Optimizing Land Use Allocation to Balance Urban Expansion, Cropland Protection, and Conservation of Ecosystem Services

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Keywords: Land use allocation optimization; Urban expansion; Cropland protection; Ecosystem services; LANDSCAPE model

SUMMARY

Dealing with the conflicts among urban expansion, cropland protection, and conservation of ecosystem services becomes the subject of increased attention in the sustainable land use planning. Previous studies explored the optimized land allocation to mitigate the trade-offs between urbanization and protection of cropland quantity, or between urbanization and protection of ecosystem services, but few studies explored the optimized land use allocation which could achieve the synergy among urban expansion, cropland protection (not only protecting its quantity but quality), and conservation of ecosystem services. Taking Hubei of China as the study area, this study aims to optimize land use allocation which can meet the demand for both urban land and cropland in quantity, while maximizing the productivity of cropland and minimizing the loss of ecosystem service value (ESV) during 2010–2030. Based on potential agricultural yield estimated by Global Agro-ecological zone (GAEZ) model and the spatial differences of ESV assessed by unit value-based approach, we optimized the land use allocation by applying the LAND System Cellular Automata model for Potential Effect (LANDSCAPE). Specifically, the spatial difference of potential agricultural yield was expressed as parameter of suitability, while the spatial difference of ESV was represented by the parameter of resistance. Results show that, the optimized land use allocation will meet the demand for both urban land and cropland in quantity, meanwhile, the potential agricultural yield will increase by 361 kg/km^2 (which can make cropland economic value increase 12.71×10^6 US\$ to 13.37×10^6 US\$), and the loss of ESV will decrease by 46.57 million US\$. The results indicated that it is feasible to allocate land resources to achieve the synergy among urban development, protection of cropland in quantity and quality, and conservation of ecosystem services. This study highlights the importance to take the spatial difference of both potential agricultural yield and ESV into consideration in land use planning.

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1. Introduction

Urban land is the basis of economic development, and it supports more than half of the global population. The global urbanization rate is expected to rise from 50% in 2009 to 69% in 2050, and more than 1.86 billion people will live in urban lands (United Nations, 2015). In this case, global urban land dramatically expands with the unprecedented urbanization (Lambin and Meyfroidt, 2011; Angel et al., 2005), and it was predicted to increase by 1.2 million km^2 during 2000–2030 (Seto et al., 2012). Meanwhile, China, as the populated country has experienced the highest rates of urban land expansion (Seto et al., 2011). Specifically, China had experienced extremely rapid urban growth from 1992 to 2012 with an average annual growth rate of 8.74%, in contrast with the global average of 3.20% (Jiang et al., 2013). Although the expansion of urban land plays an important role in improving urbanization level (Yang et al., 2018), it leads to the conversion of a large amount of cropland and ecological landss (e.g., forest, grassland, and wetland) into urban land (Deng et al., 2015). Specifically, urban expansion often occurs on croplands (Deng et al., 2015), and it was predicted to result in a 1.8–2.4% loss of global croplands by 2030 (d'Amour ET AL., 2017). In addition, some studies have assessed the loss of ecological lands, including forest, grassland, and wetland (IUCN, 2013), caused by urban expansion especially in the key biodiversity hotspots (Seto et al., 2012; Mao et al., 2018; He et al., 2011).

Given that global population will continue to increase and considerable cropland has been encroached by urban expansion, the cropland needs to be protected and supplemented to deal with the global food security issues. Specifically, the demand for global food was predicted to increase 60%–110% by year 2050 in the context of the increasingly global population (Godfray et al., 2010). It was predicted that about 2 billion hectares of additional cropland will be required to meet the increased demand for food and nutrition (Tillman et al., 2011). Therefore, the cropland will be further reclaimed to maintain cropland resource and deal with global food security issues, especially in the populated countries and regions (Stoms et al., 2009). China has the largest population in the world, and its government implements a series of strict cropland protection policies to compensate the lost cropland caused by urban expansion and maintain cropland resources (Zhang et al., 2014; Cheng et al., 2015). For example, the policy named *Requisition–Compensation Balance of Cropland* clearly states that the stakeholders occupying cropland are responsible for the compensation equivalent to the requisitioned cropland (Liu et al., 2014; Liang et al., 2015). The cropland reclamation has effectively alleviated the continuous reduction of cropland and maintain the quantity of cropland (Song and Pijanowski, 2014), however, the quality of cropland was degraded (Liu et al., 2015b). The main cause is that the quality of occupied cropland is often better than that of reclaimed cropland (Lichtenberg and Ding, 2008; Liu et al., 2015b).

To maintain cropland resources, the ecological lands, including forest, grassland, and wetland (IUCN, 2013), are inevitably encroached by cropland. van Vliet (2019) suggested that global losses of ecological lands related to forest and shrubland are primarily attributed to cropland expansion, whereas the role of urban expansion is considered minor. As for the regional scale, Lark et al. (2015) found that cropland expansion caused a great loss of grassland, with 5.7 million acres lost (accounting for 77% of all new cropland) between 2000 and 2008 in the United States. Furthermore, the area of cropland expansion replacing natural habitat was predicted to be 3.5×10^{8} hectares in 2050, which would lead to eutrophication and natural habitat destruction (Tilman et al., 2001). Meanwhile, cropland expansion is also a noticeable issue in China, and therefore, large areas of ecological lands have been converted into cropland in China (Ke et al., 2018; Zheng et al., 2018; Ke and Tang, 2019).

With the currently continued growth of urbanization in China, existing cropland at risk for conversion to urban land, and ecological lands at risk for conversion to cropland and urban land (Jiang et al., 2012). China are faced excessive urban expansion, considerable loss in both the quantity and quality of cropland, and decline of ecosystem services (Jiang et al., 2013; Zheng et al., 2019a; Zheng et al., 2019b). Both urban expansion and cropland protection can threaten ecosystem services by occupying ecological lands (Delphin et al., 2016; Shen et al., 2017; Ke et al., 2018), especially in the populated countries such as China. Ecosystem services are the benefits human beings gained from the ecosystem (Costanza et al., 1997). The ecosystem service value (ESV) indicates the economic value of ecosystem services, which is applied to guide decision-making processes of land use strategy as a useful tool (Bateman et al., 2013). In this case, how to optimize the land use allocation to allocation to balance urban expansion, cropland protection, and conservation of ecosystem services has been the subject of increased attention (Foley et al., 2005; Scarborough et al., 2012). Therefore, achieving land use optimization allocation for sustainable development has become an important issue in land use and is a critical task for reasonable allocation of limited land resources while promoting sustainability (Cao et al., 2011, 2012). Previous studies explored the optimized land allocation to mitigate the trade-offs between urbanization and protection of cropland quantity, between urbanization and protection of ecosystem services, and agriculture and ecosystem service (Zhang et al., 2016; Zheng et al., 2019b; Kennedy et al., 2016). However, few studies explored the optimisation of land use allocation based on the spatial differences of the productivity of cropland and ESV for the synergy among urban expansion, cropland protection (not only protecting its quantity but quality), and conservation of ecosystem services.

Taking Hubei province of China as the study area, this study aims to propose a spatial optimisation model of land use allocation based on the LAND System Cellular Automata model for Potential Effect (LANDSCAPE). This model is capable to realise the synergy among urban expansion, cropland protection (not only protecting its quantity but quality), and conservation of ecosystem services, based on spatial differences of both the productivity of cropland and ESV. Firstly, the spatial differences of potential agricultural yield and ESV were assessed by Global Agro-ecological zone (GAEZ) model and unit value-based approach, respectively. Then, spatial difference of potential agricultural yield was applied to calculate the parameter of suitability for the model, while spatial difference of ESV was used to calculate the parameter of resistance for the proposed optimisation model. After that, the optimisation model was used to optimise land use allocation, and we estimated the changes in urban expansion, the quantity and quality of cropland in Hubei during 2010–2030 in the optimized land use allocation. Finally, we assessed the performance of optimized land use allocation by comparing the optimized land use allocation and the non-optimized land use allocation.

2. METHODS AND DATA

2.1 Methods

2.1.1. LANDSCAPE model for land use simulation

The LANDSCAPE model, as an improved Cellular Automata (CA) -based model, can be employed to simulate cascading processes of land use changes by introducing hierarchical allocation strategies (Ke et al., 2017). The allocation of land use types is determined by two factors: suitability and resistance (Ke et al., 2018). Suitability represents the quality of the location for a target land use type, and resistance represents the difficulty for a cell to convert from current land use type to another one (Ke et al., 2018). The combined effect of suitability and resistance is calculated according to formula (1):

$$TTP_{l,tu} = \frac{S_{l,tu}}{R_{l,cu}} \quad (1)$$

where $TTP_{l,tu}$ represents the total transition possibility of a cell at location l for the target land use type tu; $S_{l,tu}$ represents the suitability for a cell at location l for the target land use type tu, and $R_{l,cu}$ represents the resistance of a cell at location l to convert from current land use type cu to another land use type (Zheng et al., 2019a).

Suitability $S_{l,tu}$ can be calculated accordingly:

$$S_{l,tu} = (1 + (-\ln\gamma)^{\alpha}) \times PSC_{l,tu} \times Con(C_{l,tu}) \times NL_{l,tu} \quad (2)$$

where $1 + (-\ln\gamma)^{\alpha}$ represents a random factor used to explain the impacts of factors not included in the model on the dependent variable, γ is a stochastic number which varies from 0 to 1, while α is an integer from 0 to 10 used as a dispersion factor to control the random number (Zheng et al., 2019a). Additionally, $PSC_{l,tu}$ reflects the impacts of location characteristics, including physical and social characteristics, such as elevation, slope, soil, and the distance to roads, etc. In this research, $PSC_{l,tu}$ was calculated by Support Vector Machines (SVM) (Ke et al., 2017). $Con(C_{l,tu})$ represents the constraint value of a cell, with a value of 0 or 1. Value 0 represents the cells that are unchangeable, while value 1 represents the cells that are changeable. The $Con(C_{l,tu})$ value of river was set as 0 since the land use maps of Hubei in 2000 and 2010 showed that the river in both location and area were stable from 2000 to 2010. $NL_{l,tu}$ represents the impacts of neighboring land use types, which is calculated accordingly:

$$NL_{l,tu} = \frac{n(SC=tu)}{TN} \quad (3)$$

where $n(SC = tu)$ represents the number of cells that represent the type of target land use in a given neighborhood at location l, and TN represents the total number of cells in the given neighborhood.

As for the resistance, it can be calculated based on the observed land use maps, and can be tested by calculating the difficulty for one land use type being occupied by another type (Zheng et al., 2019a). The resistances in this study (Table 1) were calculated by following the method used from Ke et al. (2017), and the method also was applied in the studies of Mei et al. (2017), Zheng et al. (2019a; 2019b), and Ke et al. (2018; 2019).

Table 1
Resistance for each land use type.

Land-use type	Cropland	Forest	Grassland	River	Wetland	Urban land	Rural construction land	Unused land
Resistance	1.00	1.25	1.25	1.50	1.25	1.50	1.50	1.00

The KSimulation, as the most important index in Kappa Simulation, can be used to represent the degree of agreement between the simulated and actual observed land use maps (van Vliet et al., 2011). As Table 2 shows, KSimulation values of each land use type were all greater than 0, which qualified the LANDSCAPE model for further simulations (van Vliet et al., 2011).

Table 2
Kappa Simulation values of LANDSCAPE model.

	Cropland	Forest	Grassland	Wetland	Urban land	Rural construction land	Unused land
KSimulation	0.333	0.140	0.218	0.270	0.521	0.298	0.296

2.1.2. Adjusted suitability based on potential agricultural yield

Potential agricultural yield can represent the quality of cropland (Zheng et al., 2019a). Potential agricultural yield is mainly affected by climate, soil, water resource, and irrigation. Global Agro-Ecological Zones (GAEZ) model (IIASA/FAO et al., 2012; Liu et al., 2014) was employed to calculate potential agricultural yield. Specifically, firstly, based on the climatic conditions, the GAEZ model was applied to estimate the climate suitability of crops planted. Then, based on step by step restriction, the potential agricultural yield for suitable crops was assessed (Zheng et al., 2019a). The parameter of suitability was adjusted by changing $PSC_{l,tu}$ (in formula 2). Based on the spatial differences of potential agricultural yield, the cell with higher potential agricultural yield will have the higher possibility to become cropland. Specifically, the potential agricultural yield was normalized, and normalized values range from 1.5 to 2.

2.1.3. Adjusted resistance based on ESV

ESV was calculated by using a unit value-based approach, which was used to adjust the parameter of resistance in LANDSCAPE model. The unit value-based approach was also applied in the study of Xie et al. (2017). The ESV were used to adjust the parameter of resistance in the LANDSCAPE model in order to protect the ecosystem with a higher ESV.

Land use types with higher ESV levels can be protected by means of higher resistances. Consequently, the resistances for land use types were adjusted by their ESV levels, according to the following formula:

$$R_{i\_ad}' = R_i \times \left[R_{min} + \frac{ESV_i - ESV_{min}}{ESV_{max} - ESV_{min}} \times (R_{max} - R_{min})\right] \tag{4}$$

where R_{i_ad}' is the adjusted resistance of land use type i. R_i is the original resistance of land use type i. ESV_i is the ESV of land use type i. ESV_{max} represents the maximum ESV of all the ecological lands, while ESV_{min} represents the minimum. R_{max} represents the maximum value of resistance adjustment, while R_{min} represents the minimum value. R_{adj_max} and R_{adj_min} were set as 1.5 and 1, respectively. In this study, the ESV per unit for individual land use type was adopted from Xie et al. (2017). The parameters R_{max} and R_{min} refer to the maximum and minimum resistance values, respectively.

2.2. Datasets

Six datasets were used in this study: land use data, meteorological data, terrain data, soil data, and accessibility data (Ke et al., 2017).

(1) Land use dataset was obtained from the National Land Use Database (http://www.resdc.cn). The spatial resolution of the land use data is 30 m, and the accuracy of the data is 92.7% (Liu et al., 2010). Land use types were reclassified into cropland, forest, grassland, river, wetland, urban land, rural construction land, and unused land (Liu et al., 2019; Zhou et al., 2019). (2) The meteorological dataset includes data on annual rainfall and average annual accumulated temperature which were obtained from the Chinese Meteorological Administration (CMA) (http://www.cdc.cma.gov.cn). (3) The terrain dataset includes elevation and slope. The data of elevation were obtained from the Shuttle Radar Topography Mission (SRTM). Based on the elevation, the slope raster data were generated by the “Slope” tool in ArcMap 10.2. (4) The soil dataset was obtained from the China Soil Database (http://www.gis.soil.csdb.cn), including soil plough thickness, soil organic matter content, soil phosphorous content, and soil pH value. (5) We used seven types of road networks from the Traffic Atlas of Hubei, including national roads, provincial roads, main roads, minor roads, highways, railways, and other roads. The “Euclidean Distance” tool in ArcMap 10.2 was applied to generate raster data. (6) The dataset of potential agricultural yield was obtained from Resource and Environment Data Cloud Platform (http://www.resdc.cn/DOI,2017. DOI:10.12078/2017122301). The crops in this dataset mainly includes wheat, maize, rice, soybean and sweet potato (accounting for 97.7% of the total Chinese grain output) (Jiang et al., 2013). Given that this study focused on the change of potential agricultural yield due to land use change, the short duration of the study period (2010–2030), and many uncertainties of physical and socioeconomic conditions in 2030, it is assumed that the potential agricultural yield in individual pixel does not affected by climate, soil, water, and irrigation (Zheng at al., 2019a). Therefore, the potential agricultural yield in the individual pixel in 2030 was set same as that in 2010 if its land use type maintains same.

3. RESULTS

3.1. Adjusted suitability and resistance for optimized land use allocation

Potential agricultural yield was used to adjust the parameter of suitability in the LANDSCAPE model. Generally, the potential agricultural yield in central regions of Hubei is highest, such as Jianghan, Xiaogan, and Wuhan (Fig. 1). Meanwhile, the northern part of Xiangfan also obtains high potential agricultural yield. Therefore, the adjusted values in individual pixels in these areas are high with about 1.5. In contrast, the potential agricultural yield in the western regions is relatively low, and therefore, the adjusted values were almost 1.

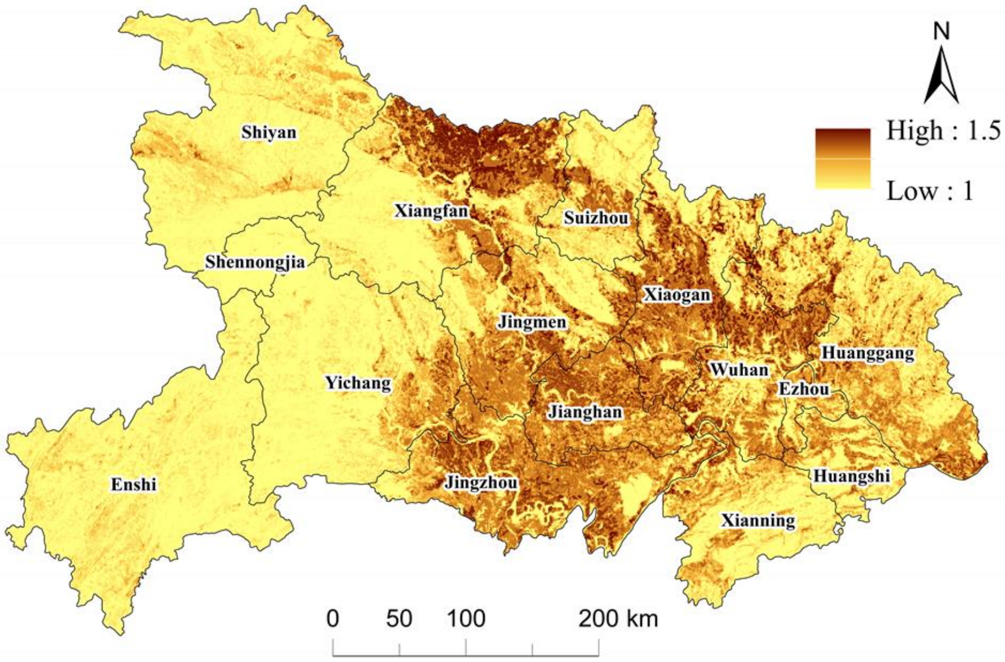

Fig. 1. The adjusted suitability and resistance for optimized land use allocation

Resistances in the LANDSCAPE model were adjusted based on the ESV to conserve ecosystem services. The individual land use type which has a higher ESV was protected by the greater resistance. The ESV in this study was calculated by using the method of Xie et al. (2017) and adjusted resistances based on formula 4 (in section 2.2.5). Then the results were shown in Table 3. The river was represented with a highest ESV value per unit, and followed by wetland, forest, grassland, unused land, and built-up area. Base on the original resistances in table 2 (Ke et al., 2017). The resistance levels of river, urban land, and rural settlements were higher than those of other land use types, while cropland showed the lowest resistance and can therefore easily be converted into other land use types. In the optimisation scenario, resistance values were adjusted based on both ESV and original resistances. River, wetland, forest and grassland showed higher resistance values than the original ones, with increased difficulty of being converted into other land use types.

Table 3

Equivalent value per unit area and adjusted resistance of individual land use type.

Land use type	Cropland	Forest	Grassland	Wetland	River	Urban land	Rural construction land	Unused land
Equivalent value*	2,956	10,524	4,367	20,497	16,972	0	0	520
Original resistance	1.00	1.25	1.25	1.25	1.50	1.50	1.50	1.00
Adjusted resistance	1.07	1.57	1.38	1.88	2.12	1.5	1.5	1.01

* (US$·$ha^{-1}$·$yr^{-1}$)

3.2. Difference between the optimized land use allocation and non-optimized land use allocation

3.2.1. Differences in land use changes

The land use changes in Hubei from 2010 to 2030 in the optimized land use allocation and non-optimized land use allocation are shown in Fig. 4a and Fig. 4b. In the optimized land use allocation (Fig. 4a), urban expansion will lead to considerable loss of cropland. The loss of cropland caused by urban expansion will be 293 km^2, accounting for 83% of the total new urban land, followed by wetland (31 km^2, 11%) and forest (22 km^2, 7%). Comparatively, cropland will encroach much ecological land, wherein wetland will lose most (216 km^2), accounting for 74% of the total added cropland. Meanwhile, forest will lose 59 km^2, while grassland will lose 11 km^2. In the non-optimized land use allocation (Fig. 4b), the loss of ecological land caused by urban expansion much more than that loss in the optimized land use allocation. In detail, the loss of wetland and forest caused by urban expansion will be 54 km^2 and 41 km^2, respectively. In addition, cropland will encroach considerable wetland with 225 km^2.

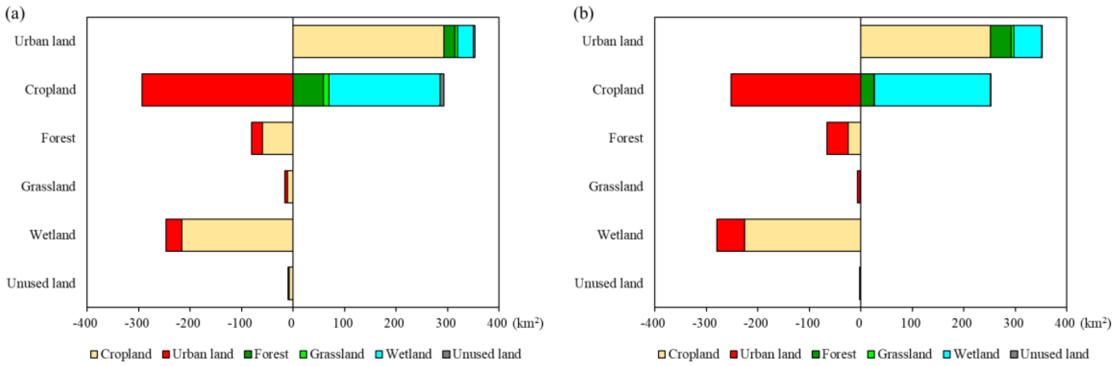

Fig. 4 Land use changes in Hubei from 2010 to 2030 in the optimized land use allocation (a) and non-optimized land use allocation (b).

3.2.2. Differences in changes of potential agricultural yield

The total of potential agricultural production in the optimized land are 24.70×10^6 kg than that production in the non-optimized land use allocation (Table 4). Furthermore, for most of city of

Hubei, the potential agricultural production in the optimized land are higher than the production in the non-optimized land use allocation. The largest difference of agricultural production between the optimized and non-optimized land use allocations will be in Xiangfan, followed by Jingzhou and Jianghan. Furthermore, the total area of cropland in 2030 in Hubei will be 68330 km^2, so the potential agricultural yield will increase by 361 kg/km^2 (which can make cropland economic value increase 12.71×10^6 US$ to 13.37×10^6 US$).

Table 4

The potential agricultural production of each region in Hubei in 2030 and the corresponding economic value

Regional name	In optimized land use allocation (10^6 kg)	In non-optimized land use allocation (10^6 kg)	Difference* (10^6 kg)	Economic value**(106 US$) increase by 7.14%	increase by 12.77%
Shiyan	1336.74	1334.77	1.96	1.01	1.06
Xiangfan	9047.35	9040.25	7.1	3.65	3.85
Jingmen	6383.4	6380.24	3.16	1.63	1.71
Xiaogan	8083.53	8082.18	1.35	0.70	0.73
Huanggang	6408.63	6406.41	2.22	1.15	1.21
Wuhan	5187.65	5187.61	0.04	0.02	0.02
Ezhou	678.67	678.64	0.03	0.02	0.02
Huangshi	1287.77	1287.35	0.43	0.22	0.24
Xianning	2054.4	2053.49	0.91	0.47	0.50
Jingzhou	9985.22	9980.03	5.18	2.67	2.81
Enshi	657.14	657.25	-0.12	-0.06	-0.07
Yichang	2398.44	2398.54	-0.1	-0.05	-0.06
Jianghan	5760.35	5757.1	3.25	1.67	1.76
Suizhou	1705.61	1706.33	-0.72	-0.37	-0.39
Shennongjia	7.14	7.13	0.01	0.00	0.00
Total	**60982.03**	**60957.33**	**24.7**	**12.71**	**13.37**

* Difference represents the difference of the potential agricultural production between the optimized and non-optimized land use allocations

** The average price of the main crops in China is 0.48 US$/kg currently, and the price was predicted to increase by 7.14% and 12.77% (Chen et al., 2012).

3.2.3. Differences in changes of ESV

The loss of ESV in Hubei from 2010 to 2030 was predicted to be 598.41×10^6 US$ in the optimized land use allocation, and to be 644.98×10^6 US$ in the non-optimized land use allocation. Therefore, the loss of ESV in the optimized land use allocation will 46.57×10^6 US$ less than that loss in non-optimized land use allocation in total.

Table 5

Loss of ESV in Hubei from 2010 to 2030 (10^6 US$)

	Optimized land use allocation	Non-optimized land use allocation

	To urban land	To cropland	To urban land	To cropland
From cropland	86.61	-	74.44	-
From forest	22.67	44.70	42.68	18.85
From grassland	2.08	1.55	1.94	0.21
From wetland	64.01	378.40	111.48	395.38
From unused land	0.14	-1.75	0.07	-0.08
Total	175.51	422.90	230.62	414.36

For most regions in Hubei, the loss of ESV in the optimized land use allocation will be less than that loss in the non-optimized land use allocation. Compared to the loss of ESV in Jingzhou in the non-optimized land use allocation, the loss will be 36.67×10^6 US$ less than that in the optimized land use allocation.

Table 6
Difference of loss in ESV in Hubei from 2010 to 2030 between the optimized and non-optimized land use allocations (10^6 US$).

	Optimized land use allocation	Non-optimized land use allocation	Difference*
Shiyan	8.18	8.02	0.16
Xiangfan	54.63	56.68	-2.05
Jingmen	40.71	42.20	-1.49
Xiaogan	42.35	48.91	-6.56
Huanggang	25.79	26.62	-0.83
Wuhan	106.83	110.63	-3.80
Ezhou	11.06	14.79	-3.73
Huangshi	8.95	13.18	-4.22
Xianning	28.05	22.89	5.16
Jingzhou	149.88	186.54	-36.67
Enshi	6.20	5.75	0.45
Yichang	12.11	17.92	-5.81
Jianghan	93.74	81.96	11.78
Suizhou	9.88	8.84	1.05
Shennongjia	0.05	0.05	0.00
Total	**598.41**	**644.98**	**-46.57**

* Difference = Loss of ESV in the optimized land use allocation - Loss of ESV in the non-optimized land use allocation

3.3. The performance of optimized land use allocation

In the most regions of Hubei, the optimized land use allocation can performance well in increasing the economic value from agriculture production and reducing the loss the ESV (Table 7). The optimized land use allocation makes Jingzhou increase economic value from agricultural production with 2.49×10^6 US$, while the loss of ESV will reduce 36.67×10^6 US$.

Therefore, Jingzhou will increase economic value by 39.16×10^6 US$ in total. This is ture for most regions. In contrast, the economic value from agricultural production in Enshi and Suizhou will decrease, but the loss of ESV will increase. Comparatively, the economic value from agricultural production in Shiyan and Xianning will increase, but the loss of ESV will also increase. The economic value from agricultural production in Yichan will decrease, and the loss of ESV will also decrease.

Table 7
The performances of the optimized land use allocation (10^6 US$).

Regional name	Performance in increasing economic value from agricultural production	Performance in reducing loss of ESV	Balance
Shiyan	0.94	-0.16	0.78
Xiangfan	3.41	2.05	5.46
Jingmen	1.52	1.49	3.01
Xiaogan	0.65	6.56	7.21
Huanggang	1.07	0.83	1.90
Wuhan	0.02	3.80	3.82
Ezhou	0.02	3.73	3.75
Huangshi	0.21	4.22	4.43
Xianning	0.44	-5.16	-4.72
Jingzhou	2.49	36.67	39.16
Enshi	-0.06	-0.45	-0.51
Yichang	-0.05	5.81	5.76
Jianghan	1.56	-11.78	-10.22
Suizhou	-0.35	-1.05	-1.40
Shennongjia	0.00	0.00	0.00

Total	**11.86**	**46.57**	**58.43**

4. DISCUSSION

An optimized land use allocation was explored in this study, which can meet the demand for both urban land and cropland in quantity, while maximizing the productivity of cropland and minimizing the loss of ESV. Given that the conflicts among urban expansion, cropland protection, and conservation of ecosystem services have been the subject of increased concern, it is significant to explore a sustainable land use allocation to balance urban expansion, cropland protection, and conservation of ecosystem services (Jiang et al., 2012; Zheng et al., 2019b). In the optimized land use allocation in this study, the urban area can be meet the demand of economic development. Moreover, it is helpful to protect the quantity and the quality of cropland. Meanwhile, the land which has high ecosystem services can be conserved with priority. The optimized land use allocation in 2030 will meet the demand for both urban land and cropland in quantity, meanwhile, the potential agricultural yield will increase by 361 kg/km^2 (which can make cropland economic value increase 12.71×10^6 US$ to 13.37×10^6 US$), and the loss of ESV will decrease by 46.57 million US$.

The proposed optimisation model in this study considered the spatial difference of both potential agricultural yield and ecosystem services into the land use allocation. The optimized model is feasible to allocate land resources to achieve the synergy among urban development, protection of cropland in quantity and quality, and conservation of ecosystem services. Previous studies mostly focused on the optimized land allocation to mitigate the trade-offs between urbanization and protection of cropland quantity, between urbanization and protection of ecosystem services, and agriculture and ecosystem service (Zhang et al., 2016; Zheng et al., 2019b; Kennedy et al., 2016). Although Zheng et al. (2019b) explored the optimized land use to balance urban development and the ecosystem services, they ignored the impacts of cropland expansion on ecosystem services. Groot et al. (2018) formed the optimized land use allocation based on the trades-offs between different ecosystem services, they did not consider the threats of urban expansion and cropland expansion on ecosystem services. Land use changes are dynamic and cascading processes, land use changes can interact with each other. Therefore, the land use allocation should be optimized in a systematic perspective. The LANDSCAPE model is widely used to simulate multiple land use changes by hierarchical allocation strategy and partition asynchronous, and can be related to the impacts of land use policies (Ke et al., 2017; Zheng et al., 2019a, 2019b). The LANDSCAPE model is suitable to be applied in optimizing the land use allocation to obtain multiple objectives, incorporating the spatial and temporal dimensions of parameters such as resistance, suitability (Zheng et al., 2019b).

The study indicated that it is feasible to consider the spatial differences of both potential agricultural yield and ESV is an available approach to achieve the synergy among urban development, protection of cropland in quantity and quality, and conservation of ecosystem services. The optimisation model of land use allocation can be used to make a sustainable land use planning. Land use planning in early years mainly focused on economic benefits, posing the threat to quality of cropland (Liu et al., 2015b) and ecological protection (Wang et al., 2018). However, with the increased attention to quality of cropland and ecosystem services nowadays, it is not reasonable in land use planning which only aims to achieve the demand for economic development or quantity protection of cropland. The conflicts among urban expansion, cropland protection, and conservation of ecosystem services not only exist in Hubei, but other regions worldwide. Therefore, the perspective and the method used in this study can be applied further in the land use planning.

The limitations in the study are as follows. (1) The price of crops to assess the economic value was from the published study of Chen et al. (2012) instead of predicting the price by ourselves. Thus, the study can't provide specific impacts economic value of agriculture production in 2030. (2) The ESV of each land use type is set at a fixed value in the unit value-based approach, but the ESV of the same type of land use can vary both from region to region and from time to time in reality. Therefore, it is necessary to consider the spatial-temporal heterogeneity of carbon density into the approach.

5. CONCLUSIONS

Based on the spatial difference of both potential agricultural yield and ESV in the LANDSCAPE model, it is feasible to optimize land use allocation was explored in this study to achieve the synergy among urban development, protection of cropland in quantity and quality, and conservation of ecosystem services. Specifically, the spatial difference of potential agricultural yield was expressed as parameter of suitability, while the spatial difference of ESV was represented by the parameter of resistance. The optimized model is feasible to allocate land resources to achieve the synergy among urban development, protection of cropland in quantity and quality, and conservation of ecosystem services. The optimized land use allocation will meet the demand for both urban land and cropland in quantity, meanwhile, the potential agricultural yield will increase by 361 kg/km^2 (which can make cropland economic value increase 12.71×10^6 US$ to 13.37×10^6 US$), and the loss of ESV will decrease by 46.57 million US$. Therefore, it is important to take the spatial difference of both potential agricultural yield and ESV into consideration in land use planning.

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