network (ANN) is considered more promising in dealing with the nonlinear and complex land-use system (Li and Yeh, 2002).

In general, an ANN contains three types of layers: an input layer (i.e. the independent spatial variables that drive land-use changes, including elevation, slope, distance to urban land, distance to road, distance to river, population, GDP and 4 aspects of soil qualities), the hidden layer (s) and an output layer (i.e. the probability of occurrence of each land-use type). In the hidden layer, the signal received by neuron j is $net_j(p,t) = \sum_i w_{i,\,j} \times x_i(p,t)$, where $x_i(p,t)$ is the input neuron i on grid cell p at training time t; $w_{i,\,j}$ is the adaptive weight between the input layer and the hidden layer, and is calibrated during the training process. To build connections between the hidden layer and the output layer, the Sigmoid function is used as the activation function, and thus the probability of occurrence of a given land-use type k on grid cell p at training time t, denoted as $P(p,k,t)$, is given by (Liu et al., 2017):

$$P(p,k,t) = \sum\nolimits_j w_{j,k} \times \frac{1}{1+e^{-net_j(p,t)}} \tag{1}$$

where $w_{j,\,k}$ is the adaptive weight between the hidden layer and the output layer and is also calibrated during the training process. A random sample (sample rate: 10%) is conducted, and the number of hidden layers is 12. After both $w_{i,\,j}$ and $w_{j,\,k}$ get trained by the training sample, the ANN model is built and can be used to estimate the probability of occurrence of each land-use type on a given grid cell.

Yet, the probability of occurrence of a specific land-use type is far from determining the final simulation result, as land-use interactions (or competitions) and the conversion difficulty must be taken into account. Therefore, a combined probability that integrates all these factors is proposed. First, land-use interactions are mainly reflected by the neighborhood effect, which is given by:

$$\Omega_{p,k}^t = \frac{\sum_{N\times N} con\left(c_p^{t-1} = k\right)}{N \times N - 1} \tag{2}$$

where $\Omega_{p,\,k}^t$ is the neighborhood effect on grid cell p with land-use type k at iteration time t; $\sum_{N\times N} con(c_p^{t-1} = k)$ is the total number of grid cells occupied by land-use type k at the last iteration time $t-1$ within the $N \times N$ window; and N can be 3, 5, 7 or any other odd number. We test different windows of 3×3, 5×5 and 7×7, and select the one with the highest goodness-of-fit as the ideal neighboring window.

Second, the inertia coefficient is introduced, to account for interactions within the land-use system (Verburg et al., 2002). It is used to automatically adjust the inheritance of the current land-uses on each grid cell, which is based on the difference between land-use demand and the allocated land-use amount in each iteration (D_k^t). The formula suite is as following:

$$inertia_k^t = \begin{cases} inertia_k^{t-1}, & if \left|D_k^{t-1}\right| \le \left|D_k^{t-2}\right| \\ inertia_k^{t-1} \times \dfrac{D_k^{t-2}}{D_k^{t-1}}, & if\ D_k^{t-1} < D_k^{t-2} < 0 \\ inertia_k^{t-1} \times \dfrac{D_k^{t-1}}{D_k^{t-2}}, & if\ 0 < D_k^{t-2} < D_k^{t-1} \end{cases} \tag{3}$$

Third, the converting difficulty CD_{k-l} is also taken into account. If the cultivated land is allowed to convert to urban land, yet the reverse transition is not possible, then $CD_{cultivated-urban} = 1$ and $CD_{urban-cultivated} = 0$. Additionally, if a grid cell p is located within the restricted area, the conditional variable $Con_p = 0$, or 1 otherwise.

Then, the combined transition probability $TP(p,k,t)$ is given by:

$$TP(p,k,t) = P(p,k,t) \times \Omega_{p,k}^t \times inertia_k^t \times CD_{k-l} \times Con_p \tag{4}$$

Finally, the CA simulation determines whether the land-use change occurs on a grid cell or not. The roulette wheel selection is applied, instead of allocating the land-use type of a grid cell to the one with the highest combined transition probability (Verburg et al., 2002). This method can take allocation opportunities of non-dominant land-use types into account, and reflect competitions among land-use types (Liu et al., 2017). When the allocated land-use amounts reach land-use demands (an error of ±2% is allowed), or iteration times reach the maximum value (set as 2000 in this study), the CA simulation is

Table 1
The data used in this study. All raster datasets are transformed into the same resolution (1 km) and projection (Xian_1980_3_Degree_GK_Zone_36) prior to model implementation.

Name	Data type & resolution	Source
Land-use data (2010 & 2015) Population raster map (2010) GDP (2010)	Raster, 1 km	Chinese Academy of Sciences (http://www.resdc.cn/)
DEM Soil quality: nutrient availability, oxygen availability to roots, excess salts and workability	Raster, 30 arc sec	Harmonized World Soil Database (HWSD) V1.2 (Fischer et al., 2008)
Traffic network	Shapefile	(Center for International Earth Science Information Network - CIESIN - Columbia University and Information Technology Outreach Services - ITOS - University of Georgia, 2013)
Protected areas	Shapefile	The World Database on Protected Areas (WDPA)
Population statistical data	PDF	The Statistical Yearbook of Chongqing (2011–2016)

terminated. The FLUS model (Liu et al., 2017) is employed to perform the simulation (and future land-use scenario projections).

2.3. Model evaluation

Three ANN-CA models with different neighboring windows: 3 × 3, 5 × 5 and 7 × 7 are built, and are used to simulate the landscape from 2010 to 2015. The model performance is evaluated through the fuzzy Kappa index (Hagen, 2003) between actual 2015 and simulated 2015. Compared with the general Kappa index, the fuzzy Kappa index is more appealing as it allows slight displacements of a simulated landscape compared with the actual one. Namely, it takes account of not only cell-by-cell agreement but also the influence of neighborhood cells (Vliet et al., 2011). As the CA simulation is a random allocation process, 20 Monte Carlo repetitions are performed for each neighborhood rule, and the average fuzzy Kappa index is used for comparisons (Table S1 in supporting material). Generally, a fuzzy Kappa index higher than 0.75 can indicate a satisfactory simulation. Finally, the simulation obtained by the 5×5 window has the highest goodness-of-fit, and thus is chosen for future projections.

2.4. Future land-use scenario definition

As uncertainties will always exist in model prediction, designing distinct land-use scenarios based on different socio-economic conditions is a wise choice to explore all possible situations. Three scenarios are developed:

(1) The business-as-usual (BAU) scenario. Based on historical land-use changes, the Markov-chain is applied, which controls temporal changes among land-use types according to the transition probability matrix (Table S2) (Aburas et al., 2017; Sun et al., 2018).

(2) The fast-urban-growth (FUG) scenario, in which the urban expansion rate is 10% higher than that of the BAU scenario. Because of the difference in the demand of urban land between the BAU and the FUG, the amount of other land-use types must be adjusted, as some of these land types will be converted to the urban land, and the adjustment formula is as follows:

$$A^k_{adjust} = \left(A^{urban}_{FUG} - A^{urban}_{BAU}\right) \times H^{k-u} \tag{5}$$

where $A^k_{adjust}$is the area subtracted from land-use type k in the BAU scenario; A^{urban}_{FUG} and A^{urban}_{BAU} is the urban land area in the FUG and BAU scenarios, respectively; and H^{k-u} is the proportion of land loss due to urban encroachment on land-use type k from 2010 to 2015 (please see Table S3 for the H^{k-u} value).

(3) The population-change-based (PCB) scenario, in which the urban expansion rate is equal to the predicted population growth rate. The predicted population growth rate is assumed to be the same as the average annual growth rate of the urban permanent population in TGRA (please see Table S4 for the detailed information). The adjustment of the land-use demand is similar to Eq. (5) but replaces A^{urban}_{FUG} with A^{urban}_{PCB}, and takes the absolute value of the difference.

2.5. Ecological network construction

An ecological network is a set of nodes and links in which nodes represent habitat patches and links represent the potential movement corridors of animals. Habitat patch selection is based on two criteria: (1) the area must be larger than the minimum home range size of the leopard (i.e., 8 km^2) to ensure the relatively long-term species viability; and (2) the area should be located more than 200 m from urban land and road (Sunde et al., 1998) to buffer the anthropogenic threats. Forested areas not identified as habitat patches are considered areas favorable to species dispersals.

Links are represented by the cost-weighted distances in the least-cost model. Measuring the connections between a pair of nodes using Euclidean distances would not be recommended for terrestrial animals, as it is necessary to take the spatial heterogeneity and the friction of the landscape matrix into account (Urban et al., 2009; Gurrutxaga et al., 2011). The landscape matrix is converted to a cost surface by assigning a cost value to grid cells belonging to a given land-use type (Table 2). Through the cost surface, the least-cost model finds an optimal route with the minimum cost value (Adriaensen et al., 2003). The least-cost model is implemented in Linkage Mapper V1.1 (McRae and Kavanagh, 2011).

2.6. Connectivity metrics

To evaluate landscape connectivity, the Probability of Connectivity (*PC*) (Saura and Pascual-Hortal, 2007) is a popular metric, and is also supported by empirical studies (Pérez-Hernández et al., 2015; Engelhard et al., 2017). Based on the probabilistic connections model, *PC* is defined as the probability that two animals randomly are positioned within the habitat patches which are connected (Saura and Pascual-Hortal, 2007). More importantly, *PC* can consider the stepping-stone effect, which is of great importance in connectivity evaluation but often ignored in other direct dispersal models (Saura et al., 2014). Two nodes in a landscape can be directly connected by a single path if they are close enough, or they can be indirectly connected by paths made up of a set of steps in which no node is traversed more than once if the nodes are more distant. The *PC* index is formulated as (Saura and Pascual-Hortal, 2007):

$$PC = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j p^*_{ij}}{{A_l}^2} \tag{6}$$

where n is the number of habitat patches; A_l is the total area of the landscape; a_i and a_j denote the area of patch i and j; and p^*_{ij} is the maximum product probability of all the potential migration paths between i and j, corresponding to the migration probability of the shortest path between i and j. The migration probability is usually formulated as an exponential function of distance units (Clark et al., 1999):

$$p_{ij} = e^{-\alpha d_{ij}} \tag{7}$$

where p_{ij} is the migration probability from i to j; d_{ij} is the cost-weighted distance unit in the least-cost model case; and α is the coefficient reflecting the dispersal abilities of species. In the least-cost modeling, the median natal dispersal distance (11.0 km) is multiplied by the

Table 2
The movement cost characterizing each land-use type in the cost surface, as in Gurrutxaga et al. (2011).

Land-use type	Description	Cost
Cropland	Sites used to grow crops, suitable for animal movements.	15
Forest	The forested areas that provide habitat for flora and fauna, the vegetation is predominantly natural, favorable to species movement.	1
Meadow	Near-natural grassland, suitable for animal movements.	30
Water body	Lakes, reservoirs and rivers. Inhospitable to terrestrial mammals.	10000
Urban land	Land used for the construction of residences, public facilities, transportation and industrial purposes. Little or no vegetation is present. Inhospitable for species movements.	10000
Unused land	Land that has not been exploited or vegetated. The impedance is higher than forest, meadow and cropland, but lower than water body and urban land.	40

median value of movement cost in the cost surface (median cost: 30), and their products corresponds to a 0.5 migration probability (Gurrutxaga et al., 2011). In other words, α is parameterized to make $e^{-\alpha\times 1.1\times 10^4\times 30}$ equal 0.5.

Despite the merits of the *PC* index, one criticism to it is that very low *PC* values may be obtained, when habitat patches are very small compared with the landscape area (Mailec, 2008), due to its dependence on the landscape area (A_l in Eq. (6)). As such, Saura et al. (2011) further modified the *PC* index and proposed an extended index, called the Equivalent Connected Area (*ECA*), which is defined as the size of a single patch that would provide the same value of the probability of connectivity as the actual habitat pattern in the landscape, which is calculated as follows:

$$ECA = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j p_{ij}^*} \tag{8}$$

Mathematically, *ECA* is the square root of the numerator of *PC* and indicates the amount of reachable habitat, which can be easily interpreted in the unit of habitat area, especially when temporal changes in habitat area are needed for comparison. In addition, the *ECA* value will not be smaller than the area of the largest patch in the landscape, thus avoiding the extreme low connectivity value calculated by *PC*. We employ Conefor 2.6 (Saura et al., 2009) to calculate these connectivity metrics.

2.7. Mapping key connecting nodes

Based on *PC*, the node importance is identified by removing a given node from a network and calculating the changes in *PC*. The node *k's* importance is represented by:

$$dPC_k = \frac{PC_{initial} - PC_{k,\ removed}}{PC_{initial}} \times 100\% \tag{9}$$

where dPC_k is the node importance of *k*, denoting how *k* contributes to landscape connectivity; $PC_{initial}$ is the *PC* value of the intact network without removing any node; and $PC_{k,\ removed}$ is the *PC* value of the remaining network after removing node *k*.

A node may contribute to the connectivity through different aspects; for example, if a node is attributed a large area, it may be important for intra-patch connectivity; however, if a node with an intermediate area is situated in a vital location in the network, the contribution might mainly lie in the inter-patch connectivity. Such detailed information, however, cannot be provided by a simple dPC_k value. Hence, we partition the dPC_k into three parts (Saura and Rubio, 2010): $dPC_k = dPC_{intra,\ k} + dPC_{flux,\ k} + dPC_{connector,\ k}$, each of which represents a different way by which node *k* contributes to habitat connectivity in the landscape and each of which is through intra-patch connectivity, by the area weighted dispersal flux and by the stepping-stone effect, respectively. We are particularly interested in the last element since those patches with large area may be protected and ecologically stable. However, patches with an intermediate area but acting as stepping-stones may be easily destroyed by new urban land. $dPC_{connector,\ k}$ corresponds to a part of $\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j p_{ij}^*$ for each pair of *i* and *j*, in which $i \neq k$, $j \neq k$, and *k* is part of the maximum probability path between them (Saura and Rubio, 2010). This fraction depends on only the topological position of a node in the network and is independent of its area. A patch with a ratio of $dPC_{connector,\ k}/dPC_k > 0.5$ is identified as a key connecting element, and a patch with a ratio between 0.25 and 0.5 is considered an important connecting element (Dilts et al., 2016).

3. Results

3.1. Future land-use scenario projections

In each future time point, the area of urban land in the FUG scenario is the largest among all scenarios (Table 3). The new urban land is mainly allocated to the current urban fringe, as well as places near the Yangtze River (Fig. 2). In contrast, the cropland suffers the most significant loss in the FUG scenario. The land-use types that will expand include urban land, forested land and water body, while cropland, meadow and unused land decrease.

3.2. How well connected are habitats in current and future land-use scenarios?

Based on the cost-weighted distances along these least-cost paths, *PC* and *ECA* indices are calculated (Fig. 3). From 2010 to 2030, the curves of functional connectivity demonstrate a U-shape trend. Generally, the projected PCB scenario has the highest connectivity degree, followed by the BAU and the FUG scenarios, and the maximum connectivity value appears in 2030 under the PCB scenario. Although *PC* and *ECA* increase between 2020 and 2030, the increasing rates in the BAU and the FUG scenarios are likely to become lower after 2025, and the FUG scenario might even have a decreasing connectivity again after 2030.

3.3. How many key connecting nodes might be encroached by urban expansion in the next 5 years?

We plot the distribution maps of important connectivity providers, which are indicated by *dPC*, *dPCconnector* and their ratio (Fig. 4). The results show that the distribution patterns of nodes with large *dPC* and *dPCconnector* values are distinct. High *dPC* nodes are mainly situated in the eastern and southern parts of TGRA; however, these nodes might not have large *dPCconnector*. More importantly, the total number of key connectors in 2015 is 9, and most of them are located on the fringe of the urban core of Chongqing.

By overlapping the projected 2020 land-use maps, we find that the number of encroached important and key connectors is the largest under the FUG scenario (Table 4). All of these key connectors, which are adjacent to the current urban core (No. 156, 161, 167, 179, 180 and 191) are projected to be exploited, partly or entirely, as new urban land under the FUG scenario.

4. Discussion

Our framework, which couples urban expansion simulation with ecological network analysis has been used to successfully compare the impacts of alternative urban development modes on landscape

Table 3
The amount of each land-use type (unit: km^2) at three future time points (2020, 2025 and 2030) with different development scenarios (the business-as-usual (BAU) scenario, the fast-urban-growth (FUG) scenario and the population-change-based (PCB) scenario).

Land-use type	2020			2025			2030		
	BAU	FUG	PCB	BAU	FUG	PCB	BAU	FUG	PCB
Cropland	21042	20982	21330	20760	20252	21190	20525	19064	20953
Forest	28408	28393	28472	28555	28440	28651	28609	28281	28705
Meadow	5434	5431	5445	4850	4830	4866	4424	4367	4440
Water body	1294	1293	1297	1438	1431	1443	1574	1554	1579
Urban land	2343	2423	1977	2919	3569	2372	3390	5256	2845
Unused land	3	2	3	2	2	2	2	2	2

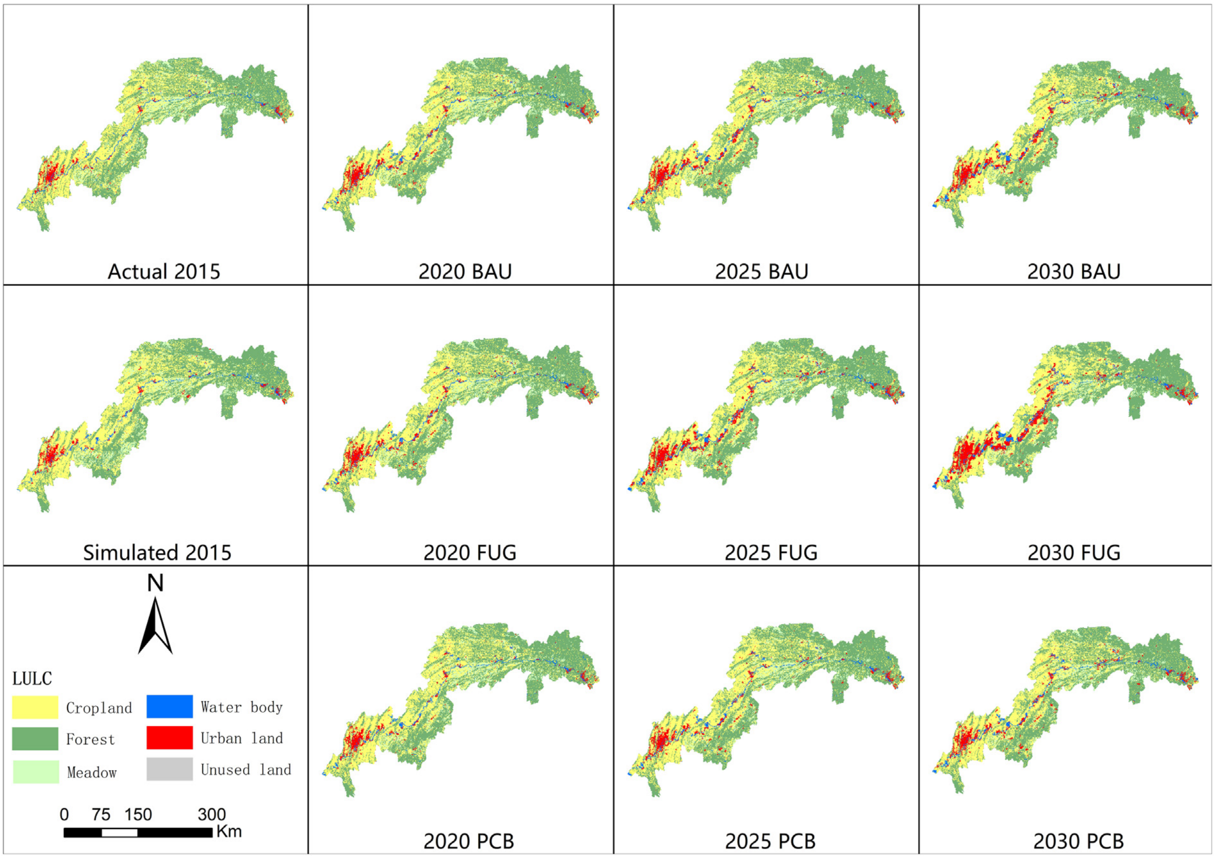

Fig. 2. The land-use maps of the actual 2015, the simulated 2015 and the future land-use scenarios (BAU, FUG and PCB in panels represent the business-as-usual scenario, the fast-urban-growth scenario and the population-change-based scenarios, respectively).

connectivity. The methods used and the results obtained have raised 4 points to discuss.

4.1. The advantages of the FLUS model

Our model has several advantages compared with the non-CA models. (1) Our model can simulate the land-use transitions among diverse land-use types, rather than only a few components of a land-use system. This feature enables the construction of the cost surface at a finer scale. (2) It takes into account the neighborhood effect. (3) It balances data requirements and simulation performance. Even compared with other CA-based models, our model is more promising because: (1) it can solve the non-linear mapping problem rooted in landscape dynamics, which cannot be solved by logistic regression in a similar way; (2) the introduced inertia coefficient can be more efficient in spatial allocation; and (3) by roulette wheel selection, our model can better reflect the interactions and competitions among diverse land-use types and can reflect the uncertainties in simulation process.

Rather than arbitrarily defining a neighborhood rule and only running the simulation once, the goodness-of-fit test for different neighboring windows and multiple Monte Carlo repetitions would be highly recommended, considering that varying simulation fitness might be obtained by different neighborhood rules, and the simulation is actually a stochastic process.

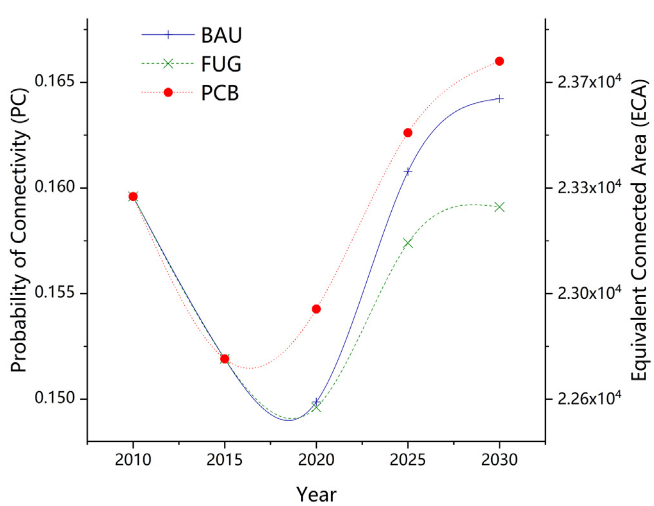

Fig. 3. Landscape connectivity (indicated as *PC*) and amount of reachable habitat (indicated as *ECA*) in the business-as-usual (BAU), the fast-urban-growth (FUG), and the population-change-based (PCB) scenarios.

4.2. Which land-use scenario gains more connectivity?

From 2010 to 2015, habitat patches remain intact from urban expansion, while connectivity decreases. This suggests that the newly developed urban land has caused a stronger barrier effect to animal movements, as a consequence, the least-cost path connecting each pair of habitat patches (**Fig. S1**) might become more twisted and longer. Moreover, an individual leaving for a new habitat must pay more costs to reach the destination node. Thus, although the number of habitats is the same in these two time points, there are fewer reachable habitats in 2015 than 2010, and both the equivalent connected area (*ECA*) and the probability of connectivity (*PC*) decline.

On the other hand, although urban land increases in all scenarios between 2015 and 2030, the landscape still gains higher connectivity. The increased landscape connectivity is probably caused by the expansion of

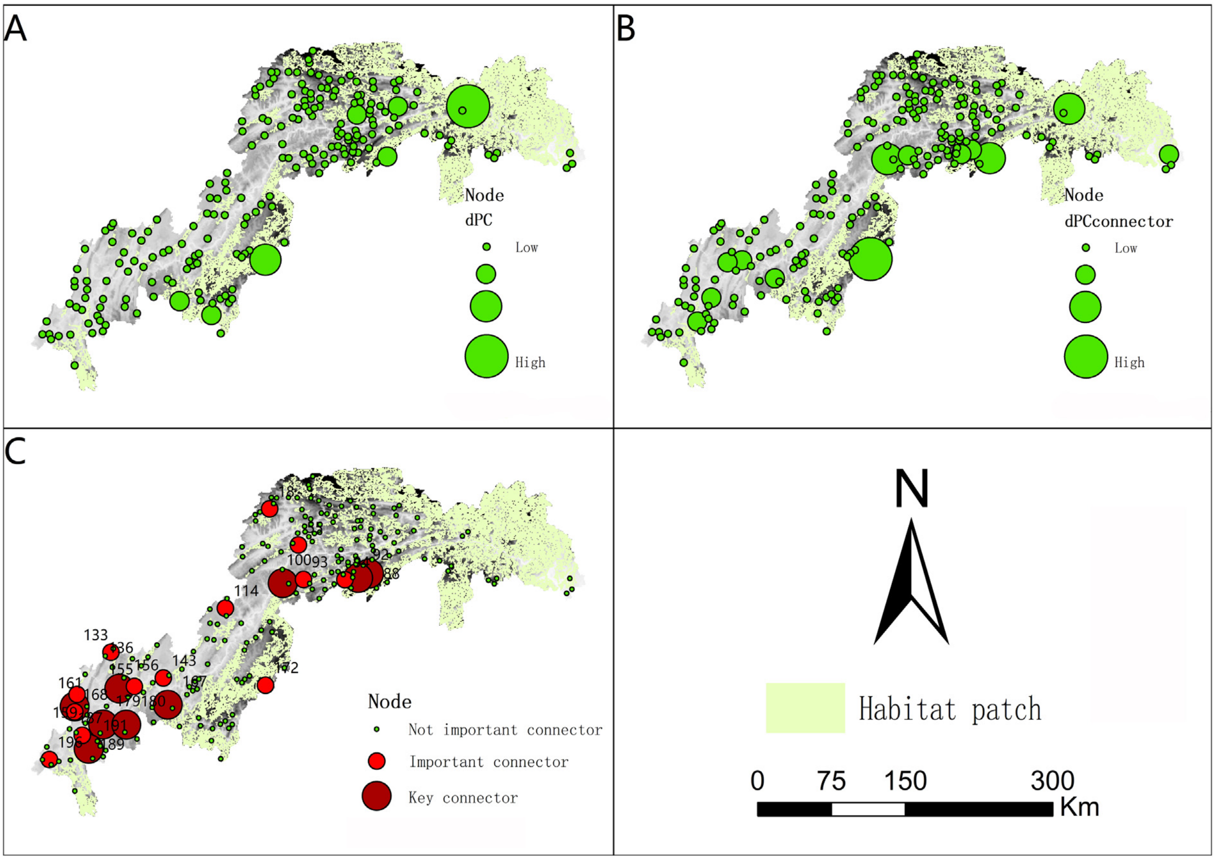

Fig. 4. The importance of each node (the centroid of the habitat patch) indicated by *dPC* (A), *dPCconnector* (B) and the ratio between them (C) in 2015.

forested land due to the Grain-for-Green Project (GFGP), which converts cropland on a steep slope to forest (Long et al., 2006). This project may contribute to improving habitat network connectivity through two aspects: (1) increasing intra-patch connectivity when the agricultural land adjacent to the current forest is reforested, and (2) facilitating inter-patch traveling by adding more patches favorable to and which act as stepping-stones for species movement. This also indicates that, the implementation of GFGP can be significant to biodiversity conservation against urbanization.

Among the three scenarios, the PCB scenario gains more connectivity compared with the other two. From 2015 to 2030, the curves of the BAU and the FUG scenarios ascend with decreasing gradients, and the curve of the FUG scenario seems to reach a peak in 2030 and may soon decline. It suggests that GFGP cannot ensure that connectivity will always be improved under an excessively rapid urban expansion scenario.

4.3. Network analysis: a guideline for conservation in urban planning

It is surprising that relatively few species have gone extinct on the global, regional or local scale (Hylander and Ehrlen, 2013), but this phenomenon called "extinction debt" is the result of the lag effect of anthropogenic landscape modifications, such as habitat degradation, fragmentation and loss. If human beings cannot stop excessively rapid urban sprawl, species extinctions can only be delayed, not avoided. The mechanism of extinction debt is widely debated, but the consensus is that it can be largely affected by landscape connectivity (Jackson and Sax, 2010). As long as the species predicted to go extinct persist within a landscape, there is time for urban planners to take actions to prevent the extinctions (Kuussaari et al., 2009). Hence, the evaluation and the protection of connectivity in an urbanizing landscape are crucial for biodiversity conservation.

For the prioritization of key connectivity providers, we find out that those nodes with high *dPC* share two common characteristics: having a large area and being located at a vital location in a network. After all, *dPC* itself is a joint result of patch area and topological location (He et al., 2018). However, even when two nodes have a similar *dPC* value, it does not necessarily indicate that they can equally contribute to landscape connectivity (Bodin and Saura, 2010). In many cases, urban planners might not be interested in knowing which patch is important for its size as patch size is very easy to compare; instead, they might be more interested in identifying patches that, if lost, would seriously isolate the remaining habitats. Therefore, in practical conservation planning, it is extremely necessary to take a closer look at the different functions of each patch in maintaining the overall landscape connectivity (Saura and Rubio, 2010). The results list which key connecting nodes are likely to be destroyed under different scenarios, these nodes deserve attentions from planners, and we suggest that they be added to the protected areas. Meanwhile, the urban land in the FUG scenario would encroach all surrounding key connectors, and thus such a development mode would not be recommended.

Table 4
The important and key connecting nodes encroached by urban expansion (partly or entirely) in 2020 under different scenarios.

	Scenario	The code No. (in Fig. 7C)	Number of nodes
2020	BAU	18, 100, 156, 172, 180, 187, 191	7
	FUG	18, 92, 100, 156, 161, 167, 172, 180, 189, 191, 196	11
	PCB	100, 156, 180, 187, 191	5

4.4. Limitations and future work

Our simulation also has some limitations though. First, the spatial resolution is quite coarse. With a finer resolution, the barrier effects of urban land, as well as the impedance effect of the landscape matrix might be better delineated (Toger et al., 2016). Hopefully, we can obtain higher resolution raster datasets in the future, and compare the results, to see how sensitive the results are to the spatial resolution. Second, despite successful applications of the least-cost modeling in this study (as well as in many others), it also has some disadvantages. (1) It can only generate an optimal path while ignoring other potential pathways. (2) Finding the least-cost path requires an individual to fully understand the landscape it is traversing, which is not ecologically realistic for most species. Therefore, a circuit analysis based on the random walk theory might be a promising complementary tool to add (McRae et al., 2008), and we intend to use the circuit theory to replace the least-cost modeling in our next research (forthcoming).

5. Conclusion

Urban expansion is far from being complete worldwide. In this context, it is necessary to evaluate the impact of urban expansion on landscape connectivity and to prioritize habitats that are too important to be lost. We couple the urban expansion simulation with landscape graphs; project alternative urban expansion scenarios in 2020, 2025 and 2030; and compare functional connectivity under each scenario. We find that (1) the population-change-based scenario is an ideal development mode that can meet socio-economic development demands while having the lowest negative impacts. (2) The Grain-for-Green Project can play roles in improving connectivity because it provides new habitats that could be colonized by animals and creates new forest areas favorable to movement. (3) Excessively rapid urban growth (e.g. the FUG scenario) will limit the improving effect of GFGP. (4) The FUG scenario has the largest number of key connectors that are at risk of being destroyed; thus, we suggest prioritizing them for protection.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.06.332.

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