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Direct and indirect loss of natural habitat due to built-up area expansion: A model-based analysis for the city of Wuhan, China

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ABSTRACT

Urbanization has been responsible for the loss of cropland worldwide, especially in China. To guarantee national food security, China has implemented a series of policies to protect cropland. One of these policies requires that one-hectare cropland should be reclaimed when urban expansion occupies one-hectare cropland. Since most cropland reclamation leads to a conversion of natural habitat, such as wetland and grassland, urban expansion may lead to (indirect) natural habitat loss in addition to direct loss from conversion of into urban area. While several studies assessed the direct habitat loss resulted from built-up area expansion, few studies investigated the indirect losses caused by cropland displacement. In this paper, a model-based approach is applied to explore both direct and indirect impacts of built-up area expansion on natural habitat loss for the city of Wuhan, China, between 2010 and 2020 using different scenarios. Our scenarios differ in the implementation of strict cropland protection policies and ecosystem conservation strategies. Results show that the indirect loss of natural habitat due to cropland displacement under strict cropland protection policies far outweighs the direct loss due to built-up area expansion alone. Moreover, we found that ecosystem conservation strategies mainly influence the type of natural habitat that is affected, while the total amount of natural habitat loss remains relatively constant.

1. Introduction

Globally, the total additional land area required to meet various demands between 2000 and 2030 is estimated to range from 285 to 792 million hectares (Meyfroidt and Lambin, 2011). This comprises built-up land, pastures, cropland, and several other land uses. Thus, a significant competition for land exists between multiple different land uses and ecosystem conservation globally. Until recently, urbanization only played a minor role, due to the small amount of urban areas worldwide (van Vliet et al., 2017). However, this has changed recently due to population growth, economic development, and rural-to-urban migration. For example, between 2009 and 2050, an increase of 1.86 billion human-beings is projected in urban areas, while urban areas are expanding on average twice as fast as that of population (Angel et al., 2011; Seto et al., 2012). These competing claims on land resources are especially relevant to China, due to its large population and increasing rural-to-urban migration. The Chinese population is expected to peak between 1.45 and 1.5 billion at around the years 2025 to 2030 (Peng, 2011). Since the implementation of Open Reform Policy in 1978, China's urban population had increased from 170 million to 730 million with an urbanization level of 54% in 2013 (Wang et al., 2015). Moreover, the average annual growth rate of urban areas was 8.7% between 1992 and 2012, compared to a rate of 3.2% globally between 1990 and 2000 (He et al., 2014). As a consequence, 65 186 km^2 of urban land was added between 1992 and 2012, while 21 011 km^2 of cropland was lost in China between 2000 and 2008 (Song and Pijanowski, 2014). In the meantime, the overall environmental quality in China has deteriorated (Cao and Ye, 2013).

To mitigate cropland losses, the Chinese government has implemented a series of policies during the past four decades (Liu et al., 2017). For example, the *Cropland Balance Policy*, which aims to maintain the quantity and quality of cropland across the country (He et al., 2013; Zhong et al., 2012). In addition, six *Key State Forestry Development Programs* have been approved formally and implemented to improve the environmental quality. One of them that relates to cropland is called the *Grain for Green Policy*, which stimulates the conversion of vulnerable cropland areas back to forest. More recently, the plan of *Ecological Civilization of the 21st Century* has been developed, with the aim of securing essential natural capital and improving local livelihoods in China. Accordingly, a zoning system for ecological conservation areas

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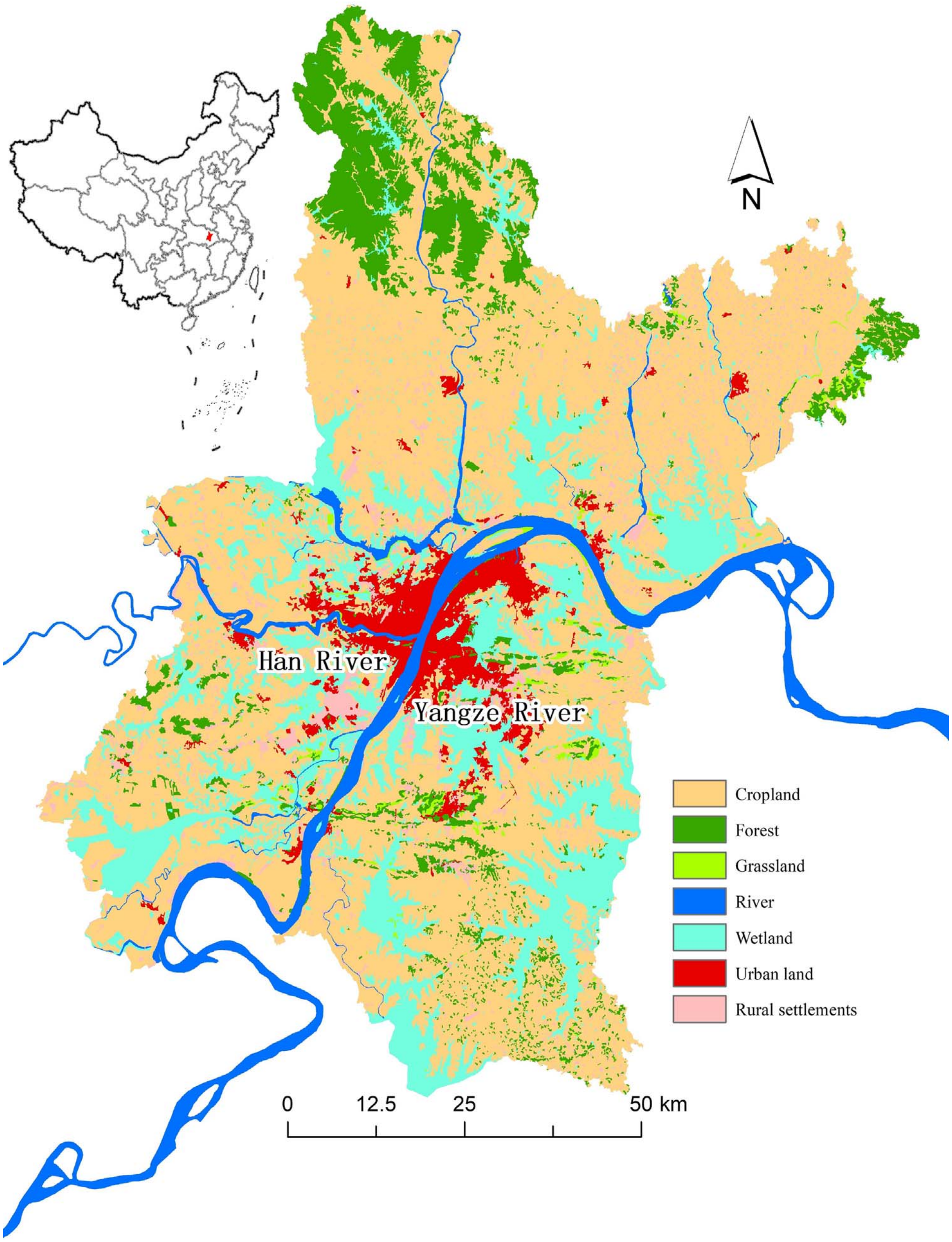

Fig. 1. Land use in the study area in 2010, and its location within China.

was introduced to achieve a balance between urban growth and economic development with nature (Daily et al., 2013; Guerry et al., 2015).

After two decades' implementation of cropland protection policies in China, the effects and performance of the policies are still doubted. Lichtenberg and Ding (2008) argued that the cropland protection may not be a necessary means to meet China's food security goals under the context of the existing institutional and policy structure. Song and Pijanowski (2014) demonstrated that cropland protection policies in China can only guarantee the balance of cropland in terms of quantity rather than quality due to the displacement of cropland to locations with inferior conditions. In addition, Zhong et al. (2012) assessed the performance of China's primary cropland protection planning and found that it was generally helpful to protect cropland in China, but failed in some areas. One study even suggested that policies aiming to preserve cropland may potentially risk an acceleration of occupying cropland because people are encouraged to move to towns and cities (Deng et al., 2015). This is consistent with an econometric analysis of the impact of land use policy, which implies a negative effect on the cropland conversion (Zhong et al., 2011).

Cropland protection, coupled with built-up area expansion, can pose both direct and indirect effects on natural habitats. "Natural habitat" here refers to those lands with non-artificial vegetation, including forest, grassland, wetlands, rocky areas and deserts, according to The Habitats Classification Scheme developed by the International Union for Conservation of Nature (IUCN, 2013). The direct impact of built-up area expansion on natural habitat loss is caused by the conversion of natural habitat into built-up area, while the indirect impacts relate to the conversion of agricultural land into built-up area and the subsequent conversion of natural habitat into agricultural land elsewhere as a compensation (van Vliet et al., 2017). Consequently, built-up area expansion may not only threaten biodiversity, but also result in the loss of terrestrial carbon stored in vegetation biomass (Seto et al., 2012). Therefore, the relation between built-up area expansion and ecosystem conservation has become increasingly important in land use management.

The loss of natural habitat caused by built-up area expansion has been discussed in several studies. McDonald et al. (2008) indicated that massive urbanization may have significant effects on the natural environment, both directly through the expansion of built-up area and indirectly through changes in consumption and pollution as humans migrate into cities. Seto et al. (2012) developed spatially explicit probabilistic forecasts of an increase of urban land-cover change by 2030 and indicated that such an increase would result in considerable loss of natural habitat globally. Moreover, He et al. (2014) explored an extreme urban expansion from 1992 to 2012 in China and revealed that the resulting natural habitat loss is significant. Furthermore, cropland expansion is considered as one of the most significant factors for natural habitat loss (McKinney, 2002). Morton et al. (2006) indicated the large and fast deforestation for cropland expansion in the southern Brazilian Amazon and defined a new paradigm of forest loss. Tilman et al. (2011) demonstrated that increasing food demand might result in about 1 billion hectare of land being cleared globally by 2050. Nevertheless, most researches only analyze the direct effect within the context of increasing food demand globally, while they overlook the indirect, cascading effects through land displacement. Yet, an assessment of cropland displacement at a global scale by van Vliet et al. (2017) found that cropland displacement from urbanization could yield up to 35 Mha of new cropland areas at a cost of natural habitat. While direct impacts of land use policies, including cropland protection policies, have been studied before, the indirect effects on natural habitat remain unknown.

This paper explores both the direct and indirect impacts of built-up area expansion on natural habitat loss by simulating land use changes under four different scenarios for the city of Wuhan between 2010 and 2020. We aim to consider different policy scenarios: (1) *A Loose Cropland Protection scenario (LCP)*; (2) *A Strict Cropland Protection scenario (SCP)* with implementation of the strict cropland protection policies which require to maintain a fixed amount of cropland during 2010–2020; (3) *An Ecosystem Conservation scenario (ECS)* with priority for the protection of lands with relatively high ecological value; and (4) *A Synergy scenario (SYN)*, with both strict cropland compensation and priority for conservation of lands with relatively high ecological value. All scenarios include the same demands for urban and rural settlements, thus allowing the comparison of the impacts of cascading effects of built-up area expansion and cropland displacement on natural habitat loss in different scenarios.

2. Materials and methods

2.1. Study area

Wuhan is a rapidly urbanizing city in central China, with an area of 8 498 km^2 and a population of about 10 million in 2013 (Hubei Bureau of Statistics, 2014). It is located at the confluence of the Yangtze and Han Rivers (Fig. 1), which are the origin of a fertile agricultural area to the east of the city. Over 80% of the population is living in urban areas, which have increased from 378 km^2 to 789 km^2 between 2000 and 2010, while the area of cropland decreased from 5 188 km^2 to 4 706 km^2 in the same period. Meanwhile, a large amount of natural habitat, including wetland, grasslands and forests, has been converted into artificial and impervious surfaces (e.g., cement, asphalt). For example, 28 km^2 of wetland in Wuhan has disappeared between 1990 and 2013, including 77% of Shahu Lake and 52% of Nanhu Lake. As a result, ecosystems in this area have become more vulnerable, as is illustrated by the flooding disaster in Wuhan in 2016. Consequently, land use change in Wuhan is driven by a severe competition between food security, economy development, and ecosystem conservation, as is the case for many other cities in China. This competition is further aggravated by Wuhan's inclusion as a core area of China's Yangtze River Economic Zone Development Strategy and the Rising of Central China Strategy, while Wuhan is also a pilot area in the first batch for China's "Resources-saving and Environment-friendly" society.

2.2. Modelling land use changes in Wuhan

We used a model-based approach to simulate land use changes in Wuhan between 2010 and 2020. This approach involved three consecutive steps. In the first step, the LANDSCAPE (LAND System Cellular Automata for Potential Effects) model was developed and calibrated based on observed land use changes between 2000 and 2010 (Ke et al., 2017). Subsequently, four different scenarios were defined and the calibrated LANDSCAPE model was employed to simulate land use changes during 2010–2020 for each scenario. In the final step, we compared simulated land use maps of 2020 in four different scenarios to explore the direct and indirect impacts of built-up area expansion on natural habitat loss.

The LANDSCAPE model is a CA-based model that is capable to simulate changes with two key characteristics: a hierarchical allocation strategy, and the possibility to allocate changes in multiple land-use types (Ke et al., 2017). In the LANDSCAPE model, land uses are categorized as either active types or passive types (following White and Engelen, 1997). Active land use types are directly driven by an exogenous demand, such as built-up land and cropland. Changes in passive land use types, such as wetland, grassland, and forest, only take place as a result of changes in active land use types (for example, a loss of wetland resulting from cropland reclamation). Accordingly, the LANDSCAPE model allocates land use types in two steps: (1) active land use types are allocated, based on their competitiveness; and (2) passive land use types are forced to change by the change of active land use types and remain the same otherwise.

The allocation of active land use types is determined by two factors: suitability and resistance. Suitability is an index representing the quality of a location for a target land use type, while resistance indicates the difficulty to convert a cell from its current land use type to another. Cells are converted into active land use types according to the ratio of the suitability and resistance:

$$TTPl,\, tu = \frac{Pl,\, tu}{Rl,\, cu} \tag{1}$$

where $TTP_{l,tu}$ is the total potential for location l to be converted to the target land use tu, $P_{l,tu}$ is the suitability of location l to be changed to the target land use tu, and $R_{l,cu}$ is the resistance for location l to be converted from current land use cu to another. $P_{l,tu}$ is determined by biophysical and socioeconomic characteristics of a location, neighborhood effects, and constraining conditions, while $R_{l,cu}$ is dependent on the current land use type cu and its resistance coefficient. Resistance indicates the difficulty associated with converting one land use to another. In the LANDSCAPE model, we calibrate the resistances of individual land uses by calculating the difficulty degree for each land use to be occupied by other land uses (Ke et al., 2017). The applied resistances for individual land uses are shown in Table 1.

Suitability $P_{l,tu}$ of a location l is calculated according to:

$$P_{l,tu} = (1 + (1 + (-\ln r))^{\alpha}) \times PG_{l,tu} \times Con(C_{l,tu}) \times \Omega_{l,tu} \tag{2}$$

where r is a random number between 0 and 1, and α is a dispersion factor controlling the effect of the stochastic noise; $PG_{l,tu}$ represents the impacts of biophysical and socioeconomic characteristics of a location,

Table 1
Resistances for individual land uses.

Land-use type	Cropland	Forest	Grassland	River	Wetland	Urban land	Rural settlements
Resistance	1	1.25	1.25	1.5	1.25	1.5	1.5

Table 2
Variables for calculating land use suitability.

Dataset	Data Source	Description and data extraction method
Land use data	Data Centre Resources and Environment, Chinese Academy of Science	Land use map in 2000 from remote sensing images interpretation
		Land use map in 2010 from remote sensing images interpretation
Terrain data	The Shuttle Radar Topography Mission (SRTM)	Elevation
		Slope extracted from DEM dataset
Accessibility data	The Traffic Atlas of Wuhan	Euclidean distance to the nearest highway
		Euclidean distance to the nearest national road
		Euclidean distance to the nearest provincial road
		Euclidean distance to the nearest main road
		Euclidean distance to the nearest minor road
		Euclidean distance to the nearest railway
		Euclidean distance to the nearest water body
Soil data	The China Soil Database	Soil type
		Soil phosphorus content
		Soil nitrogen content
Climatological data	The ground meteorological observatory in Hubei Province	Annual precipitation
		Average annual accumulated temperature

such as the elevation, slope, and the distance to roads; $Con(C_{l,tu})$ is the constraint score for each cell, with 0 for unchangeable cells and 1 for changeable cells; Ωl, tu is the neighborhood effect for target land use type.

As for $PG_{l,tu}$, the relationship between the suitability and its driving forces can be determined using different methods, including expert knowledge, statistical analysis, machine learning approaches, and econometric analysis of current land use patterns. In this paper, Support Vector Machines (SVM) is employed to calculate $PG_{l,tu}$.

2.3. Data sources

Five datasets were needed to calibrate the LANDSCAPE model (Table 2): land use data, terrain data, accessibility data, soil data, and climatological data. Land use data plays three roles in LANDSCAPE calibration: (1) calculating the suitability; (2) representing the initial land use map for the simulation; and (3) serving as reference map for assessing simulation accuracy. Accessibility data, terrain data, soil data, and climatological data were used as input for the SVM algorithm, to derive the relationship between suitability of locations for each land use type and characteristics of these locations.

Land use data were obtained from the Data Centre of Resources and Environment, Chinese Academy of Science (CAS) (Liu et al., 2010). Land uses are classified into 6 types and 25 sub-types in the CAS land-use dataset (Song and Deng, 2017). In this paper, we reclassified land use types in order to figure out the impacts of built-up area expansion on natural habitat loss. Accordingly, we used 7 land use types in this research: cropland, forest, grassland, river, wetland, rural settlements, and urban areas. Particularly, wetland is defined as water body other than a river, while built-up area includes both urban land and rural settlements. We assess the impacts of built-up area expansion on the combined effect of urban land and rural settlements changes. Of these land use types, river was included as a static land use since the observed land use maps show that the location and the area of the river was relatively stable during 2000 to 2010. The land use data of both 2000 and 2010 has a spatial resolution of 30 m. Since the maximum size of land use data in current version of the LANDSCAPE model is 4000 × 4000 cells, land use data was resampled to a spatial resolution of 100 m using a majority aggregation.

For the calculation of the accessibility, we considered both the distance to the nearest urban area and the distance to the nearest road. We obtained the locations of urban area from land use maps directly. For infrastructure, we used 6 types of infrastructure networks to calculate the distance to the nearest roads: railways, highways, national roads, provincial roads, main roads, and minor roads. All transport networks were extracted from the Traffic Atlas of Wuhan as follows: (1) the traffic atlas of Wuhan was scanned to digital images; (2) the images were registered to the spatial reference of land use maps; (3) the registered images were digitized to lines for each road type; and (4) the raster datasets for distance to roads were generated using Euclidean distances.

There are two types of terrain datasets used in this research, representing elevation and slope. Both of them are used for calculating suitability maps. The DEM dataset was obtained from the Shuttle Radar Topography Mission (SRTM) (Berry et al., 2007). The spatial resolution of the SRTM DEM in the study area is 90 m. A slope dataset was derived from the SRTM DEM dataset by the SLOPE function. Finally, both datasets were resampled to the spatial resolution of 100 m to make them consistent with the spatial resolution of the land use datasets.

Soil data was used for calculating the suitability maps in this research since soil conditions are crucial for agriculture. We obtained soil datasets such as soil types, soil phosphorous content, and soil nitrogen content, from the China Soil Database (gis.soil.csdb.cn). All the original soil datasets were in shapefile format with a measuring scale of 1:1 000 000. To match the format and spatial resolution of the land use datasets, we converted soil datasets in shapefile format to raster datasets with a spatial resolution of 100 m.

We obtained climatological data for daily precipitation and temperature during 1981–2010 from the ground meteorological observatory in Hubei Province. Subsequently, we applied Kriging to interpolate between these point data for both annual average accumulated temperature and annual precipitation.

2.4. Model calibration

We used Kappa Simulation to assess the accuracy of the LANDSCAPE model. Kappa simulation assesses the accuracy of the simulated land use changes, and corrects for the accuracy that can be expected by chance, and gives the distribution of land use changes relative to the original land use map (van Vliet et al., 2011), and is implemented in the Map Comparison Kit (Visser and de Nijs, 2006). In that sense Kappa Simulation overcomes some of the limitations of the conventional kappa statistic (Pontius and Millones, 2011; van Vliet et al., 2013). The Kappa Simulation score holds values ranging from −1 to 1, where 1 indicates a perfect agreement, and 0 indicates that the agreement is only as good as a random distribution of given class transitions. A negative Kappa Simulation score demonstrates a lower accuracy, while a positive value can be interpreted as being more accurate than a random distribution. In this research, the initial land use map in 2000, the observed land use map in 2010, and the simulated land use map in 2010 were used to evaluate the accuracy of simulation result in the Map Comparison Kit. Table 3 shows the Kappa Simulation

Table 3
Kappa Simulation results for the calibration period (2000–2010).

	Cropland	Forest	Grassland	Wetland	Urban land	Rural settlements
Kappa Simulation	0.323	0.155	0.209	0.229	0.516	0.254
KTransLoc	0.543	0.228	0.461	0.506	0.577	0.288
KTransition	0.595	0.680	0.454	0.453	0.894	0.880

score for the calibration period, since the available datasets did not allow for an independent validation.

Kappa Simulation values for all land uses are greater than 0 in Table 3, which indicates that the calibrated LANDSCAPE model performs better than it could be expected by chance. Active land use types, including urban land, rural settlements and cropland hold relatively high values of Kappa Simulation, while passive land use types have relatively low scores. The values for KTransition are generally higher than those for KTransLoc, indicating that changes in quantity for land uses were simulated more accurately than changes in location (van Vliet et al., 2011). The high values for KTransition indicate that in many cases the correct type of land use transition was simulated. This is especially relevant to this study, as the assessment of direct and indirect losses of natural habitat primarily depends on the type of land use conversions, irrespective of their exact location.

2.5. Scenarios of land use strategies

Four land use scenarios were designed in this research, differing in the implementation of strict crop protection policies and ecosystem conservation strategies. Each scenario has the same demand for both urban land and rural settlements to ensure comparability (while we acknowledge that the policies may also impact the quantity of land change). The first land use scenario is a *Loose Cropland Protection scenario (LCP)*, which follows the current land use change trend of urban expansion, cropland loss and natural habitat decrease with less strict cropland protection policies. The second one is the *Strict Cropland Protection scenario (SCP)*, which assumes a strict regulation to maintain the quantity of cropland constant. The third one is the *Ecosystem Conservation scenario (ECS)*, which is characterized by a higher resistance on natural land with higher ecological value. The last one is a *Synergy scenario (SYN)*, which aims to maintain quantity of cropland as well as protect natural land with relatively higher ecological value in priority.

Different combinations of demands and resistances in the LANDSCAPE model were used to define different scenarios (Table 4). Generally, demands of cropland were given in scenarios with strict cropland protection policies (*SCP scenario* and *SYN scenario*), while scenarios with less strict cropland protection policies (*LCP scenario* and *ECS scenario*) had no explicit demand for cropland. Moreover, resistances for all land use types in scenarios without ecosystem conservation strategies (*LCP scenario* and *SCP scenario*) were kept the same with that from the LANDSCAPE model calibration, while resistances for all land use types in scenarios with ecosystem conservation strategies (*ECS scenario* and *SYN scenario*) were adjusted by the ecological value for each land use type.

In all scenarios, demands for urban land and rural settlements were given, based on the *Land Use Planning of Wuhan (2006 to 2020)* (Government of Wuhan, 2006–2020). Changes of all other land use types, including cropland, forest, grassland, and wetland, were driven by changes of built-up area expansion, according to the land use change trend from 2000 to 2010. Meanwhile, the resistances for each land use type in the *LCP scenario* were kept the same with their resistances in the period of 2000 to 2010, which were calibrated manually to match the observed land use changes in Wuhan between 2000 and 2010.

In the *SCP scenario*, the quantity of cropland was set to remain exactly at the 2010 level, i.e. at 4706 km^2. So, demand for cropland in 2020 was set for 4706 km^2 in the *SCP scenario* to meet the requirement of strict cropland protection policies. As for the resistances for each land use type, all of them remained the same as in the *LCP scenario.*

In the *ECS scenario*, land use types with a higher ecological value are protected by means of higher conversion resistances. Consequently, resistances for land use types were adjusted by their ecological value in the *ECS scenario* according to the following equation:

$$R_i' = Ri \times [RAdj\min + \frac{ESVi - ESV\min}{ESV\max - ESV\min} \times (RAdj\max - RAdj\min)] \quad (3)$$

where, R'_i is the adjusted resistance for land use type i in *ECS scenario*; R_i is the original resistance for land use type i; ESV_i refers to ecosystem services value per unit for land use type i; $ESV_{\min}$ and $ESV_{\max}$ represent the minimum and maximum value of ecosystem services per unit for all land use types respectively. In this paper, ecosystem service values per unit for each land use type were taken from Xie et al. (2008). $RAdj_{\min}$ and $RAdj_{\max}$ indicate the minimum and maximum values of resistances adjustment, and are set for 1 and 1.25, respectively, according to the experience.

In *SYN scenario*, land use demands were set as the same as that in *SCP scenario* to meet the requirement of constant quantity of cropland by strict cropland protection policies, while the resistances for each land use type were given the same value as that in the *ECS scenario* to ensure prior protection for land use types with higher ecological value.

3. Results

Fig. 2 shows the projected land use for Wuhan in 2020 for all four

Table 4
The parameters set applied for the land use scenarios.

		Cropland	Forest	Grassland	River	Wetland	Urban land	Rural settlements
Initial	Amount (km^2) (2010)	4706	804	1456	304	1458	789	255
LCP	Demand (km^2) (2020)	–	–	–	–	–	910	443
	Resistance (2010–2020)	1.1	1.05	1	1	1	1.2	1.15
SCP	Demand (km^2) (2020)	4706	–	–	–	–	910	443
	Resistance (2010–2020)	1.1	1.05	1	1	1	1.2	1.15
ECS	Demand (km^2) (2020)	–	–	–	–	–	910	443
	Resistance (2010–2020)	1.13	1.18	1.05	1.2	1.5	1.2	1.15
SYN	Demand (km^2) (2020)	4706	–	–	–	–	910	443
	Resistance (2010–2020)	1.13	1.18	1.05	1.2	1.5	1.2	1.15

The parameters for Demand are only defined for active land use types.

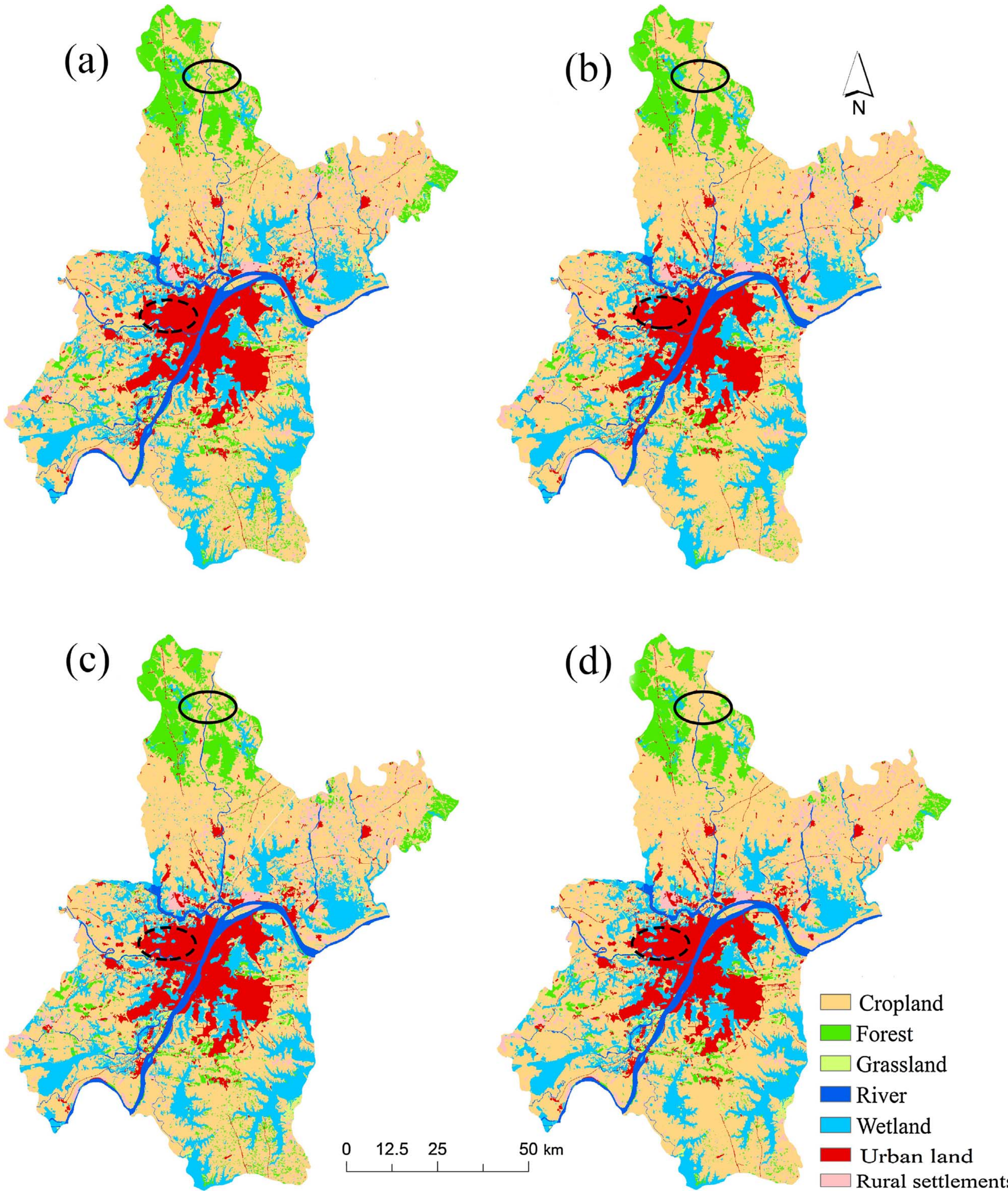

Fig. 2. Simulated land use maps of Wuhan in 2020 in scenarios of: (a) *Loose Cropland Protection (LCP)*; (b) *Strict Cropland Protection (SCP)*; (c) *Ecosystem Conservation (ECS)*; and (d) *Synergy (SYN)*. The solid black circles illustrate that more forest land is occupied by cropland displacement in scenarios with strict cropland protection policies (*SCP scenario* and *SYN scenario*) compared to those with less strict policies (*LCP scenario* and *ECS scenario*). The dashed black circles demonstrate that more wetland is taken by built-up area expansion in scenarios without ecosystem conservation policies (*LCP scenario* and *SCP scenario*) than those with such policies (*ECS scenario* and *SYN scenario*).

scenarios. Interestingly, the simulated land use maps demonstrate that the *LCP scenario* and *SCP scenario* yield a similar expansion pattern for built-up area, while the *ECS scenario* and *SYN scenario* also yield a similar expansion pattern for built-up area, which is different from the former (see the dashed black circles in Fig. 2). Moreover, the *LCP scenario* and *ECS scenario* have a similar cropland expansion pattern, while the *SCP scenario* and *SYN scenario* have a similar cropland expansion pattern which is different from the former (see the solid black circles in Fig. 2). It is clear that ecosystem conservation strategies changed expansion patterns for built-up area while cropland protection policies lead to changes in cropland expansion pattern.

In scenarios with strict cropland protection policies (*SCP scenario* and *SYN scenario*), natural habitat loss takes place because of the pressure from both built-up area expansion and cropland displacement. While all natural habitat loss may be occupied by built-up area expansion alone in scenarios with less strict cropland protection policies (*LCP scenario* and *ECS scenario*).

It is clear that strict cropland protection policies (in both *SCP scenario* and *SYN scenario*) may result in extra indirect natural habitat loss, which is significantly higher than direct loss caused by built-up area expansion. On the contrary, there is no indirect natural habitat loss in scenarios with loose cropland protection policies (*LCP scenario* and *ECS scenario*). Compared to the direct conversion of natural habitat into built-up area, indirect losses through cropland displacement may result in much more natural habitat loss in both *SCP* and *SYN* scenarios. The total area of natural habitat loss during 2010–2020 in the *SCP scenario* is 309 km^2, while the loss from cropland displacement alone is 241 km^2. In other words, 78% of the total natural habitat loss is caused indirectly by cropland displacement. In addition, in the *SYN scenario,* total loss of natural habitat is also 309 km^2 between 2010 and 2020, while the indirect effect is 85%. Since the strict cropland protection policies generally have priority over nature conservation policies in China, the loss of natural habitat is significant in the *SYN scenario* despite the implementation of ecosystem conservation policies in that scenario. Results in both the *SCP scenario* and the *SYN scenario* indicate that cropland displacement is responsible for most of the natural habitat loss in scenarios with strict cropland protection policies.

Ecosystem conservation strategies barely affect the sum of natural habitat loss. However, these strategies may influence the quantity of individual natural land loss. For example, in the *LCP scenario*, wetland decreases by 36 km^2 between 2010 and 2020, while the loss of wetland is only 18 km^2 in the *ECS scenario*. Furthermore, ecosystem conservation strategies may lead to a change in the distribution of natural habitat conversion both directly and indirectly. For instance, in the *SCP scenario*, wetland decreases by 37 km^2 and 119 km^2 as the direct and indirect effect of built-up area expansion respectively during 2010–2020, while the direct and indirect loss of wetland is 19 km^2 and 113 km^2 respectively in the *SYN scenario*.

The loss of natural habitat in scenarios with strict cropland protection policies (*SCP scenario* and *SYN scenario*) is much higher than in scenarios with loose cropland protection policies (*LCP scenario* and *ECS scenario*), as is shown in Fig. 3. Forest loss in the *SCP scenario* and the *SYN scenario* is 120 km^2 and 135 km^2 respectively, while it is 17 km^2 and 12 km^2 respectively in the *LCP scenario* and the *ECS scenario*. Grassland loss reaches 33 km^2 in the *SCP scenario* and 43 km^2 in the *SYN scenario*, while the loss of grassland is only 15 km^2 in both the *LCP scenario* and the *ECS scenario*. Furthermore, the loss of wetland in the *SCP scenario* and the *SYN scenario* reaches 156 km^2 and 132 km^2 respectively, while it is only 36 km^2 in the *LCP scenario* and 18 km^2 in the *ECS scenario*. Even in the *SCP scenario* that includes ecosystem conservation strategies, a great loss of natural habitat is foreseen. This is possible as cropland protection policies are given priority over nature conservation strategies in China.

The quantity of cropland in Wuhan in 2020 differs relatively little between the *SCP scenario* and the *SYN scenario* as well as between the *LCP scenario* and the *ECS scenario.* Cropland areas in 2020 in both the *SCP scenario* and the *SYN scenario* are exactly equal to the cropland area in 2010, because the implementation of strict cropland protection policies. Surprisingly, cropland areas in scenarios with loose cropland protection policies are 4 465 km^2 in the *LCP scenario* and 4 442 km^2 in the *ECS scenario*, which is only slightly lower than in the scenarios with strict cropland protection policies. Furthermore, quantities of cropland in Wuhan in 2020 in all scenarios would be greater than cropland demand in the Land Use Planning of Wuhan (2006–2020) (Government of Wuhan, 2006–2020), which is 3 380 km^2. This suggests that the target of cropland protection for Wuhan in 2020 in land use planning will not be challenged, even in the scenarios with loose cropland protection policies.

4. Discussion and conclusion

Rapid built-up area expansion has been recognized as an important cause for a substantial loss of natural habitat around the world (McDonald et al., 2008; Chao, 2009; Scolozzi and Geneletti, 2012; He et al., 2014). However, natural habitat loss caused by cropland displacement, which is a cascading effect of built-up area expansion, is overlooked in most researches. In this research this issue has been addressed by simulating land use changes in four different scenarios to illustrate the impacts of built-up area expansion on natural habitat loss under different land use strategies. To ensure the quality of the model simulations, we calculated parameters from observed land use maps in Wuhan in 2000 and 2010 to calibrate the model. On the one hand, we used SVM to calculate transition probability for each land use. On the other hand, we calculated activeness and resistance for each land use according to research of Ke et al. (2017). The relatively high Kappa Simulation scores for simulated land use map in 2010 indicates that such parameters are adequate for this research. At the same time, no fully independent model validation could be done due to the lack of sufficient independent data for other, relevant, time periods.

Simulation results indicate that built-up area expansion poses cascading effects on cropland displacement: (1) cropland and natural habitat are directly occupied by built-up area expansion; and (2) natural habitat loss is caused by cropland displacement because of the implementation of strict cropland protection policies. Thus, built-up area expansion is responsible for the majority of natural habitat loss in Wuhan. The loss of natural habitat caused by cropland displacement, however, only happens in scenarios with strict cropland protection policies. This process is different from cropland expansion as a result of increasing food demand and changes in food prices, as the total demand of cropland is not affected.

To guarantee food security, China's government has implemented the strictest cropland protection policies in the world (Lichtenberg and Ding, 2008). The results of our study indicate that the cropland protection policies may have negative impacts on natural habitat. Results suggest that built-up area expansion will lead to natural habitat loss directly in Wuhan during 2010–2020 in all scenarios. Furthermore, cropland displacement in scenarios with strict cropland protection policies will result in indirect loss of natural habitat that ranges between 4.32 and 7.40 times the area lost directly by built-up area expansion.

To strengthen the empirical evidence for this research beyond model simulations of the period 2010–2020, we analyzed historical land use maps of Wuhan in 2000 and 2010 to explore the direct and indirect impacts of built-up area expansion on natural habitat loss. The result shows that the total natural habitat loss during 2000–2010 in Wuhan was 246 km^2, while the direct and indirect loss caused by built-up area expansion is 213 km^2 and 33 km^2 respectively. In other words, 87% of the natural habitat loss is caused directly by built-up area expansion alone. The share of indirect natural habitat loss due to built-up area expansion is lower in the empirical result for this historic period than in the simulation result for the period 2010–2020. A possible reason for this difference is that, in reality, there were several land use policies other than cropland protection policies and ecosystem conservation strategies while there are only policies of cropland protection and/or ecosystem conservation accounted for in the simulation. However, in spite of the smaller area involved, the empirical result confirms that the indirect impacts of built-up area expansion on natural habitat loss should not be ignored.

Our study indicates that the negative impact may be imposed on natural habitat due to the implementation of the strict cropland protection policies in China. Unfortunately, natural habitat loss indirectly caused by built-up area expansion under circumstance of implementing strict cropland protection policies was ignored in numerous previous studies and disregarded in the formulation of current land use policies. It is essential for China's government to take the negative impact of strict cropland protection policies on ecosystem services into

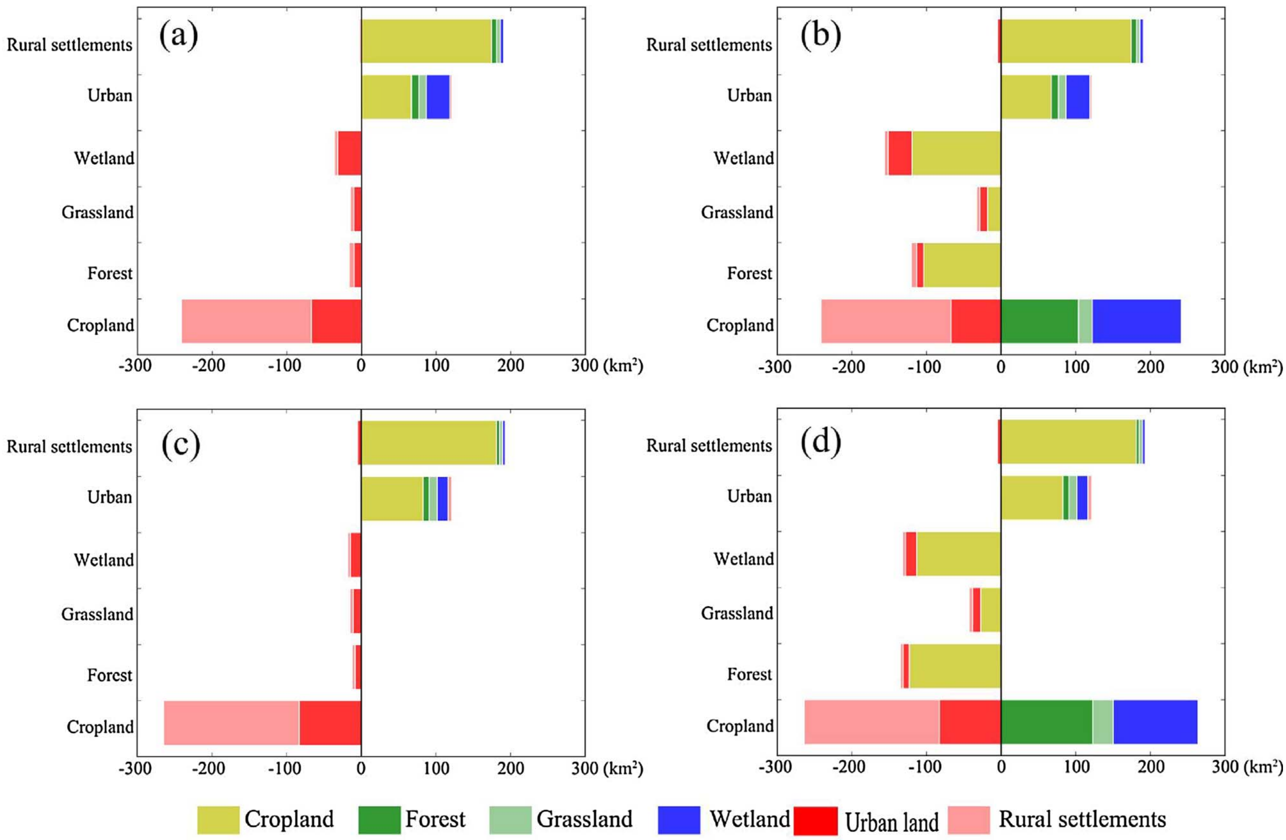

Fig. 3. Process of natural land loss during 2010–2020 in Wuhan in scenarios of: (a) *LCP*; (b) *SCP*; (c) *ECS*; and (d) *SYN*. Bars on the left side of 0 indicate losses, while bars on the right side of 0 illustrate gains. Different colors represent different land use types.

consideration to minimize tradeoffs between urbanization, food security, and ecosystem conservation. Assessments of potential policy modifications should account for cascading effects of land use change to avoid unexpected environmental deterioration or loss of natural habitats.

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