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- **1** Spatial impact of Cropland Supplement Policy on regional ecosystem
- 2 services under urban expansion circumstance: a case study of Hubei
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Spatial impact of Cropland Supplement Policy on regional ecosystem services under urban expansion circumstance: a case study of Hubei Province, China

28 Abstract: The Cropland Supplement Policy (CSP) helps maintain the total area of 29 cropland in China as urban areas expand, but can result in environmental 30 degradation as areas of more natural habitat are turned into cropland. Current and 31 future impacts of the CSP are explored under different land use change scenarios 32 by comparing the differences in ecosystem services value (ESV) at prefecture 33 level. Scenario based simulation results suggest that in Hubei province, the CSP 34 cost 19.53 billion CNY in the period 2000 to 2015 and would cost an additional 35 12.54 billion CNY in the period 2015 to 2030 in terms of ESV loss. A policy 36 analysis framework for land use planning is proposed which enables ecological 37 impacts of the CSP to be considered.

- 38 Keywords: Cropland protection; Cropland supplement policy; Ecosystem
- 39 protection; Ecosystem Services Value; Land use change model

41 **1. Introduction**

42 More than 50% of people now live in urban areas, this proportion is expected to reach 43 68.4% by 2050 (United Nations, 2018). Whilst more people can be accommodated into 44 existing urban areas, typically urbanization involves expanding urban areas (Seto et al., 45 2012). McDonald et al. (2018) forecast a worldwide increase of 120 million hectares of 46 urban land from 2000 to 2030, and in many cases the expansion will be at the expense of 47 some highly productive farmland (Angel et al., 2011; Xin & Li, 2018). Martellozzo et al. 48 (2015) reported that in Canada around 60% of the urban area built in the Calgary-49 Edmonton corridor between 1988 and 2010 occupied land that was previously cropland, 50 and unsurprisingly agricultural productivity in the area fell as a result. van Vliet et al. 51 (2017) estimates that by 2050, due to urban expansion, agricultural production in the close 52 vicinity of large cities will be 65 million tons less. Global population is expected to 53 increase significantly in the coming years, and people are preferring to consume products 54 requiring more land to produce (Seto & Ramankutty, 2016). Thus at a global scale, the 55 demand for agricultural land is increasing. What is typically being lost are many more 56 natural habitats and areas of wetland and forest, and this is a major concern documented 57 by numerous case studies (Gibbs et al., 2010). Typically, wetlands and forested areas are 58 more easily changed into cropland than more barren or wasteland areas, and similarly 59 grassland is more likely to be turned into cropland than perhaps any other land use type 60 (van Vliet et al. 2017; Gibbs et al., 2010; Zheng et al., 2019). There are major concerns 61 about the loss of natural habitats and habitat fragmentation as a result of these changes at 62 all scales. As well as direct expansion into what could be classed as natural habitat on the 63 fringes of an urban area, urban expansion has knock on indirect displacement effects 64 which may impact such habitats locally, regionally and globally (Ke et al., 2018).

65

The United Nations Human Settlements Programme (UN-Habitat) advocates

66 compact cities to mitigate the negative impacts of urban expansion (Seto & Ramankutty, 67 2016). More compact cities accommodate more people, industry and everything that 68 makes up the urban fabric within a smaller urban area footprint than a less compact, more 69 sprawling city. Cropland Protection Policies (CPP) have been introduced in some densely 70 populated parts of the world, to both restrict urban area expansion and encourage 71 agricultural production in urban areas and their periphery. In recent years, the Japanese 72 government enacted cropland protection laws to protect cropland directly, and also placed 73 restrictions on the imports of primary agricultural products to increase the price of locally 74 produced agricultural products which has had the effect of protecting cropland indirectly 75 (Monk et al., 2013). In western European countries cropland is protected by: planning 76 restrictions; delineating priority areas for cropland; and, setting targets to control cropland 77 loss (Oliveira et al., 2019).

For the last 30 years or more, there has been rapid urbanization in China. In 2017 it was estimated that 58.52% of the population lived in urban areas (National Bureau of Statistics of China, 2018). Whilst the total population of China is unlikely to change much in the next decade, the proportion of people living in urban areas is expected to rise to around 70% by 2030 (United Nations, 2018). In response to concerns about food security, various CPP have been implemented in China. (Lichtenberg & Ding, 2008).

There are natural language translation difficulties when considering land use and policy terminology. The meanings of farmland, cropland, cultivated land and natural habitat are different in different contexts. In the Chinese context, cropland, which is protected by CPP, commonly refers to areas planted with high yielding cereals: including drier tilled land used to grow wheat and barley; and, wet paddy fields where the main crop is rice. Cropland in this context may also include land where vegetables are grown 90 but is typically not where fruit is grown (Xin & Li, 2018).

91 Among various CPP enacted in China, the Cropland Supplement Policy (CSP) 92 applies when urban land expands into cropland. In general, the CSP aims to ensure that 93 overall the amount of cropland area is maintained at the province level, thus cropland 94 changed to urban land use is replaced by other land changed to cropland (via land 95 development, land consolidation, land rehabilitation, or agricultural restructuring 96 projects). The CSP mainly involves cropland supplement via land development projects, 97 which typically results in natural habitats being converted into cropland (Wu et al., 2017). 98 In this study, natural habitat refers to forest, grassland, wetland, open water, and unused 99 lands (IUCN, 2013; Ke et al., 2018).

100 The CSP in China has been variously studied. Song & Pijanowski (2014) revealed 101 that in the whole of China "the total gained cropland by land exploitation, consolidation 102 and rehabilitation" from 1999 to 2008 was 27,677 km2 and the "the total lost cropland by 103 construction occupation" was 21,011 km2. Yet in this period, the total cropland area 104 reduced by around 6% (Song & Pijanowski, 2014). Feng et al. (2015) and Song & 105 Pijanowski (2014) contend that the displacement of cropland as a result of the CSP can 106 lead to productivity decline and ecosystem degradation, and Chen et al. (2019) revealed 107 that newer cropland is generally less productive. Academic study has also focused on the 108 trade-off between changes of Ecosystem Services Value (ESV) and changes of potential 109 productivity of supplemented cropland (Zheng et al., 2018); and the amount, 110 heterogeneity, and patterns of supplemented cropland (Liu et al., 2019). Although 111 historical impacts of the CSP on ESV have been estimated in several studies (Chen et al., 112 2019), few of them identified the impacts of the CSP from other related policies, in 113 particular the Grain to Green Project, implemented during the same period (Wang et al.,

114 2017). This study begins to address a need for investigating the likely future impacts of
115 the CSP on local ecosystem services, which is arguably essential for any adaptive and
116 forward looking policy appraisal.

117 Given the landscape diversity and the CSP implementation context (will be 118 illustrated in Section 2.2), herein a case study of Hubei Province in China, which 119 investigates the impacts of the CSP on land use changes in associated with ESV variations 120 during the periods 2000-2015 and 2015-2030 is examined. It presents results of a 121 modelling exercise which explores the differences of both land use changes and ESV 122 changes under a couple of different policy scenarios: a scenario with Loose Cropland 123 Protection (LCP) and a scenario with Strict Cropland Protection (SCP). By comparing 124 the differences of land use and ESV changes between two scenarios, some impacts of the 125 CSP are identified.

126 **2.** Methodology and Data Source

127 2.1. Research framework

128 In order to investigate the impacts of the CSP on land use changes and ecosystem services, 129 the study was divided into two parts (Figure 1). The first step was to examine observed land use changes across the study area between 2000 and 2015. As the CSP was 130 131 introduced in 1998 in Hubei Province, observed land use changes were under the 132 influence of the CSP, thus a possible way to investigate the impacts of the CSP on land 133 use change is to compare observed land use changes and simulated land use changes 134 without the CSP influence. However, the CSP was not the only policy or change 135 influencing observed land use changes, the Grain for Green Project and major water 136 reservoir construction projects also had a significant influence on land use change during 137 this period. Thus, in order to identify the impacts of the CSP, two contrasting policy

138	scenarios were developed: the Strict Cropland Protection (SCP) scenario and Loose
139	Cropland Protection (LCP) scenario. Under the SCP scenario, the CSP applied, any loss
140	of cropland resulting from urban expansion was to be supplemented somewhere else in
141	the province to keep the area of cropland constant; whereas under the LCP scenario, any
142	cropland loss due to urban expansion was not required to be supplemented. The
143	LANDSCAPE model was applied to simulate the land use changes in the period 2000 to
144	2015 under both scenarios. Thus, the influence of the CSP on land use changes could be
145	examined by comparing the simulated land use from 2000 to 2015 under both LCP and
146	SCP scenarios. Then, the impacts of the CSP on ecosystem service associated with land
147	use change can be translated into ESV differences by using an equivalent factor method.
148	Based on a number of assumptions, land use change under the two scenarios was
149	simulated for the period 2015 to 2030. Again these changes were translated into estimated
150	changes in ESV to suggest the ecological impacts of the CSP under the different scenarios
151	in the next ten years.
152	
153 154	[Insert Figure 1 here]
134	
155	Figure 1. Research framework
156	
157	2.2. Study area and data sources
158	Located in the central China, Hubei Province covers an area of 185,900 km ² . Altitude
159	varies from less than 60m to more than 1800m above sea level. The western, northern
160	and eastern parts of the province are mountainous areas dominated by forest and
161	grasslands; the central and southern parts are lake plains covered by cropland, wetlands,
162	and urban land (Figure 2). Since the CSP has been implemented in the province (over the

163	last 20 years), many areas of natural habitat have been converted into cropland (Tang et	
164	al., 2020). More areas of natural habitat are expected to be converted in the future if the	
165	same CSP remains.	
166		
167 168	[Insert Figure 2 here]	
169 170	Figure 2. Land use of Hubei Province in China, 2015	
171	The data employed in the study are listed in Table 1. These include land use,	
172	terrain, accessibility, soil, climate, and socio-economic data.	
173 174	Table 1. Data Source: (Ke et al., 2018)	
175 176	[Insert Table 1 here]	
177	Land use data for Hubei Province are derived from Landsat TM images, and the	
178	overall accuracy is estimated to be above 90% in general at a spatial resolution of 30	
179	meters (Liu et al., 2005). For this study, the land use maps original twenty-five classes	
180	were reclassified to eight primary land use types (Table 2).	
181 182	Table 2. Land-use reclassification for Hubei Province, China Source: (Liu et al., 2005)	
183 184	[Insert Table 2 here]	
185	The digital elevation model (DEM) has a resolution of 90 meters. Slope was	
186	calculated from the DEM data. Soil data were obtained at a scale of 1:1,000,000. And,	
187	following Tang et al., (2020), the average annual cumulative temperature and annual	
188	precipitation for the period 1990 to 2010 were interpolated from sample points to the	

189 surface by applying Kriging approach. The absolute errors of interpolation of the average 190 annual accumulated temperature and annual precipitation were 0.20° C and 2.15 mm, 191 respectively. Soil data and climate data were used to evaluate agricultural suitability in 192 the LANDSCAPE model. Accessibility was estimated based on road network data, which 193 was extracted from the Traffic Atlas of Hubei Province (Table 1). The road network was 194 used to generate a Euclidean distance surface, which is used as a proxy for accessibility. 195 All the spatial datasets were converted to raster format with a resolution of 100 meters 196 for use in the LANDSCAPE model.

197

2.3 The LANDSCAPE model

198 The LANDSCAPE model is a cellular automata (CA) model (Ke et al., 2017; Ke et 199 al.,2018), which represents the study area as a regular gird of cells each with a single 200 (dominated) type of land use. In the LANSCAPE model, land use types are classified 201 into active or passive types, which are determined by the relationship between land use 202 and human demand (Ke et al., 2017). Changes in the area of active land use types are 203 specifically driven by demand, for example demand for new residential areas. In contrast, 204 changes in the area of passive land use types are driven by changes in the area of active 205 land use types (e.g., urban areas can expand into grassland areas, but grassland areas will 206 not expand into urban areas). The simulation of land use change is controlled by the 207 probability of transition (POT), which is the probability of occurrence of a target land-208 use type on any cell. The POT is derived from the suitability of each land use type and 209 the resistance to change of the existing land use type, formulated as Eq.(1):

210
$$POT_{j,eu,ou} = \frac{P_{j,ou}}{R_{j,eu}}$$
(1)

where $POT_{j,eu,ou}$ represents the probability that a cell *j* will transform from the existing land use type *eu* into the objective land use type *ou*; $P_{j,ou}$ refers to the suitability of land use type *ou* at cell *j*; $R_{j,eu}$ refers to the resistance to change of the existing land use type *eu*, which represents the likelihood of cell *j* being converted from the existing land use *eu* to any other land-use type.

216 Suitability
$$P_{j,ou}$$
 for a cell at location *j* is calculated as in Eq.(2):

217
$$P_{j,ou} = (1 + (-\ln r)^{\alpha}) \times PG_{j,ou} \times Con(C_{j,ou}) \times \Omega_{j,ou}$$
(2)

218 where r is a stochastic pseudo random number which is a value between 0 and 1 in the simulation; α is a dispersion factor that represents a random factor. $PG_{j,ou}$ is a factor 219 220 that represents the likelihood of change to the objective land use type ou given a 221 combination of biophysical and socioeconomic factors for the cell *j* including terrain 222 suitability, accessibility, soil and climate factor. $Con(C_{i,ou})$ is a binary constraint 223 variable, which indicates whether cell *j* is suitable for changing into a specific type of 224 land use ou (1 for suitable and vice versa). $\Omega_{j,ou}$ is the proportion of cells with the 225 objective land use type ou among all of the cells in the neighbourhood (commonly a 3×3 226 window) of the cell *j*.

Resistance in Eq.(1) refers to transition difficulty from current land use type to other land use types, which indicates the degree of neighbourhoods of the original land use can be occupied by the target type of land use, and can be calibrated and formulated as Eq.(3) (Ke *et al.*, 2017).

231
$$R_i = \frac{M_{max} - M_i}{M_{max} - M_{min}} \times (R_{max} - R_{min}) + R_{min}$$
(3)

where R_i is resistance of land use type *i*, and M_{max} , M_i , M_{min} , represent the maximum, median, minimum of degree of neighborhood of land use type *i* occupied by other land use types. In the model calibration, the degree of neighbourhood will be estimated by historical land use changes of study area. R_{max} and R_{min} are upper and lower bound of resistance range, respectively, and in this study these values were set as 1.5 and 1.0 following Ke *et al.*, (2017) and Tang *et al.*,(2020).

Once the parameters have been calibrated, the LANDSCAPE model will run iteratively with the given demand for each active land use type. The simulated change in land use of the study is then revealed iteratively year by year.

241

2.4 Evaluation of ESV changes

242 ESV has been a popular topic in ecological research (Costanza et al., 2014; Akber et al., 243 2018). de Groot et al. (2012) outlines two types of approach to evaluate ecosystem 244 services values: a so called *primary data based approach* which includes markets value 245 method and travel costs method, and is often applied to evaluate a single type of 246 ecosystem service; and, the equivalent factor method (Turner et al., 2015), where ESV is 247 assessed as the economic value per unit area of ecosystem via a basic value transfer 248 function (Costanza et al., 2014). Due to its extensive data requirements, the primary data-249 based approach is usually only employed on a small spatial scale. Therefore, given that 250 this study is a relatively-large scale study, the equivalent factor method was employed 251 with ESV calculated as in Eq.(4):

 $ESV = \sum_{f=1}^{n} (A_f \times VC_f)$ (4)

where *ESV* is the ecosystem services value for the entire study area; f refers to the land use types; A_f is the area of a land use type; and VC_f is the economic value of ecosystem services per unit area of land use type f. The values for VC_f used are given in Table 3. Table 3. Economic value of ecosystem services per unit area of each land use type
(CNY/km²)

259

260 261

[Insert Table 3 here]

Each VC_f value is taken from Xie *et al.*, (2017) and adjusted using agricultural net profit values of Hubei Province derived from social and economic data. Following Xie et al. (2017) and Song et al. (2017), the ESV of cropland was considered in this study in order to avoid underestimating the ESV at prefecture or provincial level.

266 2.5 Implementation of the LANDSCAPE model

267 2.5.1 Model calibration and validation

The probability of transition (POT) is the key parameter to calibrate the LANDSCAPE model. In this study, eight different types of land use (Table 2) were identified in the model. For each land use type, the suitability was calculated by Eq.(2). Following Ke *et al.*, (2017), the C5.0 decision tree algorithm was applied to estimate $PG_{j,ou}$ based on the four spatial driving factors, including terrain, accessibility, soil condition, and climate factors (variables are listed in Table 1). The resistance was calculated based on Eq. (3) with land use changes between 2000 and 2015.

The validation of LANDSCAPE model involve comparison between simulated land use map and real land use map. In this study, we set the demands for each type of land use in LANDSCAPE model as the total area of each land use in 2015, then run the simulation from 2000 to 2015. The Kappa Simulation approach, which is a coefficient of agreement between the observed land use changes and the simulated land use changes (van Vliet *et al.*, 2011), was used to measure the goodness of fit between the simulated and actual land use map 2015. The value of Kappa Simulation varies between -1 and 1,

282	where: 1 indicates perfect agreement; 0 indicates that the simulation is only as good as
283	results would be expected from a random model; and, negative values indicate that the
284	model is worse than random. In this research, the Kappa Simulation scores for all land
285	use types for the best fitting model are shown in Table 4, they are all above 0 although
286	for Grasslands the value is close to 0, suggesting an acceptable goodness-of-fit.
287	Table 4. Kappa Simulation scores for the model results
288 289 290	[Insert Table 4 here]
291	2.5.2 Land use changes simulation with LANDSCAPE under different scenarios
292	Urban land and cropland were set as active lands in the study as the urbanization process
293	and the implementation of the CSP in Hubei province are effectively demand driven. The
294	demand for urban land in 2015 was set as the observed area of urban land for both
295	scenarios. Under the SCP scenario, the demand for cropland in 2015 was set strictly as
296	the value in 2000; while under the LCP scenario it was set as open, the amount and
297	distribution of cropland was revealed by the simulation process.
298	As for 2030, the demand for urban land was set equal (Table 5) under both
299	scenarios, which was estimated via a simple exponential growth model with a static
300	growth rate starting from 2015. The annual growth rate was set as the average growth rate
301	of urban expansion in the period 2000 to 2015.
302	The demand for cropland between 2015 and 2030 was set the same way as the
303	simulation for the period 2000 to 2015. With the SCP scenario, demand for cropland was
304	set to be constant (as it was in 2015), and under the LCP scenario it was set open.
305	For the two periods of simulation (2000-2015 and 2015-2030), the location for
306	rural settlements and water areas was set as constant under both scenarios to establish a

307	baseline for comparison. Even though the area of water increased considerably during		
308	2000–2015 in Hubei Province - due to large scale water reservoir construction (i.e., The		
309	Three Gorges Reservoir), the water area was set to be constant for simplicity. The demand		
310	for each type of land is shown in Table 5.		
311	Table 5. The parameters applied for the land use scenarios		
312			
313	[Insert Table 5 here]		
314			

315 **3. Results**

316 3.1 Observed and simulated land use change 2000-2015

317 Figure 3 shows the observed and simulated land use change in Hubei province in the 318 period 2000 to 2015. In the real world, the total area of urban land and water expanded 319 significantly (by 3099.78 km² and 3004.17 km² respectively) in the province during this time, while the area of cropland fell by 4682.51km² despite the CSP being in place. A 320 321 considerable loss of natural habitat, including forest (667.92 km²) and wetlands (704.63 322 km²), is observed in this period. In the simulation, the urban area expanded at the same 323 speed as observed, the changes of other types of land use vary. Under the LCP scenario, 324 cropland area shrank by 1851.51 km², and the area of forest fell by 1006.56 km². Under 325 the SCP scenario, the area of cropland remained as it was in the year 2000, but there were reductions in the areas of forest (2479.74 km²) and wetland (437.87 km²). 326

The considerable differences between the observed land use change and the simulated data under the SCP scenario suggests that urbanization and the CSP are not the only driving forces for land use change. In fact, the loss of cropland during this 15 years is mainly a consequence of the large scale water reservoir construction projects (i.e. the Three Gorges Project) and the *Grain for Green Project*. Neither of these projects required

332	cropland supplement practice. The Grain for Green Project contributed to there being
333	less forest loss overall in the observed land use compared with the simulations.
334	A comparison between the simulated land use changes under different scenarios
335	(i.e. SCP vs. LCP) offers a way to investigate the impacts of the CSP in terms of land use
336	change and ecosystem services value (ESV) change.
337	
338	[Insert Figure 3 here]
339	
340	Figure 3. Observed and simulated land use changes in the period 2000 to 2015 in the
341	Hubei Province.
342	
343	3.2 Ecological impact of cropland supplement policy during 2000-2015
344	The impacts of the CSP on ecosystem can be revealed by comparing the land use changes
345	and ESV changes under LCP and SCP scenarios. As shown in Figure 3, under the LCP
346	scenario, the area of cropland decreased by 1851.51 km ² in the period 2000 to 2015,
347	whereas under SCP scenario, the area of cropland remains constant. Since large areas of

Figure 4 shows the differences of natural habitat areas between the LCP and SCP scenarios. The results show that the western part of Hubei Province, including Shiyan, Xiangyang, Yichang and Enshi, lost a significant amount more natural habitat than the eastern part of the province where higher population and urban expansion is observed.

more natural habitat were converted into cropland in the province, the total area of natural

habitat fells to 107538.51km² in 2015 under the SCP scenario – an additional loss of

1847.50km². The estimated cost in terms of loss of ESV in financial terms is 19.53 billion

356

348

349

350

351

CNY.

357 358

[Insert Figure 4 here]

Figure 4. Natural habitats areas differences among prefectures in Hubei Province between
LCP and SCP (2000-2015)

361

Figure 5 illustrates the non-urban land use changes under two scenarios (LCP and SCP) between 2000 and 2015 at prefecture level. This figure is in three parts. In parts a) and b): the horizontal axis represents the amount of land use changes, where a positive value indicates an area increase and negative value indicates an area loss; and, the results for each prefecture are shown as a bar.

367 The difference between Figure 5 a) and b), reveals a spatial effects of the CSP. 368 Under the LCP scenario, the areas of most land use types decreases and cropland 369 decreases in all prefectures. In Enshi, Shiyan and Yichang, the biggest change in land use 370 is a reduction in forest area. These three prefectures are located in a mountainous area in 371 the west of the province. The result for the more urban prefectures of Wuhan, Jingzhou, 372 and Huanggang in the east is a considerable loss in cropland, account for more than 60%373 of the total loss of all land use types. These prefectures are located in the Jianghan Plain 374 which is a major rice and other grain growing area.

Figure 5 b) shows that under SCP the results are that in some prefectures cropland will increase, but that overall the loss of forest land is huge. Wuhan is the prefecture that is likely to experience the greatest loss of cropland.

The difference between the LCP and SCP scenarios is shown in Figure 5 c). The main difference is that under SCP there is more cropland, but far less forest, wetland and grassland. But differences at the prefecture level are revealed with regard the proportion and relative amounts of change.

382	The model results are that in total: 1472.85 km ² area of forest (mainly in Shiyan,	
383	Enshi, Yichang and Xiangyang); 99.94 km ² of grassland (mainly in Enshi and Shiyan);	
384	and, 274.71 km ² of wetland (mainly in Jingzhou, Wuhan and Huanggang) would become	
385	cropland under SCP for the period 2000 to 2015.	
386		
387 388	[Insert Figure 5 here]	
389	Figure 5. Simulated change of non-urban land use type area by prefectures under two	
390	scenarios in the period 2000 to 2015 in Hubei Province.	
391		
392	3.3 Ecological impact of cropland supplement policy during 2015 and 2030	
393	This section presents the LANDSCAPE model results and the difference in ESV	

1 470 05 1

394 changes under the SCP and LCP scenarios from 2015 to 2030. Under the LCP scenario, the amount of cropland is modelled to decrease by 2108.32 km² between 2015 and 2030, 395 396 the total amount of natural habitat is modelled to decrease to 110681.19km². 397 Comparatively, under the SCP scenario, the amount of cropland remains constant, while 398 the total amount of natural habitat is modelled to decrease to 108576.61km², suggesting 399 an extra 2104.58km² loss of natural habitat compare to the LCP scenario. Figure 6 shows 400 land use change under both scenarios by land use types. It shows that new cropland often 401 replaces forest or wetland areas.

- 402
- 403 404

[Insert Figure 6 here]

405 Figure 6. Land use changes under LCP and SCP in the period 2015 to 2030 in the Hubei 406 Province.

407

408	Under the LCP scenario, the total ESV of Hubei Province falls to 925.77 billion
409	CNY by 2030, which is 11.13 billion CNY less than 2015. Under the SCP scenario, the
410	total ESV decreases to 913.23 billion CNY in 2030, suggesting an additional 12.54 billion
411	CNY loss during the period compared to the LCP scenario.
412	Figure 7 shows the spatial impact of the CSP at prefecture level. The model results
413	are that natural habitats of central Hubei prefectures (i.e., Xiangyang and Jingmen) will
414	experience the greatest loss of natural habitats under the SCP compared with LCP.
415	
416	[Insert Figure 7 here]
417	
418	Figure 7. Natural habitats areas differences between LCP and SCP (2015-2030) in the
419	Hubei Province
420	
421	Figure 8 shows the area changes of non-urban land use types at prefecture level
422	during 2015-2030. Under LCP scenario (illustrated in Figure 8 a), the area of cropland
423	drops in all prefectures. Four prefectures account for more than 50% of the total cropland
424	loss, which are Wuhan (471.01 km ²), Huangggang (257.87 km ²), Jingzhou (192.89 km ²),
425	and Jingmen (151.93 km ²). Figure 8 b) shows the land use changes by prefecture under
426	SCP scenario, where considerable increase in cropland area can be expected in Xiangyang
427	(129.56 km ²), Shiyan (126.84 km ²), Jingmen (86.94 km ²) and Enshi (60.70 km ²). Overall
428	under SCP, there is a loss of more natural habitat (i.e., 1560.44 km ² of forest, 89.6 km ²
429	of grassland, 454.54 km ² of wetland). Figure 8 c) makes the details about these
430	differences between the two scenarios clearer. The major differences under SCP

431 compared with LCP are an extra loss of wetland area in Jingzhou (97.90km²) and extra

432	losses of forest in Huanggang (208.44km ²), Jingmen (209.19km ²) and Xiangyang
433	$(224.60 \text{km}^2).$
434	
435 436	[Insert Figure 8 here]
437	Figure 8. Simulated changes of non-urban land use type area by prefecture under two
438	scenarios in the period 2015 to 2030 in Hubei Province
439	
440	Figure 9 shows the loss of the natural habitat as a proportion of the total land area
441	at prefecture level in 2015. The results suggest that Qianjiang would lose more than half
442	of its forest and all of its grassland, Tianmen and Xiaogan would lost more than half its
443	grassland under SCP.
444	
445 446	[Insert Figure 9 here]
447	Figure 9. The proportion of natural habitat loss during 2015-2030 against the level of
448	2015 in the Hubei Province
449	4. Discussion
450	Given food security concerns and considering increasing demand for food and
451	agricultural produce generally, cropland reclamation could be vital for countries with
452	large and growing populations. Many countries undergoing large scale and rapid
453	urbanization with scarce cropland resources have adopted CPP to maintain the quantity
454	and/or quality of cropland. Many countries in central Asia, South America and Africa are
455	experiencing cropland expansion (Liu et al., 2018; Zabel et al., 2019). Even though
456	cropland reclamation is a feasible option to meet future demand for food and agricultural
457	production, it is believed that cropland reclamation in association with urbanization

458 comes at the cost of natural habitat loss and ecosystem degradation (Zabel *et al.*, 2019).
459 It is essential for planners and stakeholders to further understand the spatial spill-over
460 effects of cropland reclamation practice and minimize the trade-off between crop
461 production and ecosystem protection.

462 Land use change as a result of rapid urban expansion does not have to pose 463 negative impacts in terms of agricultural productivity and ecosystems in general, but in 464 practice this is often the case. There is a legitimate concern and a need for wide reaching 465 consideration and analysis of policy and potential policy impacts at all scales. Given the 466 complex nature of spatial process, the advent of modern spatial simulation techniques (i.e. 467 Cellular Automata) offers a way to help understand spatial impacts of policy. This paper 468 demonstrated that the LANSCAPE model offers a feasible framework that is beneficial 469 for policy maker and stakeholders around the world to design local policy or assess the 470 ecological effects proactively. The framework can be employed to develop "what-if" 471 scenarios to assess the long-term consequences of different land use policies associated 472 with urban expansion in terms of changes in ESV.

473 In China, since early 2000, the CSP has been implemented in an attempt to maintain 474 agricultural productivity and food production capability. Although the CSP has been 475 largely successful in maintaining cropland area in the face of rapid urbanization, Song & 476 Pijanowski (2014) revealed that in general productivity is lower in the newly created 477 cropland areas, and Chen et al. (2019) raised concerns that the CSP contributed to 478 widespread ecosystem degradation. Whilst these and other previous studies, such as Xin 479 & Li (2018), highlight some of the general issues of the current CSP implementation, few 480 studies have investigated the impacts spatially in the way done in this study. By adopting 481 a scenario based simulation approach, this study not only identified impacts of the CSP 482 on regional ecosystem service from a series of land use related policies implemented at

the same time, but also quantified the potential impact of the CSP on ecosystem servicein the future.

485 A series of reforms have been proposed that aim to balance the productivity of 486 cropland in China (Lu et al., 2017). The impacts of these reforms at prefecture and 487 provincial levels should be investigated as they are likely to lead to a detrimental loss of 488 ecosystem services in some places adversely impacting human health and well-being. 489 According to the "ecological civilization construction" strategy promoted by the Chinese 490 government, the ecological (and social) impacts of the CSP shouldn't be ignored in 491 implementation (Lu et al., 2017). This paper adds to the call for the development of a 492 comprehensive cost, benefit and risk assessment framework for evaluating the CSP and 493 for use as a policy making instrument.

494 Some simplifying assumptions were made in the study to cope computationally 495 with the demands of the LANDSCAPE model. In particular, the mechanism of land use 496 change was simplified as a probability function in the modelling process. The land use 497 type with the highest conversion probability is the priority for grid cell allocation. 498 However, similar to previous land use changes simulation models, such as FLUS (Liu et 499 al., 2017), the probability function is widely accepted for the land use change simulations. 500 And, the simulated amount of cropland area of 2015 for both scenarios were higher than 501 the observed cropland area in 2015 mainly due to the extra cropland acquisition for 502 construction of the water reservoirs, which is not considered in the model. Additionally, 503 natural protected areas are not considered, due to lack of accurate and available data.

The area based equivalent factor approach applied in this study also introduces uncertainty into the ESV evaluation. The uniform equivalent factor method ignores the spatial heterogeneity in ecosystem service for each type of land use, and does not take the spatial patterns (e.g. natural habitat fragmentation etc.) into consideration. The difference in ESV between newly reclaimed cropland and those mature cropland areas was ignored in this study, as the maturation period for newly reclaimed cropland is assumed to be relatively short within the simulated period. This simplification may tend to slightly underestimate the impact of the CSP on ecosystem service, however it does not change the main conclusion since the expected reduction in ESV is large anyway.

The ESV for urban land was set as zero in this study, although in reality urban land can also provide some ecosystem services. Yet, there is a lack of in-depth understanding and robust approach to evaluation of ecosystem services of urban land (Yi *et al.*, 2017). From the provincial or even larger scale policy perspective, it is reasonable to ignore the ESV provided by urban land as those values are cumulatively small compared with those of cropland and natural habitats.

519 The spatially explicit nature of the LANDSCAPE model provides flexibility and 520 takes the spatial heterogeneity of land use into consideration, to evaluate the impact of 521 any land use policy on ecosystem service in the future. For cropland protection purposes, 522 a more comprehensive evaluation framework is wanted to help policy-makers and 523 stakeholders further understand the spatial impact of CPP on habitat quality, carbon 524 storage and biodiversity as well as on ESV. The simulation based policy appraisal 525 framework demonstrated in this study provides a good foundation for future policy 526 optimization practice which aims to minimize the trade-off between the crop production 527 and ecosystem protection.

528 **5.** Conclusions

529 By taking Hubei province as a case, this study identified and quantified negative impacts 530 of the CSP on natural habitats and ecosystem service under urban expansion by 531 comparing simulated land use change under two different policy scenarios (known as

532 LCP and SCP). The results suggest that not only urban expansion but also the CSP 533 threatens ecosystems in the study area. The differences of ESV changes in the simulated 534 results under both scenarios indicates how much of an effect the CSP can have at different 535 levels. There are significant differences in the expects loss of natural habitat in the 536 prefectures of Hubei Province under the two scenarios, and a general significant loss of 537 natural habitat for the province as a whole under both. During the period 2000 to 2015, 538 about 1847.50 km² of natural habitat was replaced by new cropland, and this is associated 539 with a total 19.53 billion reduction in ESV. In the period 2015 to 2030 it is estimated that 540 the current CSP implementation will require 2104.58 km² of natural habitat to be replaced 541 with new cropland, and this may lead to an additional loss of 12.54 billion CNY of ESV 542 if rapid urban expansion continues as predicted. Additionally, due to the spatial 543 heterogeneity of the land use, prefectures of Hubei Province will meet various degrees of 544 ecosystem degradation risk under the influence of the CSP. For instance, even though the 545 total area of forest and grassland are not that high in Qianjiang, Xiaogan and Tianmen, 546 the high percentage loss of this natural habitat might result in worse degradation of the 547 already fragile ecosystems in these areas.

This research reveals that implementation of the CSP in rapidly urbanizing areas has significant effects on the ecosystem services value. Decision-makers should not ignore the spatial differences of ecological impacts in economic decisions or land use planning practice. Given the negative effects of the CSP, more sophisticated policies should be proposed to balance economic growth, food security and maintain ecological balance and avoid the further environmental degradation especially of very fragile areas.

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Table 1. Data Source:	(Ke et al.,	2018)
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Dataset	Variables	Data Source
Land use data	Land use 2000	Resource and Environment Data Cloud Platform, Chinese Academy of
	Land use 2015	Science
Terrain data	Elevation	The Shuttle Radar Topography Mission (SRTM)
	Slope	
Accessibility data	Euclidean distance to the nearest railway	The Traffic Atlas of Hubei
	Euclidean distance to the nearest highway	
	Euclidean distance to the nearest state road	
	Euclidean distance to the nearest provincial road	
	Euclidean distance to the nearest main road	
	Euclidean distance to the nearest county road	
Soil data	Soil pH value	The China Soil Database
	Effective soil depth	
	Soil organic matter content	
	Soil phosphorus	
Climate data	Average annual cumulative temperature	Chinese Meteorological Administration
	Annul precipitation	
Socio-economic	Net profits of agricultural products	National Agricultural Statistics 2016
data	Planting areas of rice, wheat and maze	Hubei Provincial Statistical Yearbook 2016

Table 2. Land-use reclassification for Hubei Province, China Source: (Liu et al., 2005)

Land-use reclassification	Sub-classes of land-use
Cropland	Paddy land, and Dry land
Forest	Forest, Shrub, Woods, and Others
Grasslands	Dense grass, Moderate grass, and Sparse grass
Water area	Stream and rivers, Reservoir and ponds, and Lakes
Wetlands	Permanent ice and snow, Beach and shore, Bottomland, and Swampland
Urban land	Urban built-up, Industrial, mining and transportation construction
Rural settlement	Rural settlement
Unused land	Sandy land, Gobi, Salina, Bare soil, Bare rock, and Others

Table 3. Economic value of ecosystem services per unit area of each land use type (CNY/km²)

Land use types	Cropland	Forest	Grasslands	Water area	Wetlands	Unused land
Equivalent value	958,061	5,583,432	3,778,882	30,466,329	12,641,550	48,509

 Table 4. Kappa Simulation scores for the model results

Land use types	Cropland	Forest	Grasslands	Wetlands	Urban land	Rural settlement	Unused land
Kappa Simulation	0.105	0.026	0.008	0.186	0.307	0.037	0.101

 Table 5. The parameters applied for the land use scenarios

	2000	2015	SCP (2030)		LCP (2030)	
	Area (km ²)	Area (km ²)	Demand (km ²)	Resistance	Demand (km ²)	Resistance
Cropland	69598.07	64915.56	64915.56	1	-	1
Forest	92468.27	91800.35	-	1.25	-	1.25
Grasslands	7005.37	6815.35	-	1.25	-	1.25
Water area	6349.98	9354.15	-	1.5	-	1.5
Wetlands	4771.14	4066.51	-	1.25	-	1.25
Urban land	1487.3	4587.08	8054.95	1.5	8054.95	1.5
Rural settlement	3648.55	3796.61	-	1.5	-	1.5
Unused land	52.87	45.94	-	1	-	1



Figure 1. Research framework



Figure 2. Land use of Hubei Province in China, 2015



Figure 3. Observed and simulated land use changes in the period 2000 to 2015 in the Hubei Province.



Figure 4. Natural habitats areas differences among prefectures in Hubei Province between LCP and SCP (2000-2015)



Figure 5. Simulated change of non-urban land use type area by prefectures under two scenarios in the period 2000 to 2015 in Hubei Province.



Figure 6. Land use changes under LCP and SCP in the period 2015 to 2030 in the Hubei Province.



Figure 7. Natural habitats areas differences between LCP and SCP (2015-2030) in the Hubei Province



Figure 8. Simulated changes of non-urban land use type area by prefecture under two scenarios in the period 2015 to 2030 in Hubei Province



Figure 9. The proportion of natural habitat loss during 2015-2030 against the level of 2015 in the Hubei Province