

Supporting information

1. The FLUS model description and implementation

The parameters used in the FLUS model are listed in Table S1. We conducted a 10% uniform sample to train the ANN. The former study suggested that the simulation accuracy could reach the highest when N is 5 in this study area (Huang et al. forthcoming), and thus it was chosen as the neighbouring window size.

Table S1

The terminology, the formula and the description in the FLUS model.

Terminology	Formula	Description
The input layer, the hidden layer, the output layer and neurons in each layer	$X = [x_1, x_2, \dots, x_i]^T$ X : the input layer; x_i : the i th neuron in the input layer, corresponding to a certain driving force of land-use change.	An ANN has three types of layers: the input layer, the hidden layer and the output layer. Each layer is a set of neurons in this layer.
Signal	$net_j(p,t) = \sum_i w_{i,j} \times x_i(p,t)$ $net_j(p,t)$: the signal received by a neuron (x_j); $w_{i,j}$: the adaptive weight between the input and the hidden layers; $x_i(p,t)$: the input neuron i on grid cell p at training time t .	The signal received by a neuron (x_j) in the hidden layer from input neurons and it is calibrated in each iteration.
Output probability-of-occurrence	$P(p,k,t) = \sum_j w_{j,k} \times \frac{1}{1 + e^{-net_j(p,t)}}$ $P(p,k,t)$: probability-of-occurrence of land type k on grid cell p at training time t ; $w_{j,k}$: similar to $w_{i,j}$ but between the hidden layer and the output layer.	The Sigmoid function is used as the activity function to connect the hidden layer and the output layer,

The neighbourhood effect	$\Omega_{p,k}^t = \frac{\sum_{N \times N} con(c_p^{t-1} = k)}{N \times N - 1}$ <p>$\Omega_{p,k}^t$: the neighbourhood effect; $\sum_{N \times N} con(c_p^{t-1} = k)$: 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.</p>	and to calculate the output probability-of-occurrence. The neighbourhood effect describes the influence of the status of surrounding grid cells to the central one.
Inertia coefficient	$inertia_k^t = \begin{cases} inertia_k^{t-1}, & \text{if } D_k^{t-1} \leq D_k^{t-2} \\ inertia_k^{t-1} \times \frac{D_k^{t-2}}{D_k^{t-1}}, & \text{if } D_k^{t-1} < D_k^{t-2} < 0 \\ inertia_k^{t-1} \times \frac{D_k^{t-1}}{D_k^{t-2}}, & \text{if } 0 < D_k^{t-2} < D_k^{t-1} \end{cases}$ <p>$inertia_k^t$: the inertia coefficient at iteration t; D_k^{t-1} and D_k^{t-2}: the difference between the macro demand and the allocated amount of land use type k until iteration $t - 1$ and $t - 2$, respectively.</p>	Inertia coefficient reflects and automatically adapts the inheritance of the current land uses. It is used to implement spatial allocation more efficiently.
Conversion difficulty factor	$CD_{k-l} = 1 \text{ or } 0$ CD_{k-l} : Conversion difficulty factor.	A binary variable that equals 0 if the conversion from land-use type k to l is prohibited or 1 otherwise.
Constraint factor	$Con_p = 1 \text{ or } 0$ Con_p : Constraint factor.	A binary variable that equals 0 if grid cell p is located within restricted regions (where land-use change is prohibited) or 1 otherwise.
Total probability	$TP(p,k,t) = P(p,k,t) \times \Omega_{p,k}^t \times inertia_k^t \times CD_{k-l} \times Con_p$	Totally probability that

is used for the roulette wheel selection.

2. Urban population prediction

We assumed that the increase rate of population (r) declines with the increase in population amount (x), and thus the logistic model was used. Let $r(x)$ be a linearly decreasing function of x , we had:

$$\left\{ \begin{array}{l} r(x) = r - sx \quad (r > 0, x > 0) \quad (\text{eq.1}) \\ \frac{dx}{dt} = r(x)x, \quad x(0) = x_0 \quad (\text{eq.2}) \end{array} \right\}$$

We assumed that the carrying capacity of the environment is x_m , and the population amount will not increase when $x = x_m$ (i.e., $r_{x_m} = 0$); obviously, $s = r/x_m$. Thus, eq.1 can be transformed to: $r(x) = r(1 - x/x_m)$, and eq.2 can also be transformed to $dx/dt = rx(1 - x/x_m)$, $x(0) = x_0$. Solving the last differential equation, we had:

$$x(t) = \frac{x_m}{1 + \left(\frac{x_m}{x_0}\right)e^{-rt}} \quad (\text{eq. 3})$$

where $x(t)$ is the population amount in time t , $x(0)$ is the initial population amount; other variables denote the same meanings as above. Through the historical data (Data S1 in SI), parameters in eq.3 were obtained. We had the predicted amount of urban permanent residents in 2020 as 10.37 million (the population in 2010 is 7.05 million).

3. Other supporting tables

Table S2

Movement cost characterizing the impedance effect of each land-use type. Cost values were attributed to land-use types through literature review (Gurrutxaga et al., 2011; He et al., 2018; Tannier et al., 2016), but without sufficient information to distinguish between these costs for three target species. Transportation infrastructures such as roads and railways were not analysed separately, as they are involved in ‘‘Urban land’’ land-use type in our land-use datasets.

Land-use type	Description	Cost
Cropland	Sites used to grow crops, suitable for animal movements.	40
Forest	The forested lands that provide habitats for Flora and fauna and space favourable to species movement. The vegetation is predominantly natural.	1
Grassland	Near-natural grassland, suitable for animal movements.	30
Water body	Lakes, reservoirs and rivers. Inhospitable for terrestrial mammals.	10000
Urban land	Land used for the construction of residences, public facilities, transportation and industrial purposes. Little or no vegetation is present.	10000

Inhospitable for species movements.

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.	50
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Reference

Gurrutxaga, M., Rubio, L., Saura, S. (2011) Key connectors in protected forest area networks and the impact of highways: A transnational case study from the Cantabrian Range to the Western Alps (SW Europe). *Landscape and Urban Planning* 101, 310-320.

He, J.H., Huang, J.L., Liu, D.F., Wang, H., Li, C. (2018) Updating the habitat conservation institution by prioritizing important connectivity and resilience providers outside. *Ecological Indicators* 88, 219-231.

Tannier, C., Bourgeois, M., Houot, H., Foltete, J.C. (2016) Impact of urban developments on the functional connectivity of forested habitats: a joint contribution of advanced urban models and landscape graphs. *Land Use Policy* 52, 76-91.