Supplementary

Text S1. Description of the two models used in this study.

Urban growth scenarios were simulated by an autologistic regression–Markov chain–based cellular automata model, which integrates the auto logistic regression, Markov chain with cellular automata (Xu et al., 2019). In this model, the growth of settlement areas was simulated according to the following steps. First, considering the characteristics of the study area and the nature of the model, potential driving factors of urban growth were collected (including environmental factors, neighborhood factors, spatial characteristic factors, and socioeconomic factors). Based on these driving factors, local transition probabilities were calculated by the autologistic regression that is capable of addressing the spatial dependency that existed in the pattern of urban growth. Meanwhile, a transition probability matrix, which recorded the probability of each land-use type to change into the urban settlement, was obtained from the Markov chain analysis. Afterward, a final transition probability map was generated by combining the local transition probabilities with the transition probability matrix. Finally, according to the final transition probability map, settlement growth was allocated using the cellular automata under certain neighborhood rules. Please refer to Xu et al. (2019) for more details of this urban growth model.

Noteworthily, urban shrinkage has become another path of urban development worldwide (Haase et al., 2012). Urban shrinkage models have been developed for predicting the shrinkage of urban areas (Lauf et al., 2012). However, common urban shrinkage models were not applicable in this study because of lacking empirical evidence of urban shrinkage in this region (Xu et al., 2018). As highlighted in the previous study, the vacant land resulting from urban shrinkage offers an opportunity for the development of green spaces that can improve the quality of living environment (Hollander et al., 2009). Accordingly, an integer programming based urban green space optimization model built in the GAMS software environment was applied for simulating the urban shrinking scenarios (Pribadi and Xu, 2017). Based on previous studies, the provision of nearby green spaces is regarded to be more beneficial to residents in terms of daily short-time recreational services (Kabisch et al., 2016; Lauf et al., 2014). Thereby, the minimum size and the maximum service radius of the new green spaces to be developed were set at 2 ha and 300 meters, respectively. In this model, new green spaces were developed in the low-density settlement patches that had no green space (≥ 2 ha) available within 300 m. Besides, the beneficial areas (i.e., settlement areas within 300 m of these new green spaces) were maximized. Please refer to Pribadi and Xu (2017) for more details of this urban growth model.

Table S1. Descriptions of the landscape metrics used in this study.

Landscape metrics	Description (McGarigal and Marks, 1995; Wu et al., 2002)
Patch complexity	
Largest Patch Index (LPI)	The percentage of total landscape area comprised by the largest patch
Total Edge (TE)	The sum of the lengths (m) of all edge segments in the landscape
Edge Density (ED)	The sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2)
Landscape Shape Index (LSI)	A standardized measure of total edge or edge density that adjusts for the size of the landscape. It measures the shape complexity of the entire landscape
Mean Patch Size (AREA_MN)	The sum, across all patches in the landscape, of the area (m^2) of each patch, divided by the total number of patches
Area-Weighted Mean Patch Size (AREA_AM)	The sum, across all patches in the landscape, of the area (m^2) of each patch multiplied by the proportional abundance of the patch
Perimeter-Area Fractal Dimension (PAFRAC)	The fractal dimension of the whole landscape which equals 2 divided by the slope of regression line between the logarithm of patch area (m^2) and the logarithm of patch perimeter (m)
Mean Patch Shape Index (SHAPE_MN)	The sum, across all patches in the landscape, of the patch-level shape index, divided by the total number of patches. Shape index equals patch perimeter (m) divided by the square root of patch area (m^2)
Mean Fractal Dimension Index (FRAC_MN)	The patch-level fractal dimension averaged over all patches in the landscape. Patch fractal dimension index equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2)
Aggregation	
Contagion (CONTAG)	Measures the extent to which patches are spatially aggregated by computing the probability that two randomly selected adjacent pixels belong to the same patch type
Interspersion and Juxtaposition Index (IJI)	Measures the distribution of adjacencies among unique patch types
Percentage of Like Adjacencies (PLADj)	Measures the degree of aggregation of patch types by considering only dispersion and not interspersion

Table S1. Descriptions of the landscape metrics used in this study (*continued*).

Landscape metrics	Description (McGarigal and Marks, 1995; Wu et al., 2002)
Aggregation Index (AI)	The area weighted mean class-level aggregation index which equals the number of like adjacencies divided by the maximum possible number of like adjacencies involving the corresponding class
Landscape Division Index (DIVISION)	The probability that two randomly chosen pixels in the landscape are not situated in the same patch
Splitting Index (SPLIT)	The total landscape area (m^2) squared divided by the sum of patch area (m^2) squared, summed across all patches in the landscape
Effective Mesh Size (MESH)	The size of the patches when the landscape is subdivided into S patches, where S is the value of the splitting index
Diversity	
Patch Richness (PR)	The number of different patch types in the landscape
Patch Richness Density (PRD)	The number of different patch types divided by total landscape area (m^2)
Shannon’s Diversity Index (SHDI)	The proportional abundance of each patch type
Simpson’s Diversity Index (SIDI)	The probability that any 2 pixels selected at random would be different patch types
Modified Simpson’s Diversity Index (MSIDI)	Eliminates the intuitive interpretation of Simpson's index as a probability
Shannon’s Evenness Index (SHEI)	The observed SHDI divided by the maximum SHDI for that number of patch types. It measures the degree of evenness as the complement of dominance
Simpson’s Evenness Index (SIEI)	The observed SIDI divided by the maximum SIDI for that number of patch types. It measures the degree of evenness as the complement of dominance
Modified Simpson’s Evenness Index (MSIEI)	The observed modified MSIDI divided by the maximum MSIDI for that number of patch types. It measures the degree of evenness as the complement of dominance

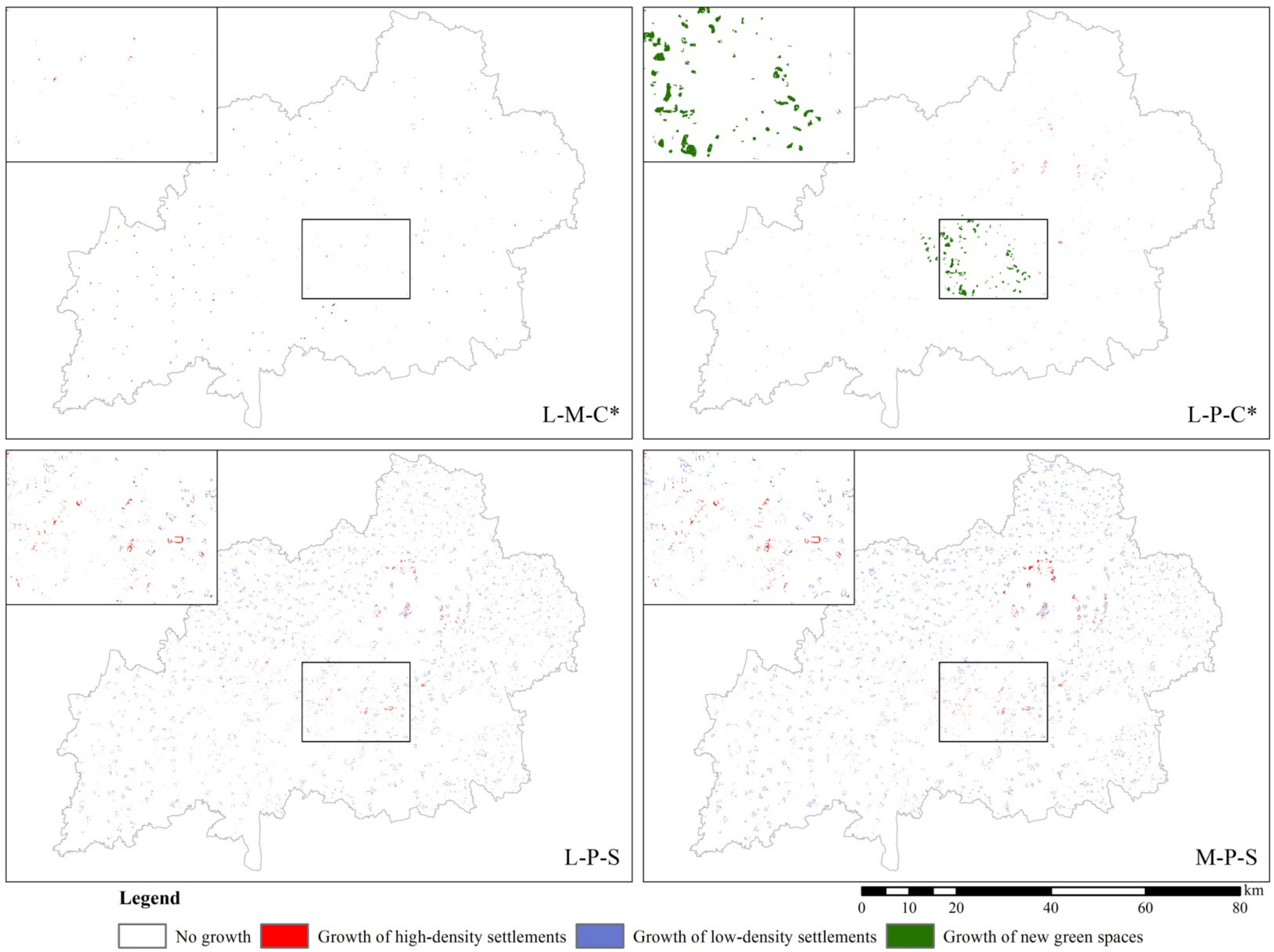

Figure S1. The spatial distribution of settlement growth in the selected scenarios (* indicates the shrinking scenarios. Figure continued on next page).

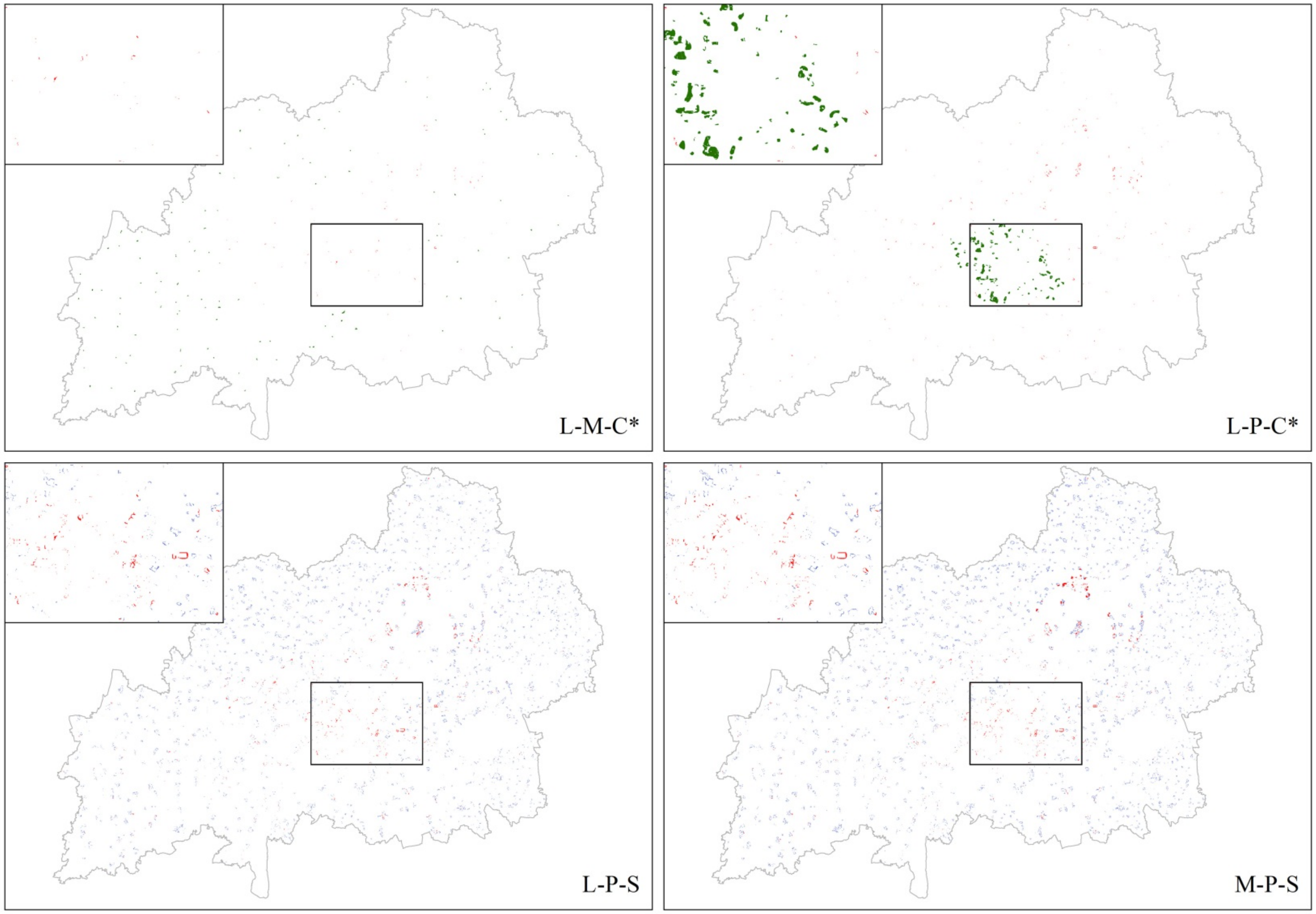

Figure S1. (*continued*).

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