Assessing spatiotemporal variations and predicting changes in ecosystem service values in the Guangdong–Hong Kong–Macao Greater Bay Area

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ABSTRACT
Rapid economic development and interference by human activities in rapid urbanization regions have caused great land use/land cover change (LUCC), which significantly affects ecosystem functions and services. It is crucial to assess the spatiotemporal evolution of ecosystem service value (ESV) in such regions, especially for the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) in China. In this study, we investigated and predicted the effect of LUCC on the ESV in the GBA from 1990 to 2030 using the latest annual dataset of land use simulation (FLUS) model, and ecosystem service evaluation approaches. The study period was divided into the historical period (1990–2015) and the forecast period (2015–2030). The results showed that forest and cropland were the dominant land-use types (>77% of the GBA), and the expansion of built-up land (3822.4 km²) was the clearest process during 1990–2015. The reduction of cropland and forest contributed the most to the decrease in the total ESV. Moreover, the results confirmed that the FLUS model is effective at predicting future LUCC in the GBA. The ESV was predicted to decrease to 4962.23 × 100 million yuan in the 2030s under the current development mode if regional forest and waterbody reductions are not constrained. This study provides a reference for promoting the rational use of land resources and ecological construction in the GBA and can help to promote ecological planning and environmental protection.

Introduction
Land use/land cover change (LUCC) is the direct response of the regional natural environment to human economic activities (Lambin and Geist 2008; Pielke 2005). Serving as a bridge between human activities and the Earth’s surface, LUCC plays a crucial role in global change (Ojima, Galvin, and Turner 1994; Smith et al. 2016; Wilbanks and Kates 1999). Human activities can directly or indirectly cause regional environmental change, which produce different land-use patterns (Veldkamp and Lambin 2001; Wu 2013). LUCC is also an indicator of human activities that modify the Earth’s landscape and societal development (Liu et al. 2010). With the increase in global population, the demand for global land resources is increasing, and the health and productivity of the land are deteriorating (Cowie et al. 2018; Ramankutty et al. 2006; Valipour, Bateni, and Jun 2021). Moreover, land-use change, as the clearest manifestation of global environmental change, can indirectly affect surface material cycles and ecological processes such as climate change, biodiversity, biogeochemical cycles, and sustainable use of resources (Imhoff et al. 2004; Liang, Hashimoto, and Liu 2021; Ojima, Galvin, and Turner 1994; Song and Deng 2017; Valipour, Bateni, and Jun 2021). The ability of an ecosystem to provide services for human well-being is directly linked to the state of the ecosystem (its structure and processes) (Costanza 2000). The increased pressure on the ecosystem or change in land-use

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types can influence the ecosystem service (ES) supply or trade-offs between different services (Bateman et al. 2013; Ma et al. 2020).

Since Costanza et al. (1997) introduced the concept of ecosystem service value (ESV) in 1997, many studies have contributed to related theories, methods, and systems (Braat and de Groot 2012; Daily et al. 2000; Shoyama et al. 2017). Because the specific ecosystem situation varies across regions, direct use may lead to overestimation or underestimation of the results (Bryant et al. 2018; Harrison et al. 2018). Therefore, many scholars have tried to improve ES classification, service value, and service value evaluation methods (Costanza et al. 2014; Luck et al. 2009; Martinez-Harms and Balvanera 2012; Roche and Campagne 2019). Urban expansion is a land-use change process that transforms non-urban land into urban land, which directly drives LUCC and changes the ecosystem (Lawler et al. 2014; Li et al. 2016). Many scholars have discussed how urban expansion affects ESV at different spatial scales (Chen et al. 2020b; Kertész, Nagy, and Balázs 2019; Shiferaw et al. 2019). However, existing research on the relationship between urban expansion and ESV has mainly focused on the correlation between the two, and it is difficult to determine the detailed quantity and spatial distribution of the ESV caused by urban expansion. In addition, ignoring the impact of urban agglomeration LUCC on ESV under multiple scenarios will limit the actual reference value of the results in government land-use planning. Moreover, the temporal scale and spatial details of most of these studies are insufficient to illustrate internal differences.

The Guangdong–Hong Kong–Macao Greater Bay Area (GBA) has been at the forefront of China’s reform and opening up (Zhang et al. 2020). The economy has developed rapidly in recent years. With the release of “the outline development plan for the GBA” in February 2019, which aims to develop the GBA into “a role of high-quality model development,” the GBA ushered in new development opportunities (Li et al. 2019). The rapid urban expansion in the GBA has accelerated the transformation of rural landscapes into urban landscapes, thereby resulting in severe damage to the landscape pattern and urban ecology, which will inevitably cause significant changes in ESV (Peng et al. 2015).

The limitations of ESV-related studies, especially in spatiotemporal analysis and predictions, are the primary gaps in previous studies. To fill these gaps, the future land use simulation (FLUS) model and ES evaluation approaches are introduced in this study to simulate LUCC and the corresponding ESV in the GBA. Specifically, this study aimed to examine (1) the spatiotemporal LUCC dynamics in the GBA; (2) the resulting changes in ESV; and (3) the prediction of the future LUCC and ESV changes in 2030. This study can provide a reference for promoting the rational use of land resources and ecological construction in the GBA and help to promote ecological civilization planning and environmental protection in the GBA.

**Study area**

The GBA is a typical example of rapid urbanization in China. It is located in China’s southern coastal area (21°32′–24°26′N, 111°20′–115°24′E) and encompasses two special administrative regions (Hong Kong and Macao) and nine cities in Guangdong Province (Guangzhou, Shenzhen, Foshan, Jiangmen, Zhongshan, Huizhou, Dongguan, Zhaoqing, and Zhuhai) (Figure 1). With a population of approximately 70 million people and a total area of approximately 56,000 km², the GBA is one of China’s most economically developed and open areas (Fig. S1). It has a diverse range of high-tech industries, manufacturing plants, overseas enterprises, financial companies, and educational resources, accounting for 12.6% of China’s gross domestic product (GDP) and 0.6% of the country’s population in 2018 (China National Bureau of Statistics 2019). The GBA is one of the four major bay areas in the world (Zhou et al. 2018). The Chinese government places a high priority on GBA construction and development (The Central Government of China 2019). Many policies and plans to simulate regional development have been announced (Chen et al. 2020c; Zhang et al. 2020).

**Methodology and Data Sources**

Detailed methodology and data sources are shown in Figure 2. Annual LUCC data sources in the GBA were collected, as described in Section 3.1. The proposed calculation approach of ESV, including different land-
Figure 1. Location and administrative division of the Guangdong–Hong Kong–Macao Greater Bay Area (GBA).

Figure 2. Flowchart of the methodologies presented in this study.
use types and the corresponding modified equivalent factor, is explained in Section 3.2. The FLUS model used to simulate LUCC through 2030 is described in Section 3.3. The predicted LUCC with satisfactory accuracy was used for corresponding future ESV analysis. We will describe these contents in detail in the following sections.

**LUCC data sources and change analysis**

The long-term series LUCC data were obtained from the latest annual 30 m LUCC database of China, which was developed by Tsinghua University, China (Xu et al. 2020). The database spans from 1980 to 2015 with 30 m spatial resolution and an annual time step. The data integrated images from the Moderate Resolution Imaging Spectroradiometer, Advanced Very High-Resolution Radiometer, and Landsat data using the Breaks for Additive Seasonal and Trend algorithm (Xu et al. 2020). More details can be found in previous studies (Tu et al. 2021; Xu et al. 2020). The dataset performed well in annual classification and change-detection accuracy (overall 75.61%), with annual average accuracy of 72.10%, 78.93%, and 91.89% for cropland, forest, and built-up land, respectively. It provides basic data for research on urban planning and ecological assessment (Tu et al. 2021; Zhao et al. 2020).

The land-use transition matrix was used to quantify the land-use change (Ferreira Filho and Horridge 2014). The land-use transition matrices were defined by comparing a successive set of images in different periods. In this study, we used ArcGIS 10.5 software to calculate transition matrices of different periods, including 1990–2000, 2000–2010, and 2010–2015. As shown in Table 1, the transition matrix displays the types of land use at periods P1 and P2. The symbol S\textsubscript{ij} represents the area of land transferred from type \(i\) to type \(j\). The diagonal elements (i.e. S\textsubscript{ii}) indicate the area of land retained in period P2. Elements excluded from the diagonal are land-use transitions from type \(i\) to type \(j\). The area of land in different types (S\textsubscript{ij} and S\textsubscript{ji}) is the sum of S\textsubscript{ij} over all \(j\) and \(i\), respectively. A further computation based on the matrix table was created to calculate the gains \((S\textsubscript{ij} - S\textsubscript{ii})\) and losses \((S\textsubscript{ii} - S\textsubscript{ij})\). The gain of one land-use type is equivalent to the transition from other land-use types between the study periods, whereas the loss represents the transition to other land-use types between periods.

**ESV analysis**

According to the United Nations, ecological services are grouped into four groups, namely provisioning services, regulating services, supporting services, and cultural services (Costanza et al. 1997). Based on the evaluation model (Costanza et al. 1997) and the real situation in China, Xie et al. (2003) proposed the equivalent factor method to evaluate China’s ESV. Subsequently, Xie et al. (2015) further revised the method and established an equivalent table of value coefficients (VCs) for different ESVs in China. In the equivalent table, the equivalent coefficient value of cropland is 1, which is the basic reference for regional correction and other land-use types (Xie et al. 2015). To ensure that the coefficients were appropriate to calculate the ESV for different regions, we revised the table for the GBA via correction coefficients based on the main grain yield in the GBA, as follows (Eq. 1):

\[
\beta = \frac{y}{Y}
\]

where \(\beta\) represents the correction coefficient at time \(t\) and \(y\) and \(Y\) are the grain yields of the GBA and China at time \(t\), respectively. In 2015, \(y\) and \(Y\) were 5.25 t/ha and 5.48 t/ha, respectively. Thus, \(\beta\) was calculated as 0.96.

Correspondingly, the equivalent values per unit area for different ecosystems in the GBA were calculated as follows (Eq. 2):

\[
E_a = \frac{1}{7} \times \frac{P \times Y}{A_g}
\]

where \(Y\) and \(A_g\) are the total yield and area of the main grains in Guangdong Province in 2015, respectively, and \(P\) is the average price of the main grains in 2015 (1939.7 yuan/t), which was acquired from the Grain Net of South China (http://www.grainmarket.com.cn).

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| Table 1. A typical transition matrix in land use/land cover change (LUCC) studies. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | P\textsubscript{2} |                 |                 |                 |
|                 | T\textsubscript{1} | T\textsubscript{2} | ... | T\textsubscript{n} | S\textsubscript{ii} | Loss |
| P\textsubscript{1} | T\textsubscript{1} | S\textsubscript{11} | S\textsubscript{12} | ... | S\textsubscript{1n} | S\textsubscript{11} + S\textsubscript{12} + ... + S\textsubscript{1n} | S\textsubscript{11} - S\textsubscript{ii} |
|                 | T\textsubscript{2} | S\textsubscript{21} | S\textsubscript{22} | ... | S\textsubscript{2n} | S\textsubscript{21} + S\textsubscript{22} + ... + S\textsubscript{2n} | S\textsubscript{21} - S\textsubscript{ii} |
| ...             | ...             | ...             | ... | ...             | ...             | ...             | ...             |
| T\textsubscript{n} | S\textsubscript{ni} | S\textsubscript{n2} | ... | S\textsubscript{nn} | S\textsubscript{ni} + S\textsubscript{n2} + ... + S\textsubscript{nn} | S\textsubscript{ni} - S\textsubscript{ii} |
| S\textsubscript{ij} | S\textsubscript{i1} | S\textsubscript{i2} | ... | S\textsubscript{in} | S\textsubscript{i1} + S\textsubscript{i2} + ... + S\textsubscript{in} | S\textsubscript{i1} - S\textsubscript{ij} |
| Gain            | S\textsubscript{ij} - S\textsubscript{ii} | S\textsubscript{i2} - S\textsubscript{ii} | ... | S\textsubscript{in} - S\textsubscript{ii} | S\textsubscript{ij} - S\textsubscript{ii} | ... | S\textsubscript{in} - S\textsubscript{ii} |
The modified equivalent factor method based on unit area value was then adopted to calculate the ESV. The ESV per unit area of different ecosystems of the GBA in 2015 is listed in Table S1.

Finally, the ESV was calculated based on Eq. (3), as follows:

$$ESV = \sum (S_k \times VC_k)$$

where $S_k$ is the area of $k$ land use (ha) and $VC_k$ is the ESV per unit area of $k$ land use (yuan/ha).

We also calculated the coefficient of sensitivity (CS) based on the ESV and VC (Bian and Lu 2013; Das and Das 2019; Kreuter et al. 2001). The results showed that the CSs of ESVs were all less than 1 (CS<1), which indicated that ESVs were inelastic in response to the VC and the modified ESV coefficient was applicable to the study area.

**ESV prediction**

**FLUS model**

The FLUS model is an improved future land-use change model that can explicitly simulate the long-term spatial trajectories of many LUCCs while accounting for human and natural environmental impacts, as well as solving complex land-use demand prediction and land-use allocation issues (Liu et al. 2017). It consists of a top-down system dynamics model and a down-top cellular automata (CA) model (Liang et al. 2018a). The artificial neural network (ANN) model is used to train non-linear relationships between historical land-use types and complex driving factors so that the probability of distribution can be calculated.

Land use data from 2005, as well as data on relevant physical, social, and economic dimensions, was used to run the FLUS model (Table 2). To represent the changes in distribution of different land-use types better, many driving factors were considered based on existing studies (Chen et al. 2020a; Zhe et al. 2020), including the digital elevation model, aspect, slope, river system, all level roads, and other data (e.g. protection zone) (Table 2). These data were used to train the ANN model for estimating the probability of occurrence in urban and non-urban areas. Ten neurons in the input layer and twelve neurons in the hidden layers made up the back-propagation ANN model used in this study. One-fifth of the pixels were chosen at random across the GBA as the training datasets. To normalize the probability values to the range of [0, 1], we used the sigmoid function as the activation function for output layers (Liang et al. 2018b). During the training process, the learning rate and terminal conditions of the ANN model are self-adaptive. In the simulation module, considering the filtering results and processing efficiency, the 3 x 3 Moore neighborhood was used to run the FLUS model based on repeated testing (Liang et al. 2018b; Wang et al. 2021). For the first iterations, the initial inertia coefficients were set to 1 and would self-adapt during the CA iteration.

**Markov chain model**

The Markov chain model can predict dynamic variations with high prediction precision and accuracy. It has been widely used in the prediction of land-use changes (Arsanjani et al. 2013).

| Category          | Data                  | Year       | Data Source                                                                 |
|-------------------|-----------------------|------------|----------------------------------------------------------------------------|
| Land use          | Land use data         | 1990–2015  | (Xu et al. 2020) From China Statistical Yearbook, China City Statistical Yearbook, Guangdong Provincial Statistical Yearbook, Hong Kong, and Macao Statistical Yearbook (Census and Statistics Department of Hong Kong 2019; China National Bureau of Statistics 2019; Statistics and Census Service of Macau 2019; Statistics Bureau of Guangdong Province 2018) |
| Socioeconomic data| Population            | 1990–2015  |                                                                               |
|                   | GDP                   | 1990–2015  | From China Statistical Yearbook, China City Statistical Yearbook, Guangdong Provincial Statistical Yearbook, Hong Kong, and Macao Statistical Yearbook (Census and Statistics Department of Hong Kong 2019; China National Bureau of Statistics 2019; Statistics and Census Service of Macau 2019; Statistics Bureau of Guangdong Province 2018) |
| Terrain           | DEM                   | SRM 30 m DEM [https://earthexplorer.usgs.gov] | Calculated using ArcGIS 10.5 from DEM |
|                   | Aspect                | Calculated using ArcGIS 10.5 from DEM |                                                                               |
|                   | Slope                 | Calculated using ArcGIS 10.5 from DEM |                                                                               |
| All levels of roads| National road         | 2015       | OpenStreetMap [https://www.openstreetmap.org/] |
|                   | Provincial road       | 2015       |                                                                               |
|                   | Highway               | 2015       |                                                                               |
| Other data        | Protection zone       | From the Geographical Information Monitoring Cloud Platform [www.dsac.cn] |                                     |
|                   | River system          | [https://www.protectedplanet.net/en] |                                     |
The land-use demand in 2030 was calculated using the Markov chain model in this study. We collected the land-use data in 2010 and 2015 and used the Markov chain transfer matrix to evaluate the reciprocal transform relationship between different land-use types. Future land-use types in 2030 were projected using a land conversion probability matrix with a five-year step, which was calculated using Eq. (4). The results are presented in Section 4.3.2.

\[
P = \begin{bmatrix}
P_{11} & \cdots & P_{1n} \\
\vdots & \ddots & \vdots \\
P_{m1} & \cdots & P_{mn}
\end{bmatrix}
\]

(4)

where \( n \) is the number of land-use types and \( P_{ij} \) is the probability that land-use type \( j \) is converted to land-use type \( i \) (\( 0 \leq P_{ij} \leq 1 \)).

**Model validation**

To validate the accuracy of the FLUS model, we compared the simulated LUCC with the remotely sensed LUCC in 2015 using four indicators, namely producer’s accuracy (PA), user’s accuracy (UA), Kappa, and the figure of merit (FoM) (Pontius et al. 2008). PA and UA are commonly used indicators for accuracy validation, and the calculation equations can be found in the study by Shao and Wu (2008). Kappa was calculated using Eq. (5), as follows:

\[
Kappa = \frac{(P_0 - P_c)}{(P_0 - P_e)}
\]

(5)

where \( P_0 \) denotes the simulation’s correct proportion, \( P_c \) denotes the model’s correct proportion in the random case, and \( P_e \) denotes the proportion of the correct simulation with ideal classification.

\( FoM \) (Eq. (6)) is the ratio of the intersection of the observed and predicted change to the union of the observed and predicted change (Murayama 2012; Perica and Foufoula-Georgiou 1996). The range of \( FoM \) is 0\% to 100\%, thereby indicating that there is no overlap between observed and predicted change and a perfectly accurate prediction (Wang and Li 2011).

\[
FoM = \frac{B}{(A + B + C + D)}
\]

(6)

where \( A \) represents the error area due to observed change predicted as persistence, \( B \) represents the correct area due to observed change predicted as change, \( C \) indicates the error area due to observed change predicted as persistence, and \( D \) indicates the error area due to observed persistence predicted as change (Hu, Li, and Lu 2018; Perica and Foufoula-Georgiou 1996).

**Results**

**Changes in LUCC**

Based on the results of land-use changes in the GBA during 1990–2015 (Figure 3 and Table 3), forest and cropland are the land-use types with the largest areas. In 2015, they accounted for over 77\% of the total area of the GBA (54\% and 23\%, respectively), whereas the proportions of wetland and unutilized land were approximately 1\%. From 1990 to 2015, the changing rates of different land-use were listed as built-up land (+102\%), wetland (−54\%), unutilized land (−67\%), cropland (−17\%), grassland (−5\%), forest (−3\%), and waterbody (+1\%). The corresponding areas were 3822.40, −163.10, −28.33, −2606.74, −70.66, −983.93, and 30.36 km².

Besides built-up land and waterbody, the areas of other land-use types showed a decreasing trend. The area of cropland decreased by 2606.74 km² from 1990 to 2015, and the most significant reduction of 1759.24 km² was observed during 1990–2000 (Table 3). Compared with that of cropland, the variation in forest was less clear, with a decrease from 30 769.15 km² to 29 785.22 km² during 1990–2015. Grassland decreased significantly from 1990 to 2010 (211.73 km²) and then increased slowly by 141.07 km² from 2010 to 2015. Based on the land-use transition matrixes of the GBA during 1990–2015 (Table 52), cropland (2147.30 km²) and forest (1015.18 km²) were the main two contributors to the increased area of built-up land. Because the total amount of grassland is small, the overall change was not clear.

**Spatiotemporal changes in ESV in the GBA**

The ESV in the GBA in 1990, 2000, 2010, and 2015 was 541.72, 545.91, 530.51, and 524.80 billion yuan, respectively. In general, the ESV increased first and then decreased from 1990 to 2015, decreasing by 16.92 billion yuan from 1990 to 2015. From 1990 to 2000, the ESV first increased by 4.20 billion and then decreased after 2000 (Table 4).
Because of the continuous decline in forest and cropland areas, their ESVs have continued to decrease. From 1990 to 2015, the ESV of forest and cropland decreased by 13.23 and 2.15 billion yuan, respectively. The variation in grassland showed a slow descending trend with a decrease of 0.54 billion yuan during 1990–2015. The changes in wetland ESV followed a similar trend to that of grassland, decreasing from 3.33 billion yuan in 1990 to 1.54 billion yuan in 2015. The ESV of unutilized land was stable owing to the small land-use change. Waterbody was the only ecosystem for which the ESV increased, but the increase was far smaller than the decrease of other ecosystems. The total ESV decreased by 3%.

The ESV of different ecosystem functions in the GBA is shown in Table 5. In 2015, the main contributors to each ecosystem function were hydrological regulation (32%), climate regulation (23%), soil conservation (9%), and biodiversity conservation (9%). The sum of hydrological regulation and climate regulation accounted for over 50% of the contribution, thereby indicating that regulating services are the
Table 4. Ecosystem service values of different land-use types in the study area from 1990 to 2015.

| LUC          | 1990 (100 million yuan) | 2000 | 2010 | 2015 | 1990–2000 | 2000–2010 | 2010–2015 | 1990–2015 |
|--------------|-------------------------|------|------|------|-----------|-----------|-----------|-----------|
| Cropland     | 124.41                  | 119.01| 104.53| 102.95| –4.34     | –12.17    | –1.51     | –17.25    |
| Forest       | 4138.57                 | 4119.64| 4045.88| 4006.23| –0.46     | –1.79     | –0.98     | –3.20     |
| Grassland    | 101.77                  | 94.28 | 85.56 | 96.36 | –7.36     | –9.25     | 12.63     | –5.32     |
| Wetland      | 33.33                   | 14.97 | 15.04 | 15.38 | –55.09    | 0.48      | 2.25      | –53.86    |
| Utilized land| 0.02                   | 0.01  | 0.01  | 0.01  | –59.35    | –15.08    | –3.83     | –66.80    |
| Water body   | 1019.01                 | 1111.18| 1054.05| 1027.08| 8.05      | –5.14     | –2.56     | 0.79      |
| Total        | 5417.11                 | 5459.09| 5305.07| 5248.01| 0.78      | –2.82     | –1.08     | –3.12     |

The sum of regulating services and supporting services was much greater than that of provisioning services and cultural services. Significant decreases in food production, maintain nutrient cycle, and gas regulation were detected owing to substantially reduced areas of wetland and cropland. Only water supply increased with a rate of change of 24% from 1990 (5.02 billion yuan) to 2015 (6.22 billion yuan), which might have been attributed to the increase in waterbody and cropland areas.

The ESV results of each city (Table 6) suggested that the ESV varies over space and time. Zhaoqing and Macao corresponded to the maximum and minimum ESVs. Dongguan (−31%) and Shenzhen (−26%) showed the two greatest historical changes in ESV during 1990–2015, decreasing by −6.12 billion yuan and −4.25 billion yuan, respectively. Historical increases in ESV were only found in Zhuhai (15%) and Jiangmen (2%). Shenzhen (−7%), Dongguan (−24%), and Zhuhai (−6%) showed significant decreases in ESV in 1990–2000, 2000–2010, and 2010–2015, respectively.

**ESV predictions**

**Results validation**

As indicated in Table 7, the verification results revealed that Kappa and FoM reached 0.79 and 0.07, respectively, which illustrated that the simulation

Table 5. Changes in ecosystem service value of each ecosystem function type in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) from 1990 to 2015.

| Ecosystem Service | 1990 (100 million yuan) | Percentage (%) | Changing rate(/%)
|-------------------|--------------------------|----------------|-------------------|
|                   |                           | 2000 | 2010 | 2015 | 1990–2000 | 2000–2010 | 2010–2015 | 1990–2015 |
| Provisioning      |                           | 2    | 2    | 2    | 2         | 2         | 2         | –9        |
| services          |                           | 2    | 2    | 2    | 2         | 2         | 2         | –4        |
| Regulating        |                           | 24   | 23   | 23   | 23        | 23        | 23        | –3        |
| services          |                           | 8    | 8    | 8    | 8         | 8         | 8         | –3        |
| Supporting        |                           | 2    | 2    | 2    | 2         | 2         | 2         | –2        |
| services          |                           | 1    | 1    | 1    | 1         | 1         | 1         | –5        |
| Cultural          |                           | 2    | 2    | 2    | 2         | 2         | 2         | –4        |

Table 6. Changes in ecosystem service value (ESV) at the city scale in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) during 1990–2015.

| Cities            | 1990 (100 million yuan) | 2000 | 2010 | 2015 | 1990–2000 | 2000–2010 | 2010–2015 | 1990–2015 |
|-------------------|-------------------------|------|------|------|-----------|-----------|-----------|-----------|
| Guangzhou         | 571.79                  | 580.44| 558.70| 554.25| 2         | –4        | –1        | –3        |
| Shenzhen          | 166.25                  | 148.59| 125.91| 123.73| –11       | –15       | –2        | –26       |
| Foshan            | 413.54                  | 430.62| 378.24| 367.48| 4         | –12       | –3        | –11       |
| Dongguan          | 196.33                  | 185.90| 140.37| 135.10| –5        | –24       | –4        | –31       |
| Zhuhai            | 108.57                  | 116.50| 132.74| 124.64| 7         | 14        | –6        | 15        |
| Jiangmen          | 884.79                  | 909.97| 909.68| 899.74| 3         | 0         | –1        | 2         |
| Zhaoqing          | 1687.41                 | 1690.43| 1702.98| 1695.59| 0         | 1         | 0         | 0         |
| Zhongshan         | 170.28                  | 173.73| 143.13| 139.93| 2         | –18       | –2        | –18       |
| Huizhou           | 1115.53                 | 1120.78| 1111.16| 1105.42| 0         | –1        | –1        | –1        |
| Hong Kong         | 101.02                  | 100.60| 100.65| 100.62| 0         | 0         | 0         | 0         |
| Macao             | 1.60                    | 1.55  | 1.52  | 1.52  | –3        | –2        | 0         | –5        |
results and accuracies were acceptable. The PA for cropland, forest, grassland, waterbody, wetland, built-up land, and unutilized land were 0.81, 0.96, 0.81, 0.77, 0.83, 0.66, and 0.76, respectively. The UA of the above-mentioned land-use types were 0.85, 0.96, 0.89, 0.78, 0.81, 0.58, and 0.70, respectively. The results showed that the simulation accuracy met the requirements and the model can accurately simulate the land-use change in the GBA. Therefore, the results of this study are reliable and can be used for future analysis in 2030.

We also conducted a comparison of actual LUCC with FLUS-predicted LUCC in 2015 (Figure 4). The actual and simulated areas of cropland, forest, grassland, waterbody, built-up land, and unutilized land in 2015 were 12 508.43 (simulated: 11 933.67), 29 785.22 (29 500.27), 1258.43 (1149.36), 3864.53 (3796.29), 139.73 (136.84), 7566.06 (8611.64), and 14.08 (13.78) km², respectively (Table 2 and 3). The spatial distribution of different land use also suggested that the performance of the FLUS model was satisfactory and could be further used for subsequent analysis.

**LUCC prediction**

The driving factors, including land use, socioeconomic data, terrain, and others, were used for the implementation of the FLUS model. The simulated results mainly reflected the future LUCC via general development mode in the GBA. The predicted areas of each land type in the GBA and subordinate cities were analyzed using 2015 as the basis. Under this specific scenario, built-up land was still predicted to be the fastest-growing land-use type

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**Table 7. Accuracy measurements of the predicted land use/land cover change (LUCC) based on the future land use simulation (FLUS) model in 2015.**

| Land use types  | Cropland | Forest | Grassland | Water-body | Wetland | Built-up land | Unutilized land | Total   | PA     | UA     |
|-----------------|----------|--------|-----------|------------|---------|---------------|-----------------|---------|--------|--------|
| Cropland        | 101,013  | 3437   | 36        | 1891       | 48      | 13,097        | 0               | 119,522 | 0.81   | 0.85   |
| Forest          | 1002     | 285,003| 1623      | 725        | 22      | 7251          | 3               | 295,629 | 0.96   | 0.96   |
| Grassland       | 5        | 725    | 10,289    | 18         | 6       | 552           | 0               | 11,595  | 0.81   | 0.89   |
| Water body      | 1895     | 1473   | 66        | 29,643     | 137     | 4665          | 2               | 37,881  | 0.77   | 0.78   |
| Wetland         | 43       | 16     | 14        | 102        | 1350    | 132           | 3               | 1660    | 0.83   | 0.81   |
| Built-up land   | 21,255   | 7734   | 613       | 6340       | 46      | 50,080        | 41              | 86,109  | 0.66   | 0.58   |
| Unutilized land | 0        | 4      | 0         | 0          | 19      | 43            | 154             | 220     | 0.76   | 0.70   |
| Total           | 125,213  | 298,392| 12,641    | 38,719     | 1628    | 75,820        | 203             | 552,616 | 0.79   | 0.07   |

**Figure 4.** Land use/land cover change (LUCC) spatial configuration in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA): (a) observed map of 2015 vs. (b) predicted map of 2015.
(9282.22 km$^2$) in 2030. However, the varying decreases in cropland (12,492.38 km$^2$), forest (28,671.07 km$^2$), grassland (11,578.2 km$^2$), waterbody (3384.76 km$^2$), wetland (134.50 km$^2$), and unutilized land (13.73 km$^2$) were predicted (Table S4). Regarding the spatial distribution, Jiangmen occupies the largest area of cropland (2499 km$^2$). The areas with the largest area of forest, grassland, waterbody, and built-up land in 2030 were Zhaoqing (10,925 km$^2$), Jiangmen (283 km$^2$), Foshan (814 km$^2$), and Guangzhou (1634 km$^2$), respectively (Figure 5). The predicted LUCC of the GBA in 2030 suggests that its spatial distribution pattern will be similar to that of 2015.

**ESV prediction**

Based on the FLUS-based LUCC and calculation framework of ESV (Sections 3.2 and 4.3.2), we predicted the ESV in 2030. The simulation results indicated that the ESV would decrease to 4962.23 × 100 million yuan in 2030 (Fig. S2). The greatest ESVs of different ESs were food production (93.28 × 100 million yuan), raw materials (121.35 × 100 million yuan), and water supply (51.44 × 100 million yuan) (Fig. S2). Compared with the ESV in 2015, the total ESV in the GBA in 2030 decreased by 285.78 × 100 million yuan owing to the reduction in ecological lands (forest, grassland, wetland, and waterbody). Among all ES types, hydrological regulation, climate regulation, and gas regulation were the three with the greatest predicted decrease in ESV in the future.

Among the individual cities in 2030, Zhaoqing was predicted to contribute the most to the total ESV in the GBA in 2030 (Table 8). The corresponding contribution in descending order was Zhaoqing (1623.22 × 100 million yuan), Jiangmen (822.80 × 100 million yuan), Foshan (334.05 × 100 million yuan), Shenzhen (127.86 × 100 million yuan), Dongguan (141.56 × 100 million yuan), Guangzhou (518.02 × 100 million yuan), Hong Kong (100.10 × 100 million yuan), Zhuhai (104.02 × 100 million yuan), and Macao (1.55 × 100 million yuan). Compared with historical ESV in 1990–2015, clear changes in ESV were found in the regions with rapid urban expansion, such as Guangzhou, Shenzhen, and Zhuhai. The decreased ESV was also relevant to the reduction in regional forest and waterbody.
Table 8. Ecosystem service value (ESV) of each land-use type for different cities in the study area.

| Cities     | Cropland | Forest  | Grassland | Water  | Wetland | Unutilized land | Total  |
|------------|----------|---------|-----------|--------|---------|-----------------|--------|
| Guangzhou | 17.33    | 387.39  | 7.59      | 103.45 | 2.25    | 0               | 518.01 |
| Shenzhen  | 2.04     | 104.39  | 2.25      | 18.65  | 0.54    | 0               | 127.87 |
| Foshan     | 8.27     | 107.04  | 0.94      | 216.41 | 1.39    | 0               | 334.05 |
| Dongguan  | 3.93     | 79.72   | 5.38      | 52.21  | 0.32    | 0               | 141.56 |
| Zhuhai    | 3.39     | 62.47   | 0.48      | 35.33  | 2.35    | 0               | 104.02 |
| Jiangmen  | 20.57    | 585.09  | 21.69     | 190.41 | 5.04    | 0               | 822.80 |
| Zhaoping  | 20.01    | 1469.52 | 18.47     | 114.32 | 0.9     | 0               | 1623.22|
| Zhongshan | 3.70     | 46.95   | 0.30      | 85.96  | 0.36    | 0               | 137.27 |
| Huizhou    | 23.09    | 930.52  | 19.55     | 77.38  | 1.24    | 0               | 1051.78|
| Hong Kong | 0.5      | 82.42   | 12.01     | 4.77   | 0.41    | 0               | 100.10 |
| Macao     | 0        | 0.86    | 0         | 0.69   | 0       | 0               | 1.55   |

Discussion

Eco-environmental effects of LUCC

LUCC is the most direct interaction between anthropogenic activities and the natural environment (Liu et al. 2017; Song and Deng 2017) and a main cause of environmental changes. Over the past decades, rapid LUCC changes have occurred in the GBA (Fang et al. 2020; Gong et al. 2020a; Liu et al. 2020). Population, economic activity changes, and transportation development have been recognized as the most significant drivers of LUCC and the key link of the coupled human–environment system (Li et al. 2017; Zhang et al. 2020), especially after China’s reform and opening up in the 1970s (Govada and Rodgers 2019) (Jiang, Ye, and Ma 2014). Regional industrial structure, consumption patterns, and dietary structure can also affect LUCC (Meng et al. 2021).

In this study, we investigated and predicted the effect of LUCC on the ESV of the GBA from 1990 to 2030 using the latest annual 30 m LUCC database of China, the FLUS model, and ESV evaluation approaches. Analysis of the spatiotemporal evolution process and characteristics of LUCC and ESV of the GBA is an important basis for optimizing ecosystem management and improving ecosystem quality. Correspondingly, the estimation of regional ESV can help to understand the synergistic effects of ESs with ecological coupling models. The related contents can provide insights into the relationships and mechanisms among different ESs and provide references for regional ES management and socioeconomic development. From this study, we can conclude that the ESV in the GBA is mainly composed of the ESs of forest, wetland, and waterbody. However, owing to the needs of urban development, the expansion of built-up land has crowded out other land-use types, thereby resulting in inevitable declines in other natural and semi-natural ecosystem areas. Therefore, the total ESV in the GBA decreased by 201.20 \times 100 million yuan from 1990 to 2015. Based on our simulated results, the ESV will decrease to 4962.23 \times 100 million yuan in the 2030s.

Urbanization is one of the most important drivers of the variations in ecosystem types and ESVs in the GBA. From 1986 to 2017, the total GDP increased from 284,245 million yuan to 10,032,690 million yuan, and the number of permanent residents increased from 2395.21 \times 10^4 to 6797.7 \times 10^4, an increase of 34 times and two-fold, respectively. Meanwhile, the expansion of cities and construction land continue to occupy cropland, forests, and wetlands, and human activities also affect the pattern of ecosystems and their potential functions. Guangdong had the fourth largest reclamation area. Jiang et al. (2021) found that over the past 30 years, the area of the GBA affected by reclamation activities was close to 600 km². The types of reclamation and utilization have changed from cropland and aquaculture pond land to urban expansion. Excessive reclamation has seriously affected the ecological functions of coastal wetland purification and pollution, beach protection, and bank protection. The saltwater marshes and mangroves along the coast of the GBA have been destroyed, which in turn has affected the water conservation function. This is consistent with our finding that the amount of water supply (hydrological regulation) in coastal cities such as Shenzhen, Dongguan, and Zhongshan has decreased. The decrease in supporting services (soil conservation and biodiversity conservation) may be attributed to the expansion of urban land and ineffective implementation of forest protection and restoration policies.
**Policy implications and suggestions**

Over the past few decades, China’s urban agglomeration areas have developed rapidly. Adhering to the concept of development as the main line, many phenomena such as land urbanization and population urbanization are common, which result in the loss of the overall ecological space and the deterioration of the ecological environment of the urban area, thereby making it difficult to form a sustainable urbanization development process (Fang and Yu 2017). Therefore, the latest measures of land and space planning and new urbanization planning have raised economic and social development and ecological environmental protection to the highest level (Chen, Liu, and Lu 2016).

Our results show that significant reduction and degradation of ESV have occurred during the rapid urbanization process in the GBA, which have caused significant damage to the ecosystem and serious environmental problems. For example, as a result of human disturbance, such as coastal zone development and wetland reclamation, natural wetlands have been sharply reduced and their functions have declined. In accordance with our results, from 1980 to 2015, the coastal reclamation area reached 467.33 km\(^2\) and the natural coastline declined by 289.62 km\(^2\) (18.71%) (Zhao et al. 2019). Natural mangroves in the GBA face the problems of shrinking areas, alien species invasion, and biodiversity loss (Yu et al. 2019). Moreover, landscape fragmentation has been greatly increased in the GBA and the area of the traditional reservoir pit in the GBA has sharply decreased by 47.33% since 1980 (Gong et al. 2020b). In 2018, the population density of Shenzhen was 6522 people/km\(^2\), which was the highest among all cities in China. Dongguan, Foshan, and Guangzhou are also among the top 10 cities with the highest population density in China (China National Bureau of Statistics 2019). With the economic development and urban expansion of the GBA, the population will continue to grow. It is expected that the population of the GBA will reach 150 million in 2022 and the conflict between increasing population and limited land will increase. Thus, governments need to establish more scientific and rational urban planning policies and regulations with a strong emphasis on protecting the natural ecosystems of the GBA.

**Limitations and perspectives**

Implementing the ES compensation system has emphasized ESV-related research (Chen et al. 2020b; Shiferaw et al. 2019; Zhang, Yushanjiang, and Jing 2019). Although this study tried to reveal the regional past-present-future spatiotemporal evolution patterns of ESV and provide necessary references for effective ecological planning and sustainable development, there are still some unavoidable uncertainties. As ecological services and ecological functions cannot be completely matched, there are insurmountable obstacles in the accurate calculation of ESV (Costanza et al. 2014; Shoyama et al. 2017). In our future research, various ES functions need to be refined. Moreover, a more accurate accounting system (classification and design) will help to accurately explain the variations in the ESV in the GBA. In this study, the FLUS model was used to predict the ecological landscapes and the spatial evolution of ESV. Considering the inherent principle of the FLUS model, we resampled the LUCC data. Conventional studies have only relied on transition probability to predict future evolution trends (Chen et al. 2020b; Song and Deng 2017). In comparison, this study has made progress in spatial simulation of ESV, and the corresponding simulation results are satisfactory.

Quantifying the regional ESV is the first step; a deep understanding of ESV is the key. Theoretically, our understanding of ecosystem value is constantly changing. Many ESVs exist, but they have not been included in the existing ESV accounting system because a universal measurement method has yet to be established. As a result, we should conduct related explorations, further expand the scope of accounting, and explore the value measurement methods of the contribution of ecosystems to urban development. In terms of specific operational applications, we intend to develop a comprehensive platform that includes both accurate extraction of LUCC and comprehensive measurement of ESV and deploy the platform in a cloud computing environment, such as Google Earth Engine. It is expected that the developed platform will link contributions from government departments and scientific simulations via remotely sensed data.

ESV-related studies also need to consider the synergy and restrictions between economic development and the ecological environment, as well as
the correlation between economic gains and ecological losses (Ma et al. 2020). Therefore, we need to analyze the coupling trend between economic development and environmental change under different development paths using dynamic change models and to establish a database of ecological service trade-off thresholds. Although not implemented in this study, we intend to develop a spatial allocation model by coupling the multiple LUCC dynamic simulation model to predict the spatial distribution of land use under more scenarios and depict different socioeconomic developments (population, GDP, and technological innovation) and natural climate changes (temperature and precipitation). Our study provides support to improve policymaking and understanding of the laws of LUCC.

**Conclusion**

This study analyzed the spatiotemporal LUCC dynamics and the resulting changes in ESV in the GBA from 1990 to 2015. Based on the results and other auxiliary data, the FLUS model was further used to simulate future ESV in the 2030s in the GBA.

Over the past decades, forest and cropland were the dominant land-use types, covering >77% of the GBA. From 1990 to 2015, the expansion of built-up land (3822.4 km²) was the clearest process. The reduction in cropland (2606.74 km²) and forest (983.93 km²) determined the decrease in the total ESV in the GBA during 1990–2015 to a great extent. The sum of hydrological regulation and climate regulation accounted for over 50% of the contribution, thereby indicating that the specific service type of regulating services is the greatest contributor. In terms of historical ESV changes in different cities in the GBA, Zhaoqing and Macao had the maximum and minimum ESV, respectively. Moreover, the results suggest that the FLUS model is an effective method to predict FLUS results satisfactorily, with a *Kappa* coefficient and *FoM* of 0.79 and 0.07, respectively. Based on the FLUS-based LUCC, the simulation results indicate that the ESV will decrease to almost 4962.23 × 100 million yuan in the 2030s. The decrease in ESV is also relevant to the reduction of regional forest and waterbody.

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**Data availability**

The data that support the findings of this study are available in figShare at https://figshare.com/s/089f5aa177bcefa0b2db.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

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**References**

Arsanjani, J. J., M. Helbich, W. Kainz, and A. D. Boloorani. 2013. “Integration of Logistic Regression, Markov Chain and Cellular Automata Models to Simulate Urban Expansion.” *International Journal of Applied Earth Observation and Geoinformation* 21: 265–275. doi:10.1016/j.jag.2011.12.014.

Bateman, I. J., A. R. Harwood, G. M. Mace, R. T. Watson, D. J. Abson, B. Andrews, A. Binner, A. Crowe, B. H. Day, and S. Dugdale. 2013. “Bringing Ecosystem Services into Economic Decision-making: Land Use in the United
Kingdom.” *Science* 341 (6141): 45–50. doi:10.1126/science.1234379.

Bian, Z., and Q. Lu. 2013. “Ecological Effects Analysis of Land Use Change in Coal Mining Area Based on Ecosystem Service Valuing: A Case Study in Jiawang.” *Environmental Earth Sciences* 68 (6): 1619–1630. doi:10.1007/s12665-012-1855-0.

Braat, L. C., and R. de Groot. 2012. “The Ecosystem Services Agenda: Bridging the Worlds of Natural Science and Economics, Conservation and Development, and Public and Private Policy.” *Ecosystem Services* 1: 4–15. doi:10.1016/j.ecoser.2012.07.011.

Bryant, B. P., M. E. Borsuk, P. Hamel, K. L. L. Oleson, C. J. E. Schulp, and S. Willcock. 2018. “Transparent and Feasible Uncertainty Assessment Adds Value to Applied Ecosystem Services Modeling.” *Ecosystem Services* 33: 103–109. doi:10.1016/j.ecoser.2018.09.001.

Census and Statistics Department of Hong Kong. 2019. *Hong Kong Statistics*. Accessed 1 July 2020. https://www.censtatd.gov.hk/hkstat/.

Chen, G., X. Li, X. Liu, Y. Chen, X. Liang, J. Leng, X. Xu, et al. 2020a. “Global Projections of Future Urban Land Expansion under Shared Socioeconomic Pathways.” *Nature Communications* 11 (1): 537. doi:10.1038/s41467-020-14386-x.

Chen, M., W. Liu, and D. Lu. 2016. “Challenges and the Way Forward in China’s New-type Urbanization.” *Land Use Policy* 55: 334–339. doi:10.1016/j.landusepol.2015.07.025.

Chen, S., Y. Feng, X. Tong, S. Liu, H. Xie, C. Gao, and Z. Lei. 2020b. “Modeling ESV Losses Caused by Urban Expansion Using Cellular Automata and Geographically Weighted Regression.” *Science of the Total Environment* 712: 136509. doi:10.1016/j.scitotenv.2020.136509.

Chen, W., H. Ran, X. Cao, J. Wang, D. Teng, J. Chen, and X. Zheng. 2020c. “Estimating PM2.5 With High-resolution 1-km AOD Data and an Improved Machine Learning Model over Shenzhen, China.” *Science of the Total Environment* 746: 141093. doi:10.1016/j.scitotenv.2020.141093.

China National Bureau of Statistics 2019. China Statistical Yearbook. Beijing, China.

Costanza, R., R. d’Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, et al. 1997. “The Value of the world’s Ecosystem Services and Natural Capital.” *Nature* 387 (6630): 253–260. doi:10.1038/387253a0.

Costanza, R., R. de Groot, P. Sutton, S. van der Ploeg, S. J. Anderson, I. Kubiszewski, S. Farber, and R. K. Turner. 2014. “Changes in the Global Value of Ecosystem Services.” *Global Environmental Change* 26: 152–158. doi:10.1016/j.gloenvcha.2014.04.002.

Costanza, R. 2000. “Social Goals and the Valuation of Ecosystem Services.” *Ecosystems* 3 (1): 4–10. doi:10.1007/s100210000002.

Cowie, A. L., B. J. Orr, V. M. Castillo Sanchez, P. Chasek, N. D. Crossman, A. Erlewein, G. Louwagie, et al. 2018. “Land in Balance: The Scientific Conceptual Framework for Land Degradation Neutrality.” *Environmental Science & Policy* 79: 25–35. doi:10.1016/j.envsci.2017.10.011.

Daily, G. C., T. Söderqvist, S. Aniyar, K. Arrow, P. Dasgupta, P. R. Ehrlich, C. Folke, A. Jansson, B.-O. Jansson, and N. Kautsky. 2000. “The Value of Nature and the Nature of Value.” *Science* 289 (5478): 395–396. doi:10.1126/science.289.5478.395.

Das, M., and A. Das. 2019. “Dynamics of Urbanization and Its Impact on Urban Ecosystem Services (Uess): A Study of A Medium Size Town of West Bengal, Eastern India.” *Journal of Urban Management* 8 (3): 420–434. doi:10.1016/j.jum.2019.03.002.

Fang, C., and D. Yu. 2017. “Urban Agglomeration: An Evolving Concept of an Emerging Phenomenon.” *Landscape and Urban Planning* 162: 126–136. doi:10.1016/j.landurbplan.2017.02.014.

Fang, X., W. Zhao, C. Zhang, D. Zhang, X. Wei, W. Qiu, and Y. Ye. 2020. “Methodology for Credibility Assessment of Historical Global LUCC Datasets.” *Science China Earth Sciences* 63 (7): 1013–1025. doi:10.1007/s11430-019-9555-3.

Ferreira Filho, J. B. D. S., and M. Horridge. 2014. “Ethanol Expansion and Indirect Land Use Change in Brazil.” *Land Use Policy* 36: 595–604. doi:10.1016/j.landusepol.2013.10.015.

Gong, P., X. Li, J. Wang, Y. Bai, B. Chen, T. Hu, X. Liu, et al. 2020a. “Annual Maps of Global Artificial Impervious Area (GAIA) between 1985 and 2018.” *Remote Sensing of Environment* 236: 111510. doi:10.1016/j.rse.2019.111510.

Gong, Q., H. Zhang, Y. Ye, and S. Yuan. 2020b. Planning Strategy of Land and Space Ecological Restoration under the Framework of Man-land System Coupling: Take the Guangdong-Hong Kong-Macao Greater Bay Area as an Example. *Geographical Research* 39: 2176–2188. in Chinese.

Govada, S. S., and T. Rodgers. 2019. “Towards Smarter Regional Development of Hong Kong within the Greater Bay Area.” In *Smart Metropolitan Regional Development: Economic and Spatial Design Strategies*, edited by T. M. Vinod Kumar, 101–171. Singapore: Springer Singapore.

Harrison, P. A., R. Dunford, D. N. Barton, E. Kelemen, B. Martín-López, L. Norton, M. Terramensen, et al. 2018. “Selecting Methods for Ecosystem Service Assessment: A Decision Tree Approach.” *Ecosystem Services* 29: 481–498. doi:10.1016/j.ecoser.2017.09.016.

Hu, X., X. Li, and L. Lu. 2018. “Modeling the Land Use Change in an Arid Oasis Constrained by Water Resources and Environmental Policy Change Using Cellular Automata Models.” *Sustainability* 10 (8): 2878. doi:10.3390/su10082878.

Imhoff, M. L., L. Bounoua, R. DeFries, W. T. Lawrence, D. Stutzer, C. J. Tucker, and T. Ricketts. 2004. “The Consequences of Urban Land Transformation on Net Primary Productivity in the United States.” *Remote Sensing of Environment* 89 (4): 434–443. doi:10.1016/j.rse.2003.10.015.

Jiang, J. J., B. Ye, and X. M. Ma. 2014. “The Construction of Shenzhen’s Carbon Emission Trading Scheme.” *Energy Policy* 75: 17–21. doi:10.1016/j.enpol.2014.02.030.
Liang, S., N. Xu, Z. Li, and C. Huang. 2021. “Satellite Derived Coastal Reclamation Expansion in China since the 21st Century.” *Global Ecology and Conservation* 30: e01797. doi:10.1016/j.gecco.2021.e01797.

Kertész, Á., L. A. Nagy, and B. Balázs. 2019. “Effect of Land Use Change on Ecosystem Services in Lake Balaton Catchment.” *Land Use Policy* 80: 430–438. doi:10.1016/j.landusepol.2018.04.005.

Kreuter, U. P., H. G. Harris, M. D. Matlock, and R. E. Lacey. 2001. “Change in Ecosystem Service Values in the San Antonio Area, Texas.” *Ecological Economics* 39 (3): 333–346. doi:10.1016/S0921-8009(01)00250-6.

Lambin, E. F., and H. J. Geist. 2008. *Land-use and Land-cover Change: Local Processes and Global Impacts*. Berlin, Heidelberg: Springer.

Lawler, J. J., D. J. Lewis, E. Nelson, A. J. Plantinga, S. Polasky, J. C. Withey, D. P. Helmers, S. Martinuzzi, D. Pennington, and V. C. Radeloff 2014. Projected Land-use Change Impacts on Ecosystem Services in the United States. Proceedings of the National Academy of Sciences, 111 (20): 7492–7497. doi:10.1073/pnas.1405557111.

Li, B., D. Chen, S. Wu, S. Zhou, T. Wang, and H. Chen. 2016. “Spatio-temporal Assessment of Urbanization Impacts on Ecosystem Services: Case Study of Nanjing City, China.” *Ecological Indicators* 71: 416–427. doi:10.1016/j.ecolind.2016.07.017.

Li, Q., Y. Yu, X. Jiang, and Y. Guan. 2019. “Multifactor-based Environmental Risk Assessment for Sustainable Land-use Planning in Shenzhen, China.” *Science of the Total Environment* 657: 1051–1063. doi:10.1016/j.scitotenv.2018.12.118.

Li, X., G. Chen, X. Liu, X. Liang, S. Wang, Y. Chen, F. Pei, and X. Xu. 2017. “A New Global Land-Use and Land-Cover Change Product at A 1-km Resolution for 2010 to 2100 Based on Human–Environment Interactions.” *Annals of the American Association of Geographers* 107: 1040–1059. doi:10.1080/24694452.2017.1303357.

Liang, X., X. Liu, D. Li, H. Zhao, and G. Chen. 2018a. “Urban Growth Simulation by Incorporating Planning Policies into a CA-based Future Land-use Simulation Model.” *International Journal of Geographical Information Science* 32 (11): 2294–2316. doi:10.1080/13658816.2018.1502441.

Liang, X., X. Liu, X. Li, Y. Chen, H. Tian, and Y. Yao. 2018b. “Delineating Multi-scenario Urban Growth Boundaries with a CA-based FLUS Model and Morphological Method.” *Landcape and Urban Planning* 177: 47–63. doi:10.1016/j.landurbplan.2018.04.016.

Liang, Y., S. Hashimoto, and L. Liu. 2021. “Integrated Assessment of Land-use/land-cover Dynamics on Carbon Storage Services in the Loess Plateau of China from 1995 to 2050.” *Ecological Indicators* 120: 106939. doi:10.1016/j.ecolind.2020.106939.

Liu, H., P. Gong, J. Wang, N. Clinton, Y. Bai, and S. Liang. 2020. “Annual Dynamics of Global Land Cover and Its Long-term Changes from 1982 to 2015.” *Earth System Science Data* 12 (2): 1217–1243. doi:10.5194/essd-12-1217-2020.

Liu, J., Z. Zhang, X. Xu, W. Kuang, W. Zhou, S. Zhang, R. Li, et al. 2010. “Spatial Patterns and Driving Forces of Land Use Change in China during the Early 21st Century.” *Journal of Geographical Sciences* 20: 483–494.

Liu, X., X. Liang, X. Li, X. Xu, J. Ou, Y. Chen, S. Li, S. Wang, and F. Pei. 2017. “A Future Land Use Simulation Model (FLUS) for Simulating Multiple Land Use Scenarios by Coupling Human and Natural Effects.” *Landscape and Urban Planning* 168: 94–116. doi:10.1016/j.landurbplan.2017.09.019.

Luck, G. W., R. Harrington, P. A. Harrison, C. Kremen, P. M. Berry, R. Bugter, T. P. Dawson, et al. 2009. “Quantifying the Contribution of Organisms to the Provision of Ecosystem Services.” *BioScience* 59 (3): 223–235. doi:10.1525/bio.2009.59.3.7.

Ma, X., J. Zhu, H. Zhang, W. Yan, and C. Zhao. 2020. “Trade-offs and Synergies in Ecosystem Service Values of Inland Lake Wetlands in Central Asia under Land Use/cover Change: A Case Study on Ebinur Lake, China.” *Global Ecology and Conservation* 24: e01253. doi:10.1016/j.gecco.2020.e01253.

Martínez-Harms, M. J., and P. Balvanera. 2012. “Methods for Mapping Ecosystem Service Supply: A Review.” *International Journal of Biodiversity Science, Ecosystem Services & Management* 8 (1–2): 17–25. doi:10.1080/21513732.2011.663792.

Meng, F., J. Guo, Z. Guo, J. C. K. Lee, G. Liu, and N. Wang. 2021. “Urban Ecological Transition: The Practice of Ecological Civilization Construction in China.” *Science of the Total Environment* 755: 142633. doi:10.1016/j.scitotenv.2020.142633.

Murayama, Y. 2012. “Progress in Geospatial Analysis.” Berlin, Germany: Springer Science & Business Media.

Ojima, D. S., K. A. Galvin, and B. L. Turner. 2004. “The Global Impact of Land-Use Change.” *BioScience* 44: 300–304. doi:10.3383/0006-3568(200403)44:3<300::AID-BIOS145>3.0.CO;2-9.

Peng, J., Y. Liu, J. Wu, H. Lv, and X. Hu. 2015. “Linking Ecosystem Services and Landscape Patterns to Assess Urban Ecosystem Health: A Case Study in Shenzhen City, China.” *Landcape and Urban Planning* 143: 56–68. doi:10.1016/j.landurbplan.2015.06.007.

Perica, S., and E. Foufoula-Georgiou. 1996. “Model for Multiscale Disaggregation of Spatial Rainfall Based on Coupling Meteorological and Scaling Descriptions.” *Journal of Geophysical Research: Atmospheres* 101 (D21): 26347–26361. doi:10.1029/96JD01870.

Pielke, R. A. 2005. “Land Use and Climate Change.” *Science* 310 (5754): 1625–1626. doi:10.1126/science.1120529.

Pontius, R. G., W. Boersma, J.-C. Castella, K. Clarke, T. de Nijs, C. Dietzel, Z. Duan, et al. 2008. “Comparing the Input, Output, and Validation Maps for Several Models of Land Change.” *The Annals of Regional Science* 42 (1): 11–37. doi:10.1007/s00168-007-0138-2.

Ramanukutty, N., L. Graumlich, F. Achard, D. Alves, A. Chhabra, R. S. DeFries, J. A. Foley, et al. 2006. “Global Land-Cover Change: Recent Progress, Remaining Challenges.” In Land-
Use and Land-Cover Change: Local Processes and Global Impacts, edited by E. F. Lambin and H. Geist, 9–39. Berlin, Heidelberg: Springer Berlin Heidelberg.

Roche, P. K., and C. S. Campagne. 2019. “Are Expert-based Ecosystem Services Scores Related to Biophysical Quantitative Estimates?” Ecological Indicators 106: 105421. doi:10.1016/j.ecolind.2019.05.052.

Shao, G., and J. Wu. 2008. “On the Accuracy of Landscape Pattern Analysis Using Remote Sensing Data.” Landscape Ecology 23 (5): 505–511. doi:10.1007/s10109-008-9215-x.

Shiferaw, H., W. Bewket, T. Alamirew, G. Zeleke, D. Teketay, K. Bekele, U. Schaffner, and S. Eckert. 2019. “Implications of Land Use/land Cover Dynamics and Prosopis Invasion on Ecosystem Service Values in Afar Region, Ethiopia.” Science of the Total Environment 675: 354–366. doi:10.1016/j.scitotenv.2019.04.220.

Shoyama, K., C. Kamiyama, J. Morimoto, M. Ooba, and T. Okuro. 2017. “A Review of Modeling Approaches for Ecosystem Services Assessment in the Asian Region.” Ecosystem Services 26: 316–328. doi:10.1016/j.ecoser.2017.03.013.

Smith, P., J. I. House, M. Bustamante, J. Sobocká, R. Harper, G. Pan, P. C. West, et al. 2016. “Global Change Pressures on Soils from Land Use and Management.” Global Change Biology 22 (3): 1008–1028. doi:10.1111/gcb.13068.

Song, W., and X. Deng. 2017. “Land-use/land-cover Change and Ecosystem Service Provision in China.” Science of the Total Environment 576: 705–719. doi:10.1016/j.scitotenv.2016.07.078.

Statistics and Census Service of Macau. 2019. Macau Yearbook of Statistics. Accessed 15 July 2020, https://www.dsec.gov.mo/getAttachment/9e71e788-2269-4e45-b222-d40a030b1819/E_AE_PUB_2019_Y.aspx.

Statistics Bureau of Guangdong Province. 2018. Guangdong Province Statistics Year Book. Guangzhou, China.

The Central Government of China. 2019. The Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area. Beijing, China: Central Government of China.

Tu, Y., B. Chen, L. Yu, Q. Xin, P. Gong, and B. Xu. 2021. “How Does Urban Expansion Interact with Cropland Loss? A Comparison of 14 Chinese Cities from 1980 to 2015.” Landscape Ecology 36: 243–263. doi:10.1007/s10109-020-01137-y.

Valipour, M., S. M. Bateni, and C. Jun. 2021. “Global Surface Temperature: A New Insight.” Climate 9 (5): 81. doi:10.3390/cli9050081.

Veldkamp, A., and E. F. Lambin. 2001. “Predicting Land-use Change.” Agriculture, Ecosystems & Environment 85 (1–3): 1–6. doi:10.1016/S0167-8809(01)00199-2.

Wang, Q., Q. Guan, J. Lin, H. Luo, Z. Tan, and Y. Ma. 2021. “Simulating Land Use/land Cover Change in an Arid Region with the Coupling Models.” Ecological Indicators 122: 107231. doi:10.1016/j.ecolind.2020.107231.

Wang, Y., and S. Li. 2011. “Simulating Multiple Class Urban Land-use/cover Changes by RBFN-based CA Model.” Computers & Geosciences 37 (2): 111–121. doi:10.1016/j.cageo.2010.07.006.

Wilbanks, T. J., and R. W. Kates. 1999. “Global Change in Local Places: How Scale Matters.” Climatic Change 43 (3): 601–628. doi:10.1023/A:1005418924748.

Wu, J. 2013. “Landscape Sustainability Science: Ecosystem Services and Human Well-being in Changing Landscapes.” Landscape Ecology 28 (6): 999–1023. doi:10.1007/s10180-013-9894-9.

Xie, G.-D., C.-X. Lu, Y. Leng, D. Zheng, and S. Li. 2003. Ecological Assets Valuation of the Tibetan Plateau. Journal of Natural Resources 18: 189–196. in Chinese.

Xie, G., C. Zhang, C. Zhang, Y. Xiao, and C. Lu. 2015. The Value of Ecosystem Services in China. Resources Science 37: 1740–1746. in Chinese.

Xu, Y., L. Yu, D. Peng, J. Zhao, Y. Cheng, X. Liu, W. Li, R. Meng, X. Xu, and P. Gong. 2020. “Annual 30-m Land Use/land Cover Maps of China for 1980–2015 from the Integration of AVHRR, MODIS and Landsat Data Using the BFAST Algorithm.” Science China Earth Sciences 63 (9): 1390–1407. doi:10.1134/s11940-019-9606-4.

Yu, L., S. Lin, X. Jiao, X. Shen, and R. Li. 2019. Ecological Problems and Protection Countermeasures of Mangrove Wetland in Guangdong-Hong Kong-Macao Greater Bay Area. Acta Scientiarum Naturalium Universitatis Pekinensis 55: 782–790. in Chinese.

Zhang, F., A. Yushanjiang, and Y. Jing. 2019. “Assessing and Predicting Changes of the Ecosystem Service Values Based on Land Use/cover Change in Ebinur Lake Wetland National Nature Reserve, Xinjiang, China.” Science of the Total Environment 656: 1133–1144. doi:10.1016/j.scitotenv.2018.11.044.

Zhang, J., L. Yu, X. Li, C. Zhang, T. Shi, X. Wu, C. Yang, W. Gao, Q. Li, and G. Wu. 2020. “Exploring Annual Urban Expansions in the Guangdong-Hong Kong-Macao Greater Bay Area: Spatiotemporal Features and Driving Factors in 1986–2017.” Remote Sensing 12 (16): 2615. doi:10.3390/rs12162615.

Zhao, J., L. Yu, Y. Xu, X. Li, Y. Zhou, D. Peng, H. Liu, et al. 2020. “Exploring Difference in Land Surface Temperature between the City Centres and Urban Expansion Areas of China’s Major Cities.” International Journal of Remote Sensing 41 (23): 8965–8985. doi:10.1080/01431161.2020.1797216.

Zhao, M., J. Kou, J. Yang, and W. Zhao. 2019. Study on the Ecological Security and Protection Measures of the Coastal Zone in Guangdong-Hong Kong-Macao Greater Bay Area. Environmental Protection 47: 29–34. in Chinese.

Zhe, T., G. Qingyu, L. Jinkuo, Y. Lijin, L. Haiping, M. Yunrui, T. Jing, W. Qingzheng, and W. Ning. 2020. “The Response and Simulation of Ecosystem Services Value to Land Use/land Cover in an Oasis, Northwest China.” Ecological Indicators 118: 106711. doi:10.1016/j.ecolind.2020.106711.

Zhou, Y., Y. Shan, G. Liu, and D. Guan. 2018. “Emissions and Low-carbon Development in Guangdong-Hong Kong-Macao Greater Bay Area Cities and Their Surroundings.” Applied Energy 228: 1683–1692. doi:10.1016/j.apenergy.2018.07.038.