Chin. Geogra. Sci. 2021 Vol. 31 No. 1 pp. 93−108
https://doi.org/10.1007/s11769-021-1177-9

Springer Science Press
www.springerlink.com/content/1002-0063

Rapid Urbanization Induced Extensive Forest Loss to Urban Land in the Guangdong-Hong Kong-Macao Greater Bay Area, China

YANG Chao[1, 2], LIU Huizeng[1], LI Qingquan[1], CUI Aihong[3], XIA Rongling[4], SHI Tiezhu[1, 5], ZHANG Jie[1], GAO Wenxiu[5], ZHOU Xiang[1], WU Guofeng[1, 5]

(1. *MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area & Guangdong Key Laboratory of Urban Informatics & Shenzhen Key Laboratory of Spatial Smart Sensing and Services*, *Shenzhen University*, *Shenzhen* 518060, *China*; 2. *College of Information Engineering*, *Shenzhen University*, *Shenzhen* 518060, *China*; 3. *Department of Geography*, *Hong Kong Baptist University*, *Hong Kong* 999077, *China*; 4. *School of Land and Resources Engineering*, *Kunming University of Science and Technology*, *Kunming* 650093, *China*; 5. *School of Architecture and Urban Planning*, *Shenzhen University*, *Shenzhen* 518060, *China*)

Abstract: China has experienced rapid urbanizations with dramatic land cover changes since 1978. Forest loss is one of land cover changes, and it induces various eco-environmental degradation issues. As one of China's hotspot regions, the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) has undergone a dramatic urban expansion. To better understand forest dynamics and protect forest ecosystem, revealing the processes, patterns and underlying drivers of forest loss is essential. This study focused on the spatiotemporal evolution and potential driving factors of forest loss in the GBA at regional and city level. The Landsat time-series images from 1987 to 2017 were used to derive forest, and landscape metrics and geographic information system (GIS) were applied to implement further spatial analysis. The results showed that: 1) 14.86% of the total urban growth area of the GBA was obtained from the forest loss in 1987–2017; meanwhile, the forest loss area of the GBA reached 4040.6 km^2, of which 25.60% (1034.42 km^2) was converted to urban land; 2) the percentages of forest loss to urban land in Dongguan (19.14%), Guangzhou (18.35%) and Shenzhen (15.81%) were higher than those in other cities; 3) the forest became increasingly fragmented from 1987–2007, and then the fragmentation decreased from 2007 to 2017); 4) the landscape responses to forest changes varied with the scale; and 5) some forest loss to urban regions moved from low-elevation and gentle-slope terrains to higher-elevation and steep-slope terrains over time, especially in Shenzhen and Hong Kong. Urbanization and industrialization greatly drove forest loss and fragmentation, and, notably, hillside urban land expansion may have contributed to hillside forest loss. The findings will help policy makers in maintaining the stability of forest ecosystems, and provide some new insights into forest management and conservation.

Keywords: forest loss to urban land; urbanization; spatiotemporal pattern; remote sensing; Guangdong-Hong Kong-Macao Greater Bay Area (GBA)

Citation: YANG Chao, LIU Huizeng, LI Qingquan, CUI Aihong, XIA Rongling, SHI Tiezhu, ZHANG Jie, GAO Wenxiu, ZHOU Xiang, WU Guofeng, 2021. Rapid Urbanization Induced Extensive Forest Loss to Urban Land in the Guangdong-Hong Kong-Macao Greater Bay Area, China. *Chinese Geographical Science*, 31(1): 93−108. https://doi.org/10.1007/s11769-021-1177-9

Received date: 2020-05-21; accepted date: 2020-09-01

Foundation item: Under the auspices of National Natural Science Foundation of China (No. 41890854), Basic Research Program of Shenzhen Science and Technology Innovation Committee (No. JCYJ20180507182022554), National Key R & D Program of China (No. 2017YFC0506200), National Natural Science Foundation of China (No. 7181101150), National Natural Science Foundation of China (No. 41901248), Shenzhen Future Industry Development Funding Program (No. 201507211219247860)

Corresponding author: LI Qingquan. E-mail: liqq@szu.edu.cn; WU Guofeng. E-mail: guofeng.wu@szu.edu.cn

1 Introduction

Urbanization has experienced a remarkable speed during the past half century, the ratio of urban population to global population increased from 30% in 1950 to 54% in 2014 (World Bank, 2015), and it will reach 66% in 2050 (Madanian et al., 2018). The urbanization processed in Africa and Asia is faster compared with those in other continents, and it is predicted they will reach 56% and 64% by 2050, respectively (Madanian et al., 2018). China started to implement its reform and opening up polices in 1978, initiating a socioeconomic transformation process. Over the past 40 years, urbanization and industrialization have reached an unprecedented rate. China gradually marched toward a mid- and post-industrialization period, and the urbanization rate increased by 26% from 1978 to 2009 (NBSC, 2010; Liang et al., 2015). In addition, China experienced an explosive population growth during this period, the urban population increased from 210 million in 1982 to 660 million in 2010, and the corresponding urbanization rate increased from 20.91% to 49.68% (NBSC, 2013). Continual demands for urban housing, business and construction land in rapid urbanization period resulted in a dramatic conversion of land use/land cover types, and the cropland converted into urban land has become the main source of urban lands (Liu et al., 2010; Liu et al., 2012; Liu et al., 2014).

Forests are critical natural resources for the survival and development of humankind, and they play an irreplaceable role in fighting global climate change (Department, 2010; FAO, 2012; Wu et al., 2019; Garcia et al., 2020; Seymou, 2020). According to the United Nations Food and Agriculture Organization (FAO), the global forest area approaches 40 million km^2 and accounts for 31% of the Earth's land surface. Forests provide socioeconomic benefits and invisible environmental health products for human beings, such as wood production, oxygen and climate regulation (Gao and Liu, 2011). However, forest ecosystems are often disturbed by dramatic human activities, especially the urbanization and industrialization in recent decades (Lele et al., 2008; Gao and Liu, 2011; FAO, 2012). The studies from around the world revealed that the degradation or even extinction of forest ecosystems could be largely attributed to anthropologic disturbances (Lele et al., 2008, Lambin and Meyfroidt, 2010; Liu et al., 2013; Liu et al., 2016a). The deterioration of forest ecosystems is usually associated with forest loss and fragmentation (Laurance et al., 2000; Miller, 2012), which also have induced many negative eco-environmental consequences, including species degradation or extinction, soil erosion and sandy storm attacks (Reddy et al., 2013; Carranza et al., 2015). Notably, rapid urbanization and industrialization are currently the largest factor for urban land expansion in developing and developed countries of the world (Turner II et al., 2007; Liu et al., 2010b; Yang et al., 2019a; Xu et al., 2020), affecting ecosystems in local and global scales (Shen et al., 2008; Yang et al., 2017a; Girardet, 2020). The demands for commercial and residential land development exacerbate forest loss and fragmentation in rapid urbanization periods (Song et al., 2014). Therefore, investigating forest loss and fragmentation under the background of rapid urbanization is essential for forest ecosystem management and conservation.

Since 1978, China has experienced a transformation from a socialism planned economy to a market economy. Large-scale deforestation gradually occurred in different cities in China due to commercial timber market opening (Liu et al., 2016a). Moreover, local governments were given the authority to regulate land use types (e.g., agriculture, building) through land market reform (Du et al., 2014). As a result, many cities suffered from persistent forest net loss, because timbers were harvested for urban construction (Li et al., 2010). Be conscious of the seriousness of forest loss, the Chinese government issued a series of policies for forest recovery and conservation, including the 'Returning Farmland to Forest' program (i.e., increasing forest covers and preventing soil erosion), and the 'Grain for Green' policy in 1999 (i.e., conversion of farmland to forest or grassland) (Cao et al., 2009; Deng et al., 2012; 2014; Van Den Hoek et al., 2014). However, the effects of forest loss prevention programs vary with different cities and regions, due to the interference of different local land use planning policies (Mao et al., 2019; Trac et al, 2013; van Den Hoek et al., 2014). Therefore, revealing the processes and spatiotemporal patterns of forest changes and forest loss in different cities and regions will be helpful for understanding the dominant driving forces of forest loss.

The combination of remote sensing images and geographic information system (GIS) has been widely applied in forest dynamic studies, because they can provide timely and cost-effective information and analyze the long-time processes and spatiotemporal patterns of forest changes at multiple scales (Xie et al., 2012; Song et al., 2014; Jia et al., 2015; Lindquist and D'Annunzio, 2016; Lechner et al., 2020). Landscape metrics provide new insights in characterizing the detailed patch dynamics of forest changes (Herold et al., 2002; Zengin et al., 2018; Lv et al., 2019). Landscape indices are employed to multi-scale or multi-temporal datasets to imply scale effect and temporal variation. By combination of remote sensing images, GIS and landscape approaches, the forest loss in various cities and urban agglomerations around the world have been quantified (Li et al., 2012; Han et al., 2018). Considering various remote sensing images, high-resolution satellite images show limitations in geographic coverage and historical archive, and low-resolution satellite data can not characterize the detailed changes of forest loss (Setiawan et al., 2014). Landsat TM (Thematic Mapper) and OLI (Operational Land Imager) can provide images for over four decades (Li et al., 2017; Yang et al., 2019a) with a middle spatial resolution, and they have ability in mapping forest areas at a moderate scale (Kline et al., 2009; Wahyudi et al., 2018).

Over the past four decades, many researches emphasized the spatiotemporal patterns of forest loss and fragmentation at a single scale (city or individual region) (Song et al., 2014; Jia et al., 2015; Xie et al., 2017; Navarro Cerrillo et al., 2019), and few studies were focused on the systematic analysis at multiple levels or cross-city comparisons with spatially consistent datasets. Moreover, the analysis of forest loss to urban land, which is a general phenomenon in the rapid urbanization regions of China, is scarce. The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) is one of the four bay areas in the world, and it has experienced a rapid urban growth since 1987 (Yang et al., 2019a). The population of the GBA accounts for only 5% of China; however, it created 11% of China's total gross domestic product (GDP) in 2017. To promote sustainable development, the Chinese government issued the 'Development Plan for the GBA' in 2019. According to this plan, the GBA planed a world-class urban agglomeration and a high-quality life circle. However, the urbanization process in the GBA may greatly affect its forest ecosystem. The phenomenon of occupying forests in the urbanization process in the GBA has been exposed from high-resolution Google Earth images. Therefore, it is particularly urgent and significant to investigate and understand the processes of forest loss and fragmentation in the GBA at different scale perspectives, especially for the forest loss to urban land. This study focused on revealing the spatiotemporal evolution and underlying forces of forest loss in the GBA at the regional and city levels by employing Landsat time-series images (1987–2017), landscape metrics and GIS. It is hoped that this study can contribute to forest management and conservation.

2 Materials and Methods

2.1 Study area

The GBA is located in south China (21°32′N–24°26′N, 111°20′E–115°24′E), and it includes eleven cities: Foshan, Huizhou, Shenzhen, Zhaoqing, Zhuhai, Hong Kong, Zhongshan, Dongguan, Jiangmen, Guangzhou and Macao (Fig. 1). The population of the GBA is approximately 70 million, and it has a total area of 56 000 km^2. The GBA belongs to typical humid subtropical climate regions, with a large amount of precipitation in summer (Yu et al., 2019). The urban land of the GBA has expanded from 605.71 km^2 in 1987 to 1996.27 km^2 in 1997, 4481.96 km^2 in 2007 and 7568.19 km^2 in 2017 (Yang et al., 2019a; Fig. 1c). The GBA contributed approximately 11% of the gross domestic product (GDP) of China in 2017. The GBA is becoming a world-class bay area and a well-known urban agglomeration.

2.2 Data source and pre-processing

The satellite data and products used in this study included time-series Landsat images, digital elevation model (DEM) and Google Earth high-resolution images. Thirty-two cloudless or low-cloud Landsat TM and OLI images covering the GBA around 1987, 1997, 2007 and 2017 were obtained from the United States Geological Survey (USGS). The time interval of the satellite data was 10 years. Most of the images used in this study were captured in the dry season (October to March), considering the minimal cloud and low vegetation variations in this season. Therefore, dry season satellite images had better capacity in studying land cover change analysis (Hasan et al., 2019; Yang et al., 2020). Landsat images have eight (for OLI) or six (for TM) bands at visible to shortwave wavelengths, with spatial resolution of 30 m. ASTER GDEM products covering the GBA with a 30 m resolution were also collected from USGS. The historical high-resolution images of forests in the GBA were obtained from Google Earth Pro®.

The auxiliary data included urban land dataset, elevation, slope, socioeconomic data (i.e., GDP and population data), and vector data of the GBA administrative division boundary. The spatial distribution of the urban land from 1987 to 2017 was also extracted from the aforementioned Landsat images, which was detailed in Yang et al. (2019a). Urban land dataset with a spatial resolution of 30 m provides reliable information on urban expansion dynamics in the GBA (Fig. 1c). The elevation and slope data were derived from ASTER GDEM using ArcGIS 10.2 (Figs. 1d and 2e). Socioeconomic data were collected from Local Statistical Yearbooks in 1987–2017. The projection system used for the vector and satellite data was WGS_84_UTM_49N. All Landsat images and DEM data were clipped with the GBA boundary dataset. The software ENVI 5.3 was used to process the Landsat images, including band combination, FLAASH atmospheric correction, image mosaic, and image clipping.

2.3 Methods

This study analyzed the changing processes and patterns of forests during a rapid urbanization period and revealed the spatiotemporal characteristic and driving forces of forest loss at two scales (the regional level and city level) with remote sensing, landscape ecology and spatial analysis method, including three parts: forest extraction and accuracy assessment, forest landscape pattern analysis, and forest loss to urban land dynamic detection.

2.3.1 Forest extraction and accuracy assessment

The forest of the GBA was extracted with an object-oriented support vector machine (O-SVM) in this study. O-SVM method can combine the high efficiency of bi-level scale-sets model (BSM) in processing large-scale images and SVM's high accuracy in applying small training samples (Foody and Mathur, 2004; Li et al., 2010; Hu et al., 2016). Therefore, O-SVM is more efficient in forest extraction than other methods, and can handle large-scale images while provide high accuracy (Yu et al., 2017; Yang et al., 2019a). The O-SVM method was performed through integrating the Scale-Sets-Image-Analysis-Toolkit (https://github.com/zwhoo/Sca-

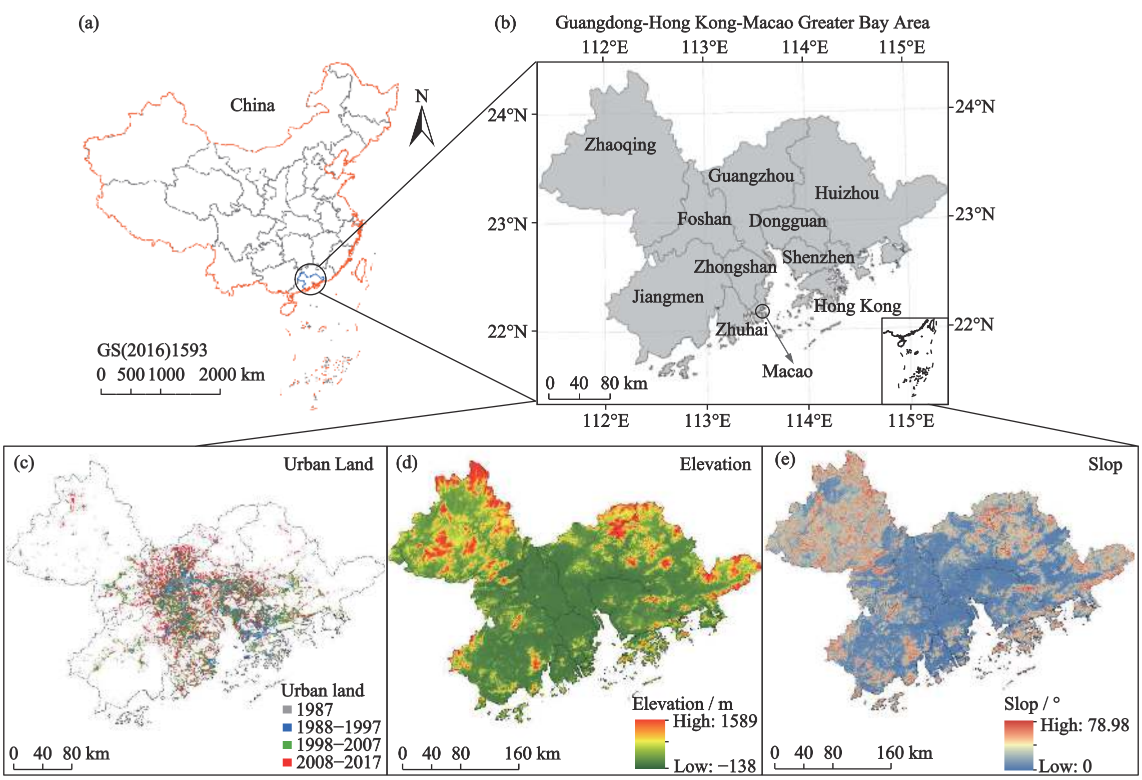

Fig. 1 Typical regions of forest loss to urban land in the GBA (Guangdong-Hong Kong-Macao Greater Bay Area): evidence from high-resolution Google Earth images

le-Sets-Image-Analysis-Toolkit) and SVM algorithm in this study. The parameters of object segmentation scales in O-SVM were set to 30 (for TM) and 45 (for OLI), and four kinds of characteristics for each object were applied for forest information extraction, i.e., texture (Texture-Variance, Texture-Entropy, Texture-Mean and Texture-Range), spectral (Spectral-Max, Spectral-Min, Spectral-Mean and Spectral-STD), spatial (Area, Length, Compactness, Roundness and Elongation) and normalized differential vegetation index (NDVI) (Yang et al, 2019a). A radial basis function (RBF) was used to construct SVM classifier; the SVM's Gamma coefficient was set to $1/n$ (n refers to the band number for Landsat images, i.e., n equals six for TM and eight for OLI, respectively), and penalty cost was 100, suggesting higher extraction accuracy (Yu et al., 2017). Totally, 692 forest training datasets covering the GBA evenly from 1987–2017 were selected directly from TM/OLI segmented images, 225 samples in 1987, 150 samples in 1997, 147 samples in 2007 and 170 samples in 2017; while 226 validation samples of forest (81 samples in 1987, 47 samples in 1997, 42 samples in 2007 and 56 samples in 2017) from study area in 1987–2017 were chosen randomly and evenly from Google Earth Pro®. The forest extraction accuracy was assessed using four basic metrics (i.e., Overall Accuracy, Kappa coefficient, User Accuracyand Producer's Accuracy) (Congalton, 1991; Yang et al., 2017b; 2019b).

2.3.2 Forest landscape pattern analysis

Four landscape metrics were used to evaluate the complex degree, contiguous level, and fragmented degree of forest cover (McGarigal, 2015). Landscape shape index (LSI) was applied to analyze the landscape complexity, and a larger LSI value indicates a greater complexity and implies a stronger impact of human activities (Liang et al., 2015). Patch cohesion index (Cohesion) was applied to assess the contiguous level of forest at the landscape level. Patch density (PD) and mean patch size (MPS) were used to quantify forest fragmentation. A larger PD and a smaller MPS indicate a higher fragmentation of forest landscape (Liang et al., 2015). The software FRAGSTATS 4.2 was employed to calculate these four metrics with the eight-neighborhood rule (McGarigal and Marks, 1995). The spatial resolution of forest raster data were set to 30 m in FRAGSTATS 4.2, which is consistent with original data source. LSI, MPS (ha), PD (number/100 ha) and Cohesion (%) were calculated according to Eqs. (1)–(4), respectively:

$$LSI = \frac{0.25E}{\sqrt{A}} \tag{1}$$

$$MPS = \frac{\sum_{i=1}^{N} a_i}{N} \tag{2}$$

$$PD = \frac{N}{A} \times 10\,000 \times 100 \tag{3}$$

$$Cohension = \left(1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij}\sqrt{a_{ij}}}\right) \Big/ \left(1 - \frac{1}{\sqrt{Z}}\right) \times 100 \tag{4}$$

where A is the total area of landscapes, E represents the total length (m) of patch boundary, N is the number of forest patches, a_i is the area of i forest patch, p_{ij} means the perimeter of patch ij in terms of the number of cell surfaces, a_{ij} represents the area of patch ij in terms of the number of cells, and Z is the total number of cells in the landscape (McGarigal, 2002; Liang et al., 2015).

2.3.3 Forest loss to urban land dynamic detection

The original forest changed to urban land was defined as 'forest loss to urban land' (Fig. 2). An equation (Equation (5)) was proposed to quantify and detect the spatial distribution of forest loss to urban land areas at the regional and city level from 1987 to 2017 in this study. In addition, the elevation and slope were employed to identify the spatiotemporal evolution of forest loss to urban land on different terrain conditions, because the suburbs of the GBA are hills and mountains.

$$F = f_t \cap u_{t+1} \tag{5}$$

where F represents the area of forest loss to urban land, f_t is the forest area in t period, u_{t+1} is the urban land in $t+1$ period, and $\cap$ represents intersection operation.

3 Results

3.1 Forest extraction and accuracy assessment

The results of accuracy assessment, quantitative statistics and spatiotemporal evolution of forest in the GBA are shown in Fig. 3, Table 1, and Figs. 4 and 5, respectively. The accuracy metrics were more than 84%, with the all accuracy's average value of each period approaching 90% in this study (Fig. 3). Forests were extracted effectively using the O-SVM method (accuracy's

Fig. 2 Typical forest loss to urban area : Evidence from high-resolution Google Earth images

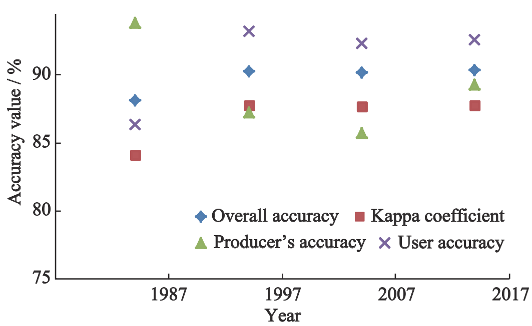

Fig. 3 Accuracy metrics of forest extraction from 1987 to 2017 in the GBA (Guangdong-Hong Kong-Macao Greater Bay Area) of China

average value = 88% in 1987, 90% in 1997, 89% in 2007 and 90% in 2017), and the accuracy of all years satisfies the requirement of land cover change analysis (Foody, 2002; Zhang et al., 2010). Generally, the forest experienced a dynamic change at the regional and city level from 1987 to 2017, and the spatial distribution of forest was concentrated in urban suburbs, hills and mountains (Fig. 4 and Fig. 5). At the regional level, the forest of the GBA increased first then decreased (Fig. 4a), the area decreased from 30 230.26 km^2 in 1987 to 26 189.66 km^2 in 2017, and the total loss area was 4040.6 km^2 (Table 1 and Fig. 4b). At the city level, the trends of forest changes of all cities were consistent with the GBA, except for Zhaoqing, Huizhou and Macao (Fig. 4a). Among the eleven cities, Zhaoqing had the largest forest area, and the average area exceeded 10 000 km^2 in 1987–2017 (Fig. 4a). In contrast, Macao had the smallest forest area, with an average forest area of only 3.52 km^2 (Fig. 4a). Notably, the total change of forest areas in Huizhou, Dongguan and Guangzhou showed gain, while the forest areas of other cities showed loss during 1987–2017 (Fig. 4b and Table 1).

3.2 Forest landscape pattern analysis

Fig. 6 shows the features and trends of four landscape metrics for the forest area changes of the GBA and eleven cities in 1987–2017. Generally, a disparity of landscape responses to forest area changes was observed during the study period. For the GBA level, the fragmentation degree of forest cover showed a trend of first increasing (1987–2007) and then decreasing (2007–2017); the increased PD and decreased MPS of forest cover indicated that the forests were becoming scattered patches in 1987–2007 (Figs. 6a and 6b). Moreover, the forest cover of the GBA had the largest fragmentation degree in 2007, which can be inferred from the maximum PD value (0.067/100 ha) and minimum MPS value (724.57 ha) (Figs. 6a and 6b). Notably, the first decreasing trend (1987–2007) and then increasing trend (2007–2017) of LSI in the GBA showed that

Table 1 Forest area and forest area changes in the GBA (Guangdong-Hong Kong-Macao Greater Bay Area) and eleven cities from 1987 to 2017 (km^2)

Study areas	Forest area				Forest area changes			
	1987	1997	2007	2017	1987–1997	1997–2007	2007–2017	1987–2017
GBA	30230.26	35176.35	26975.70	26189.66	4946.09	–8200.65	–786.04	–4040.60
Foshan	752.17	1151.59	787.62	535.05	399.42	–363.97	–252.56	–217.11
Huizhou	6594.42	9360.21	6376.80	7259.95	2765.79	–2983.41	883.16	665.53
Jiangmen	4996.75	6832.38	4395.81	2489.26	1835.63	–2436.57	–1906.54	–2507.49
Zhaoqing	12406.50	9720.70	9056.87	10776.80	–2685.80	–663.83	1719.93	–1629.70
Zhuhai	479.59	635.02	368.60	266.06	155.43	–266.41	–102.54	–213.52
Zhongshan	344.26	373.70	352.31	244.67	29.44	–21.38	–107.64	–99.59
Hong Kong	629.09	657.67	676.29	470.32	28.57	18.62	–205.97	–158.77
Macao	5.33	4.78	1.19	2.78	–0.55	–3.59	1.59	–2.55
Dongguan	445.82	990.46	595.32	451.69	544.64	–395.14	–143.63	5.88
Shenzhen	908.83	921.11	728.55	727.30	12.28	–192.56	–1.25	–181.53
Guangzhou	2656.73	4517.96	3627.60	2956.75	1861.23	–890.36	–670.85	300.01

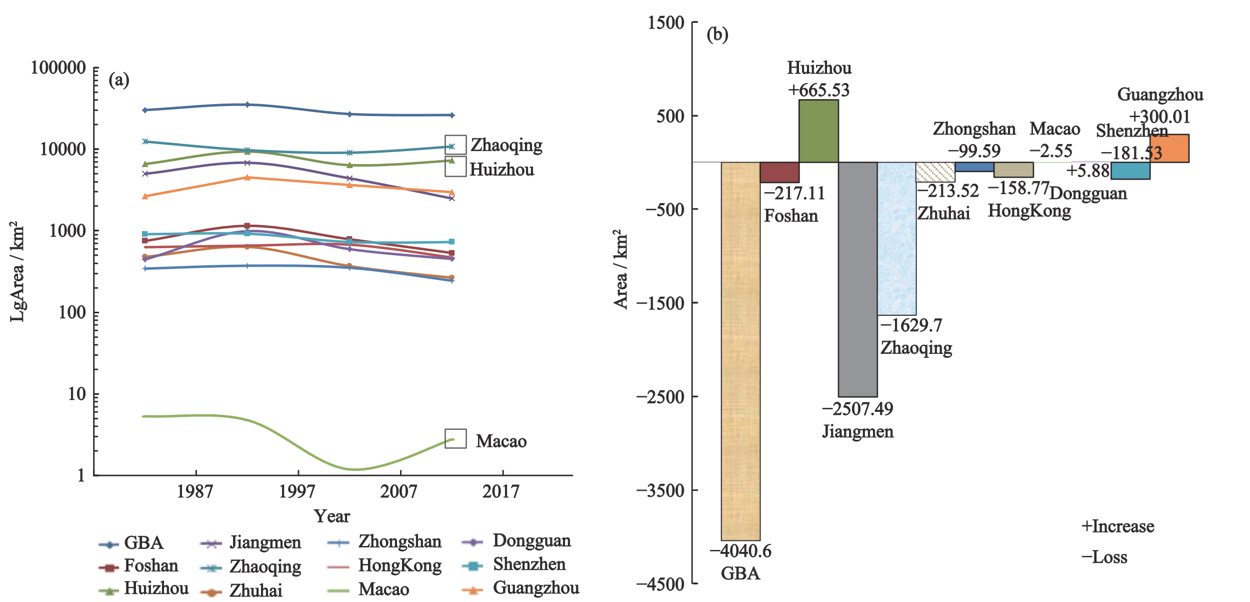

Fig. 4 Forest dynamics in the GBA (Guangdong-Hong Kong-Macao Greater Bay Area) from 1987 to 2017: (a) change trend of forest area; (b) total change of forest area

the human disturbance to forests increased first and then decreased (Fig. 6c). The decreasing Cohesion of the GBA also indicated that the connections among forest patches became increasingly weaker in 1987–2007 (Fig. 6d). On the contrary, the increasing Cohesion of the GBA indicated the strong connections among forest patches in 2007–2017 (Fig. 6d). The Cohesion changes also demonstrated the fragmentation variations of forest covers. The Cohesion decreased by 0.023% from 1987 to 2007 in the GBA (Fig. 6d), suggesting that forest patches' spatial distribution tended to be scattered and decentralized. The exploitation of construction environment during 1987–2007 likely contributed to this transformation to a certain extent.

From the perspective of city level, the PD of forests in different cities presented first increasing and then decreasing trend during 1987–2017, except for Zhuhai, Huizhou and Jiangmen (Fig. 6a). The trends of MPS were contrary to those of PD in all cities (Fig. 6b). The trends of PD and MPS in Zhaoqing, Zhongshan, Guang-

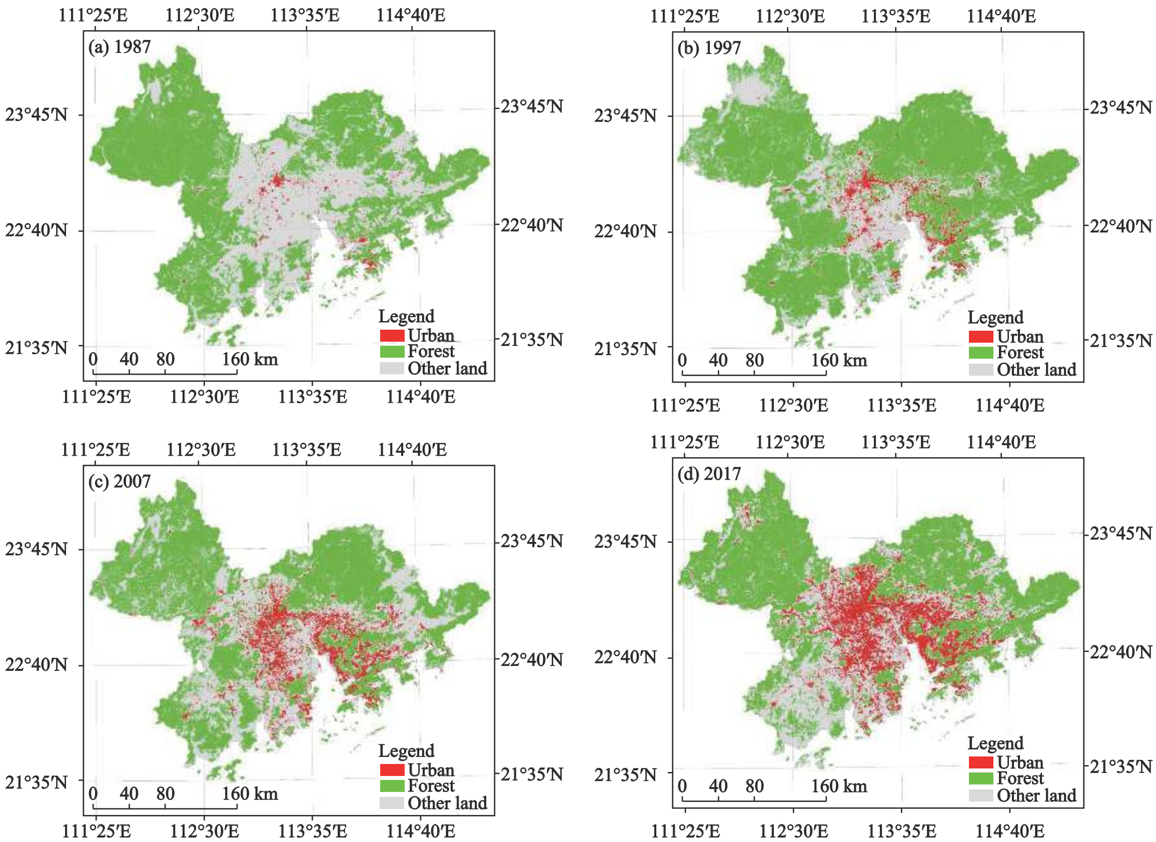

Fig. 5 Spatiotemporal characteristics of forest during 1987 and 2017 in the GBA (Guangdong-Hong Kong-Macao Greater Bay Area)

zhou and Shenzhen were consistent with those of the GBA during 1987–2017, but the values of PD and MPS were different (Figs. 6a and 6b). The PD values of Zhaoqing were lower than those of the GBA, and the MPS values of Huizhou were higher than those of the GBA (Figs. 6a and 6b). It is noteworthy that Macao had the lowest MPS, LSI and Cohesion values in all cities in 1987–2017 (Figs. 6b, 6c and 6d), suggesting that the patch areas, patch numbers and complexity of forests in Macao were smaller than those in other cities.

3.3 Forest loss to urban land dynamics from 1987 to 2017

Fig. 7 and Table 2 show the spatiotemporal characteristics of forest loss to urban land at the regional and city level. Generally, the forest area loss to urban land was a dynamic process during study period, and the spatial feature of forest loss to urban land was mainly concentrated in the regions with low elevations (< 80 m) and gentle slopes (< 5°) (Fig. 8, Tables 3 and 4). However, some patches of forest loss to urban land were transitioned from lower-elevation and gentle-slope terrains to higher-elevation (80–400 m) and steep-slope (5°–30°) terrains over time, especially for Jiangmen, Zhaoqing, Shenzhen and Hong Kong (Fig. 8, Tables 3 and 4). The changes of forest loss to urban land at different elevations and slopes may result from the urbanization and industrialization in suburbs. At the regional level, the forest loss to urban land experienced a first increase then declining trend during 1987–2017 (Fig. 9a), and reached the maximum value (585.27 km^2) in 1997–2007. In addition, the total area of forest loss to urban land in the GBA was 1034.42 km^2 during 1987–2017 (Table 2).

At the city level, the trends of forest loss to urban land were also first increasing then decreasing during 1987–2017, except for Guangzhou, Foshan and Zhongshan (Fig. 9b). Shenzhen had the largest transformation area of forest to urban land (reaching 47.05 km^2, almost 50% of the GBA during 1987–1997 (Table 2), resulting from rapid urbanization. During 1997–2017, the maximum transformation areas of forest to urban land were observed in Dongguan (1997–2007) and Guangzhou (2007–2017), and reached 145.41 km^2 and 92.56 km^2, respectively. Moreover, the total areas of forest loss to

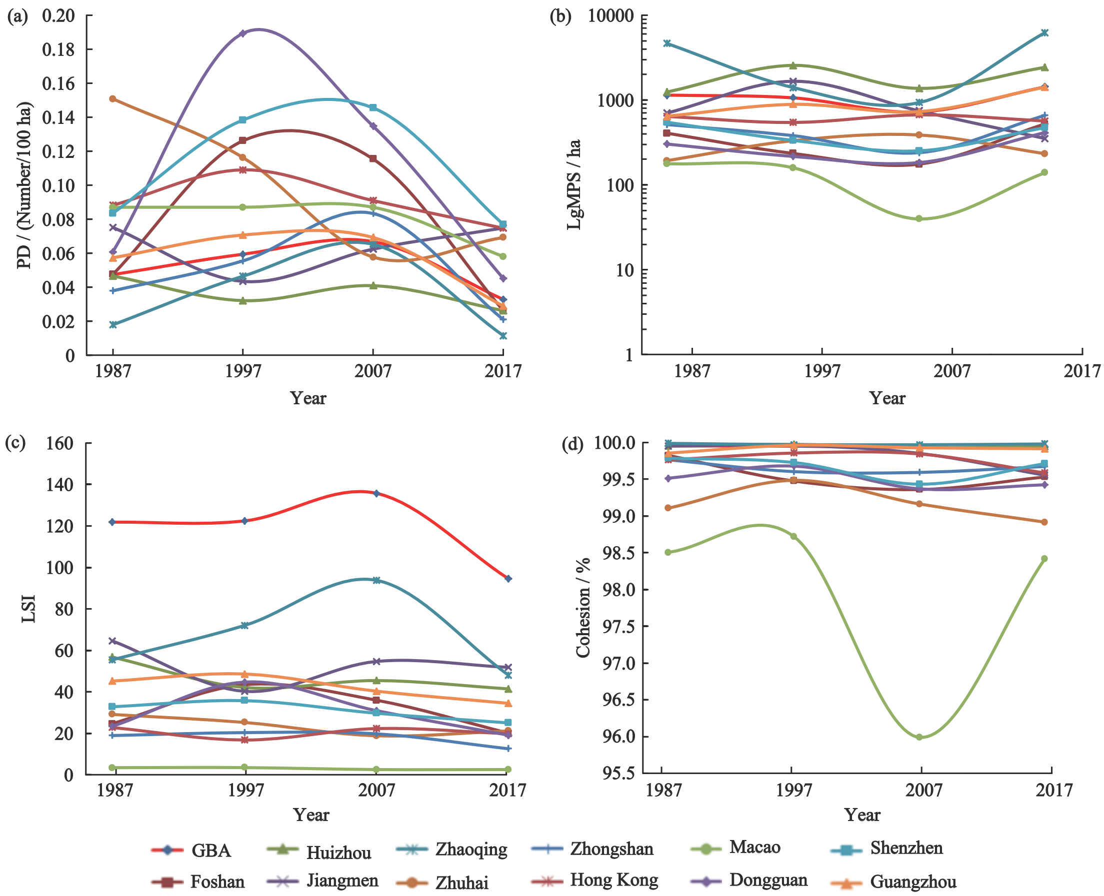

Fig. 6 The landscape patterns of forest cover changes from 1987 to 2017: (a) Patch density (PD), (b) mean patch size (MPS), (c) landscape shape index (LSI) and (d) patch cohesion (Cohesion)

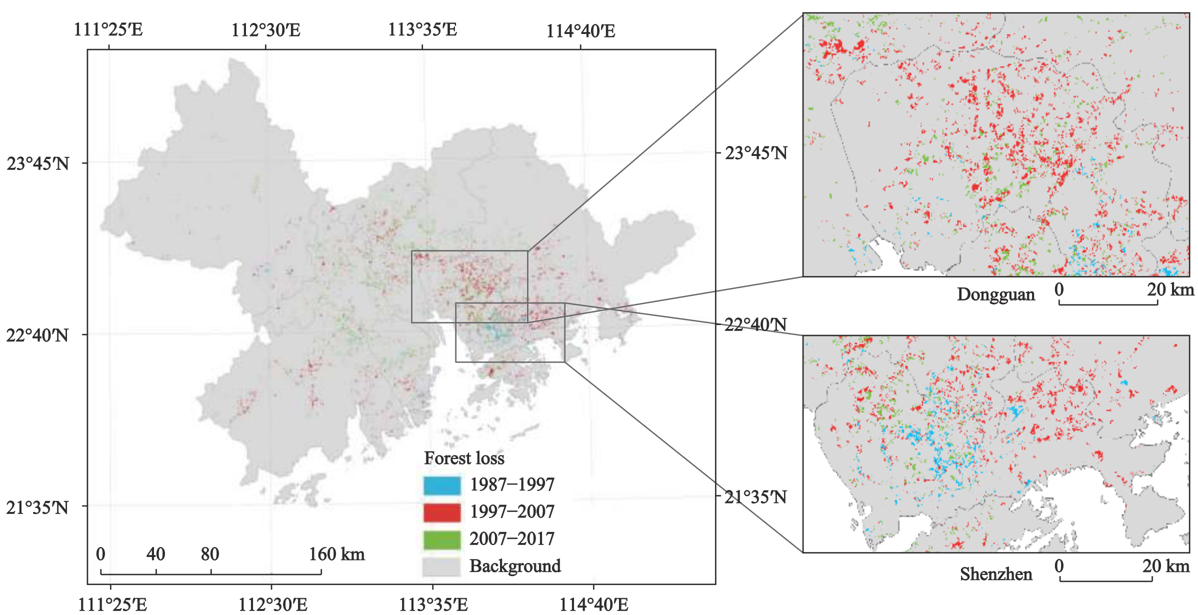

Fig. 7 The spatiotemporal characteristics of forest loss to urban land in the GBA from 1987 to 2017

urban land in Dongguan, Guangzhou and Shenzhen ranked as the top three of the GBA in 1987–2017, and their percentages accounted for 19.14%, 18.35%, and 15.81%, respectively (Table 2). In contrast, this percent-

Table 2 Forest loss to urban land at regional and city level in GBA from 1987 to 2017 / km^2

Region	1987–1997	1997–2007	2007–2017	Total loss
GBA	92.97	585.27	356.18	1034.42 (100.00)
Foshan	2.34	32.40	58.77	93.51 (9.04)
Huizhou	2.87	90.33	20.15	113.35 (10.96)
Jiangmen	2.67	64.43	43.04	110.14 (10.65)
Zhaoqing	11.29	17.80	17.04	46.13 (4.46)
Zhuhai	4.80	18.85	6.09	29.74 (2.88)
Zhongshan	3.42	18.67	25.71	47.8 (4.62)
Hong Kong	3.31	25.28	12.66	41.25(3.99)
Macao	0.09	0.76	0	0.85 (0.08)
Dongguan	9.04	145.41	43.57	198.02 (19.14)
Shenzhen	47.05	79.93	36.56	163.54 (15.81)
Guangzhou	6.10	91.19	92.56	189.85 (18.35)

Note: The figures in brackets indicate the proportion of the total loss of each city to the total loss of GBA / %

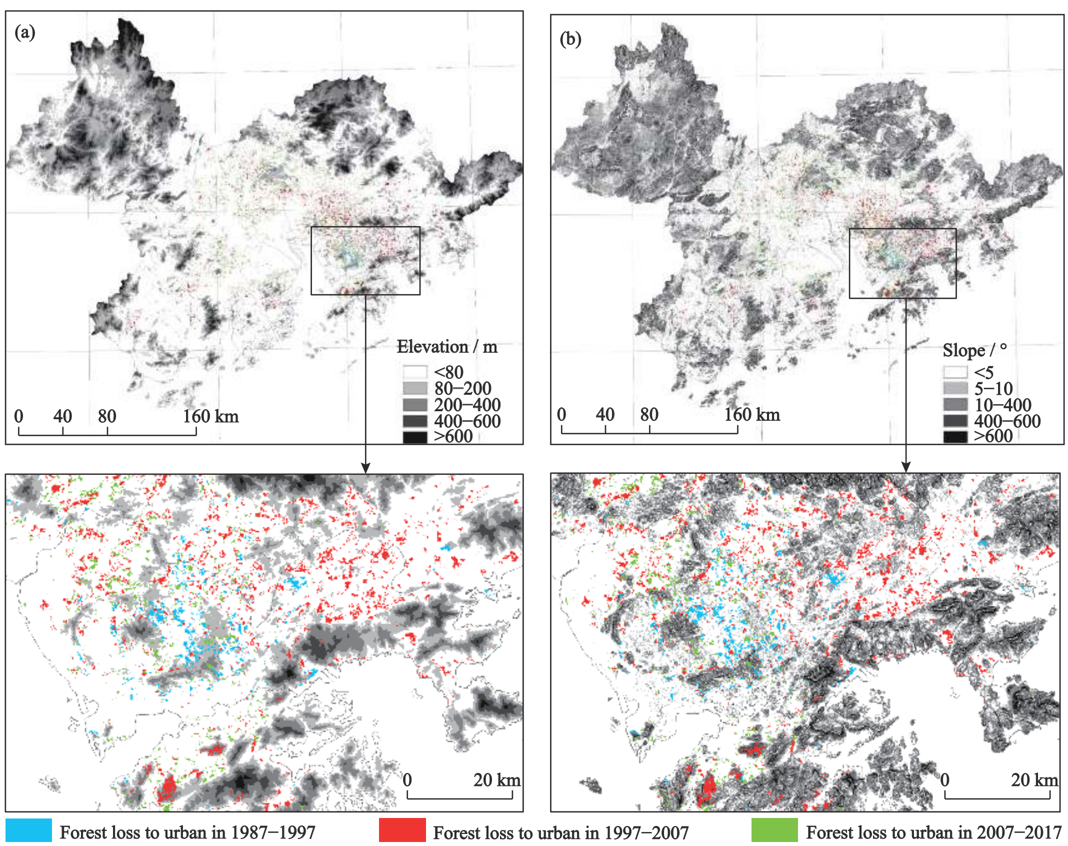

Fig. 8 The spatiotemporal characteristics of forest area loss to urban land at different elevations and slopes from 1987 to 2017 in GBA

age was less than 0.1% in Macao, which was the lowest among all eleven cities (Table 2). It is noteworthy that the spatial distribution of patches of forest loss to urban land in Shenzhen, Dongguan, Zhongshan and Foshan were distributed evenly over time, and the process of urban growth occupied many suburban forest (Fig. 7), suggesting that the urbanization and industrialization of suburbs were extensive and decentralized.

Table 3 Forest loss to urban land at different elevations from 1987 to 2017 in the GBA / km^2

Region	Forest loss to urban land during 1987–1997					Forest loss to urban land during 1997–2007					Forest loss to urban land during 2007–2017				
	< 80	80–200	200–400	400–600	> 600	< 80	80–200	200–400	400–600	> 600	< 80	80–200	200–400	400–600	> 600
GBA	78.10	12.64	1.35	0.68	0	550.66	23.72	9.69	1.51	0	332.30	19.47	2.53	1.40	0.43
Foshan	2.25	0.03	0	0	0	32.17	0	0	0	0	58.22	0.52	0.03	0	0
Huizhou	2.46	0.38	0.03	0	0	81.91	7.27	1.05	0	0	16.74	2.75	0.64	0	0
Jiangmen	2.44	0	0.22	0	0	62.49	1.53	0.06	0	0	39.58	1.98	0.38	0.68	0.43
Zhaoqing	9.49	0.15	0.93	0.68	0	16.38	0.97	0.31	0.01	0	11.40	4.40	0.61	0.63	0
Zhuhai	4.78	0	0	0	0	18.71	0.16	0	0	0	5.38	0.71	0.01	0	0
Zhongshan	3.46	0	0	0	0	18.72	0.06	0	0	0	25.50	0.20	0	0	0
Hong Kong	2.90	0.38	0	0	0	9.95	7.06	7.19	1.35	0	11.39	0.66	0.50	0.10	0
Macao	0.09	0	0	0	0	0.52	0.23	0	0	0	0	0	0	0	0
Dongguan	8.36	0.64	0	0	0	145.34	0.40	0	0	0	43.33	0.23	0	0	0
Shenzhen	36.50	10.38	0.14	0	0	74.39	5.33	0.25	0	0	30.63	5.66	0.28	0	0
Guangzhou	5.36	0.68	0.04	0	0	90.07	0.71	0.82	0.15	0	90.12	2.34	0.10	0	0

Table 4 Forest loss to urban land at different slopes from 1987 to 2017 in the GBA / km^2

Region	Forest loss to urban land in 1987–1997					Forest loss to urban land in 1997–2007					Forest loss to urban land in 2007–2017				
	< 5	5–10	10–20	20–30	> 30	< 5	5–10	10–20	20–30	> 30	< 5	5–10	10–20	20–30	> 30
GBA	63.04	18.40	9.07	1.90	0.36	468.55	69.03	36.99	10.09	0.92	255.33	65.17	29.62	5.31	0.69
Foshan	1.42	0.49	0.29	0.06	0.01	26.14	5.02	0.90	0.09	0.01	48.31	7.59	2.55	0.27	0.05
Huizhou	1.58	0.64	0.56	0.09	0	67.65	10.98	9.84	1.69	0.07	13.74	3.09	2.65	0.63	0.02
Jiangmen	1.98	0.40	0.23	0.05	0	51.90	7.95	3.29	0.83	0.12	27.06	9.67	5.04	0.10	0.28
Zhaoqing	7.88	1.66	1.26	0.31	0.14	11.01	3.60	2.19	0.67	0.20	6.11	5.14	4.52	1.18	0.10
Zhuhai	3.93	0.60	0.22	0.03	0	15.80	1.67	1.12	0.27	0.01	3.18	1.13	1.29	0.45	0.03
Zhongshan	2.30	0.89	0.26	0.01	0	16.37	1.84	0.53	0.04	0	20.95	3.36	1.22	0.15	0.03
Hong Kong	1.36	0.87	0.88	0.14	0.01	5.35	4.62	9.95	5.25	0.38	9.44	1.69	1.01	0.40	0.11
Macao	0.05	0.03	0.01	0	0	0.17	0.16	0.30	0.14	0	0	0	0	0	0
Dongguan	6.08	1.74	1.00	0.16	0.03	135.39	8.47	1.64	0.19	0.06	37.14	5.09	1.20	0.14	0
Shenzhen	33.58	9.53	3.20	0.63	0.09	64.55	11.44	3.54	0.39	0.05	22.86	9.14	4.05	0.49	0.02
Guangzhou	2.87	1.56	1.17	0.41	0.08	74.23	13.26	3.70	0.54	0.03	66.55	19.26	6.08	0.62	0.05

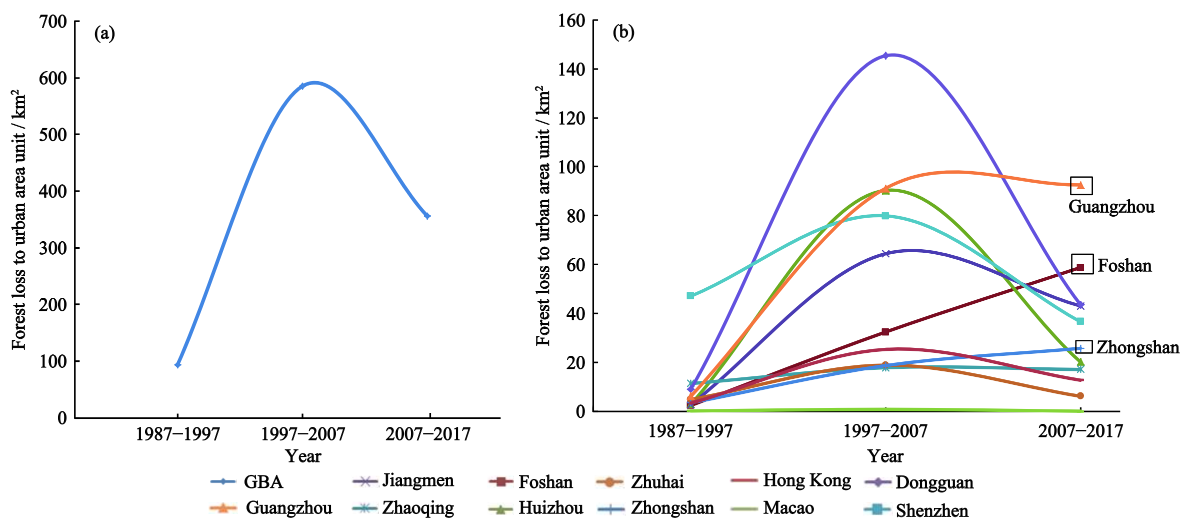

Fig. 9 The trends of forest loss to urban land at regional and city level from 1987 to 2017: (a) GBA and (b) 11 cities within GBA

4 Discussion

4.1 Driving forces of forest loss and fragmentation

China has experienced remarkable urbanizations since 1978, especially in the GBA (Zhang and Weng, 2016; Zhang et al., 2016; Yang et al., 2019a). The urban land in the GBA expanded from 605.71 km^2 to 7568.19 km^2 (a total expansion of 6962.48 km^2) in 1987–2017, and the GBA is experiencing a rapid transition period from urbanization to suburbanization (Yang et al., 2019a). The forest loss to urban land in the GBA was 1034.42 km^2 during 1987–2017, and 14.86% of total urban growth area in the GBA was obtained from forest loss. During this period, urbanization and rural industrialization have induced large-scale transformation of land use types (Jordan et al., 2007; Liang et al., 2015), one of which was the transformation of low-altitude forests to built-up lands (Li et al., 2010). In the early stage of the reform and opening-up, the eco-environmental problems caused by forest loss were not taken into account in economic development. Low-altitude flat forests also became the primary choice for urban construction, due to their ideal terrain. Extensive infrastructure constructions occupied a large area of forests in Shenzhen, which led to the maximum transformation area of forest to urban land in 1987–1997. It is worth noting that local governments developed many satellite towns and industrial parks to control urban sprawl and evacuate overcrowded population and industries in the original urban core (NDRC, 2014; Zhang et al., 2016; Yang and Li et al., 2019), and thus industrial parks and satellite towns arose in the suburbs of Guangzhou, Shenzhen, Foshan, Zhongshan, Dongguan and Zhuhai in 1997–2017. However, satellite towns and industrial parks inevitably occupied some forests, resulting in a large forest loss to urban land in the suburbs in the GBA during 1997–2017 (585.27 km^2 for 1997–2007 and 356.18 km^2 for 2007–2017). Some studies prove that the growing urban transportation networks could divide the landscape formed by land cover into countless small patches, resulting in landscape fragmentation (Gobattoni et al., 2011; Liang et al., 2015). Therefore, forest fragmentation in the GBA can be attributed to rapid urban sprawl and industrialization to a certain extent.

Urban expansion always prefers to choose farmland for development because generally the terrain of farmland is plains and the development costs are low. China has converted extensive farmlands into urban lands since reform and opening-up (Liu et al., 2014; Liu et al., 2015; Liu et al., 2016b; Hu et al., 2018). Being aware of the seriousness of farmland loss, the Chinese government issued a series of policies, such as China's National General Land Use Plan (1997–2010 and 2006–2020), to prevent the loss of farmland (Zhong et al., 2014; Xu et al., 2015). The high-quality cultivated land (Class I and II types) in China is distributed in flat regions with slopes of 0°–6°, and most of them belong to the basic farmland, which can not be developed. The mandatory measures and requirements of strict farmland conservation policies push local governments to develop urban lands on hillsides or mountains with low elevations and gentle slopes. A large amount of high quality farmlands in the plain areas were converted into urban lands in the early stage of the reform and opening up (1987–1997). Therefore, it is not surprising that the areas of forest loss to urban land gradually moved towards hillsides in the GBA during 1997–2017, especially for hilly cities with less farmland, such as Shenzhen and Hong Kong.

It is worth noting that urban development and GDP growth are closely associated with political achievements in China (Liu et al., 2014c). The local governments within the GBA tended to develop industrial clusters in pursuit of high GDP growth to reach political achievements; however, the basic farmland protection regions were forbidden for development, which resulted in a large number of industrial parks in suburbs and hillsides being developed during 1997–2017, especially for Dongguan, Foshan, Zhongshan and Shenzhen. The development of industrial clusters usually occupies some forests, resulting in eco-environment degradation. These results suggest that more attentions to forest conservation are needed.

4.2 Landscape responses to forest dynamics

Our results revealed that the effects of forest changes on the landscape varied at regional and city level. For the regional level, we found that forest fragmentation and complexity increased in the early stage (1987–2007), which confirmed the general observation that urbanization leads to increasing landscape fragmentation and complexity (Collinge, 1996; Chen et al., 2007). However, a decreasing trend of forest landscape fragmentation was observed in 2007–2017, suggesting that a reduction of human disturbance and a growth of environmental protection awareness can adjust forest distributions to avoid the acceleration of landscape fragmentation and complexity. In addition, the landscape responses to forest changes are not always monotonic, but vary with spatial and temporal scale. For the city level, forest distributions in most cities presented a decreasing suburb-to-central urban areas gradient (i.e., the farther away from the city centers, the more forests were distributed), which is similar to the general observation in the GBA. Moreover, we found that a higher fragmentation and lower contiguous degree of forests appeared in the farther mountainous regions, confirming that the disturbance of anthropologic activities in forests is mainly concentrated in highly urbanized areas. The fragmentation trends of Zhaoqing, Zhongshan, Guangzhou and Shenzhen were consistent with those of the GBA during 1987–2017, while the fragmentation trends of Zhuhai, Huizhou and Jiangmen were different from those of the GBA, moreover their fragmentation degrees were different. These results suggested that the urbanization levels and volumes of forest resources for these cities were different in 1987–2017. Therefore, the landscape responses to forest changes at the city level were also not monotonic, but varied according to space and time scale.

4.3 Limitations and future works

There are some limitations in our study, which need to be further explored. The GBA has a wide geographical coverage and heavy rainfall in summer, which makes it difficult to obtain enough cloudless Landsat images in a same season. The resolution of Landsat images is 30 m, which makes it difficult to obtain more precise forest boundaries; thus, high-resolution images may hold potential in improving forest loss to urban land studies. This study was focused on the forest loss and forest loss to urban land of the GBA in 1987–2017, and the forest recovery was not analysed in depth. Forest change is a dynamic process, and the forest area in the GBA had a recovery period in 1987–1997, with a restoration area of 4946.09 km^2. Among the eleven cities, Huizhou, Jiangmen and Guangzhou had more restoration areas than other cities, which could be attributed to the reforestation project 'Greening Guangdong in 10 Years' initiated in 1985 and the mountainous terrain of these three cities (Trac et al., 2013; Hasan et al., 2019). Therefore, the forest recovery in the GBA needs to be discussed in depth in the future. In order to balance the contradiction of urban growth and eco-environment protection, studying the ecological effects of forest loss and the correlation between urbanization and forest landscape changes is urgently required by local governments.

5 Conclusions

This study first extracted forest boundaries of GBA from 1987 to 2017 using Landsat time-series images by object-oriented support vector machine method, and then revealed the spatiotemporal features of forest loss to urban land, landscape patterns of forest dynamics at regional and city level by combining landscape metrics, and GIS techniques. The main conclusions were as follows: 1) The spatial distribution of forest was concentrated in urban suburbs, hills and mountains of the GBA. Forest of the GBA increased first then decreased, and the trends of forest changes of all cities were consistent with the GBA, except for Zhaoqing, Huizhou and Macao. 2) Landscape responses to forest change varied with spatial and temporal scale. Forests became increasingly fragmented in 1987–2007, and then fragmentation decreased in 2007–2017 at the regional level, which was consistent with that in Zhaoqing, Zhongshan, Guangzhou and Shenzhen. 3) The total urban growth area in the GBA was 6962.48 km^2, of which 14.86% was obtained from forest loss. The total area of forest loss in the GBA reached 4040.6 km^2 in 1987–2017, of which 25.60% was converted to urban lands. The percentages of forest loss to urban land in Dongguan (19.14%), Guangzhou (18.35%) and Shenzhen (15.81%) were higher than those in other cities. 4) Urbanization and industrialization drove forest loss to urban land. Hillside urban land expansion contributed to mountain or hillside forest loss in the GBA. These findings will be helpful to policy makers for maintaining the stability of forest ecosystem, and provide some new insights into forest management and conservation. Our results also suggest that urban lands on hillsides are at risk, because the changes of regional topographic features at higher-elevation and steeper-slope terrains may cause surface subsidence and deterioration of ecological quality.

References

Cao S X, Chen L, Liu Z D, 2009. An investigation of Chinese attitudes toward the environment: case study using the grain for green project. *AMBIO: A Journal of the Human Environment*, 38(1): 55–64. doi: 10.1579/0044-7447-38.1.55

Carranza M L, Hoyos L, Frate L et al., 2015. Measuring forest fragmentation using multitemporal forest cover maps: forest loss and spatial pattern analysis in the Gran Chaco, central Argentina. *Landscape and Urban Planning*, 143: 238–247. doi: 10.1016/j.landurbplan.2015.08.006

Cerrillo R M N, Vieira D J E, Ochoa-Gaona S et al., 2019. Land cover changes and fragmentation in mountain neotropical ecosystems of Oaxaca, Mexico under community forest management. *Journal of Forestry Research*, 30: 143–155. doi: 10.1007/s11676-017-0568-3

Chen M W, Zong Y G, Ma Q et al., 2007. Quantitative study on spatio-temporal change of urban landscape pattern based on RS/GIS: a case of Xi'an metropolitan area in China. In: *Proceedings of SPIE 6752*, *Geoinformatics 2007*: *Remotely Sensed Data and Infor-mation*. Nanjing: SPIE. doi: 10.1117/12.760778

Collinge S K, 1996. Ecological consequences of habitat fragmentation: implications for landscape architecture and planning. *Landscape and Urban Planning*, 36(1): 59–77. doi: 10.1016/S0169-2046(96)00341-6

Congalton R G, 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37(1): 35–46. doi: 10.1016/0034-4257(91)90048-B

Deng L, Shangguan Z P, Li R, 2012. Effects of the grain-for-green program on soil erosion in China. *International Journal of Sediment Research*, 27(1): 120–127. doi: 10.1016/S1001-6279(12)60021-3

Deng L, Liu G B, Shangguan Z P, 2014. Land-use conversion and changing soil carbon stocks in China's 'Grain-for-Green' program: a synthesis. *Global Change Biology*, 20(11): 3544–3556. doi: 10.1111/gcb.12508

Department of Forest Resources Management (DFRM), SFA, 2010. The 7th national forest inventory and status of forest resources. *Forest Resources Management*, (1): 1–8. (in Chinese)

Du J F, Thill J C, Peiser R B et al., 2014. Urban land market and land-use changes in post-reform China: a case study of Beijing. *Land-scape and Urban Planning*, 124: 118–128. doi: 10.1016/j.landurbplan.2014.01.012

FAO-Food and Agricultural Organization of the United Nations, 2012. *State of the World'S Forests*, *2012*. Rome, Italy: FAO. http://www.fao.org/docrep/016/i3010e/i3010e00.htm.

Foody G M, 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1): 185–201. doi: 10.1016/S0034-4257(01)00295-4

Foody G M, Mathur A, 2004. A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42(6): 1335–1343. doi: 10.1109/TGRS.2004.827257

Gao J, Liu Y S, 2011. Deforestation in Heilongjiang Province of China, 1896-2000: severity, spatiotemporal patterns and causes. *Applied Geography*, 35(1-2): 345–352. doi: 10.1016/j.apgeog.2012.08.001

Garcia C A, Savilaakso S, Verburg R W et al., 2020. The global forest transition as a human affair. *One Earth*, 2(5): 417–428. doi: 10.1016/j.oneear.2020.05.002

Girardet H, 2020. People and nature in an urban world. *One Earth*, 2(2): 135–137. doi: 10.1016/j.oneear.2020.02.005

Gobattoni F, Pelorosso R, Lauro G et al., 2011. A procedure for mathematical analysis of landscape evolution and equilibrium scenarios assessment. *Landscape and Urban Planning*, 103(3-4): 289–302. doi: 10.1016/j.landurbplan.2011.08.011

Han R, Cui N X, Guo L, 2018. Monitoring the effects of the grain to green projects using landscape metrics: a case study in eastern Si-chuan, China. *IOP Conference Series: Earth and Environmental Science*, 189: 052009. doi: 10.1088/1755-1315/189/5/052009

Hasan S, Shi W Z, Zhu X L et al., 2019. Monitoring of land use/land cover and socioeconomic changes in south China over the last three decades using Landsat and Nighttime light data. *Remote Sensing*, 11(4): 1658. doi: 10.3390/rs11141658

Herold M, Scepan J, Clarke K C, 2002. The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. *Environment and Planning A: Economy and Space*, 34(8): 1443–1458. doi: 10.1068/a3496

Hu Y J, Kong X B, Zheng J et al., 2018. Urban expansion and farmland loss in Beijing during 1980-2015. *Sustainability*, 10(11): 3927. doi: 10.3390/su10113927

Hu Z W, Li Q G, Zou Q et al., 2016. A bilevel scale-sets model for hierarchical representation of large remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, 54(12): 7366–7377. doi: 10.1109/TGRS.2016.2600636

Jia M M, Wang Z M, Zhang Y Z et al., 2015. Landsat-based estimation of mangrove forest loss and restoration in Guangxi Province, China, influenced by human and natural factors. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(1): 311–323. doi: 10.1109/JSTARS.2014.2333527

Jordan N, Boody G, Broussard W et al., 2007. Environment: sustainable development of the agricultural bio-economy. *Science*, 316(5831): 1570–1571. doi: 10.1126/science.1141700

Kline J D, Moses A, Azuma D et al., 2009. Evaluating satellite imagery-based land use data for describing forestland development in western Washington. *Western Journal of Applied Forestry*, 24(4): 214–222. doi: 10.1093/wjaf/24.4.214

Lambin E F, Meyfroidt P, 2010. Land use transitions: socio-ecological feedback *versus* socio-economic change. *Land Use Policy*, 27(2): 108–118. doi: 10.1016/j.landusepol.2009.09.003

Laurance W F, Vasconcelos H L, Lovejoy T E, 2000. Forest loss and fragmentation in the Amazon: implications for wildlife conservation. *Oryx*, 34(1): 39–45. doi: 10.1046/j.1365-3008.2000.00094.x

Lechner A M, Foody G M, Boyd D S, 2020. Applications in remote sensing to forest ecology and management. *One Earth*, 2(5): 405–412. doi: 10.1016/j.oneear.2020.05.001

Lele N, Joshi P K, Agrawal S P, 2008. Assessing forest fragmentation in northeastern region (NER) of India using landscape matrices. *Ecological Indicators*, 8(5): 657–663. doi:

10.1016/j.ecolind.2007.10.002

Li M S, Mao L J, Zhou C G et al., 2010. Comparing forest fragmentation and its drivers in China and the USA with Globcover v2.2. *Journal of Environmental Management*, 91(12): 2572–2580. doi: 10.1016/j.jenvman.2010.07.010

Li M S, Mao L J, Lu C et al., 2012. Temporal change in fragmentation in China's primary forest ecoregions. *Advanced Materials Research*, 433-440: 1286–1296. doi: 10.4028/www.scientific.net/AMR.433-440.1286

Li X, Zhou Y, Asrar G R et al., 2017. Characterizing spatiotemporal dynamics in phenology of urban ecosystems based on Landsat data. *Science of the Total Environment*, 605-606: 721–734. doi: 10.1016/j.scitotenv.2017.06.245

Liang C, Jiang P H, Chen W et al., 2015. Farmland protection policies and rapid urbanization in China: a case study for Changzhou city. *Land Use Policy*, 48: 552–566. doi: 10.1016/j.landusepol.2015.06.014

Lindquist E J, D'Annunzio R, 2016. Assessing global forest landuse change by object-based image analysis. *Remote Sensing*, 8(8): 678. doi: 10.3390/rs8080678

Liu J Y, Zhang Z X, Xu X L et al., 2010. Spatial patterns and driving forces of land use change in china during the early 21st century. *Journal of Geographical Sciences*, 20(4): 483–494. doi: 10.1007/s11442-010-0483-4

Liu Jiyuan, Zhang Qian, Hu Yunfeng, 2012. Regional differences of China's urban expansion from late 20th to Early 21st Century based on remote sensing information. *Chinese Geographical Science*, 22: 1–14. doi: 10.1007/s11769-012-0510-8

Liu J Y, Kuang W H, Zhang Z X et al., 2014. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *Journal of Geographical Sciences*, 24(2): 195–210. doi: 10.1007/s11442-014-1082-6

Liu T, Liu H, Qi Y J, 2015. Construction land expansion and cultivated land protection in urbanizing China: insights from national land surveys: 1996-2006. *Habitat International*, 46: 13–22. doi: 10.1016/j.habitatint.2014.10.019

Liu Tingxiang, Zhang Shuwen, Tang Junmei et al., 2013. Comparison and analysis of agricultural and forest land changes in typical agricultural regions of northern mid-latitudes. *Chinese Geographical Science*, 23(2): 163–172. doi: 10.1007/s11769-012-0576-3

Liu Y L, Feng Y H, Zhao Z et al., 2016a. Socioeconomic drivers of forest loss and fragmentation: a comparison between different land use planning schemes and policy implications. *Land Use Policy*, 54: 58–68. doi: 10.1016/j.landusepol.2016.01.016

Liu Fang, Zhang Zengxiang, Shi Lifeng et al., 2016b. Urban expansion in China and its spatial-temporal differences over the past four decades. *Journal of Geographical Sciences*, 26(10): 1477–1496. doi: 10.1007/s11442-016-1339-3

Liu Y S, Wang J Y, Long H L, 2010b. Analysis of arable land loss and its impact on rural sustainability in Southern Jiangsu Province of China. *Journal of Environmental Management*, 91(3): 646–653. doi: 10.1016/j.jenvman.2009.09.028

Liu Y S, Fang F, Li Y H, 2014b. Key issues of land use in China and implications for policy making. *Land Use Policy*, 40: 6–12. doi: 10.1016/j.landusepol.2013.03.013

Liu Z, Geng Y, Zhang P et al., 2014c. Emergy-based comparative analysis on industrial clusters: economic and technological development zone of Shenyang area, China. *Environmental Science and Pollution Research*, 21(17): 10243–10253. doi: 10.1007/s11356-014-2854-3

Lv H L, Yang Y B, Zhang D et al., 2019. Perimeter-area ratio effects of urbanization intensity on forest characteristics, landscape patterns and their associations in Harbin city, northeast China. *Urban Ecosystems*, 22(4): 631–642. doi: 10.1007/s11252-019-00850-0

Madanian M, Soffianian A R, Koupai S S et al., 2018. Analyzing the effects of urban expansion on land surface temperature patterns by landscape metrics: a case study of Isfahan city, Iran. *Environmental Monitoring and Assessment*, 190(4): 189. doi: 10.1007/s10661-018-6564-z

Mao D H, He X Y, Wang Z M et al., 2019. Diverse policies leading to contrasting impacts on land cover and ecosystem services in Northeast China. *Journal of Cleaner Production*, 240: 117961. doi: https://doi.org/10.1016/j.jclepro.2019.117961

McGarigal K, Marks B J, 1995. *FRAGSTATS*: *Spatial Pattern Analysis Program for Quantifying Landscape Structure*. Portland: USDA Forest Service, 122.

McGarigal K, 2002. Landscape pattern metrics. In: El-Shaarawi A H and Piegorsch W W (eds.). *Encyclopedia of Environmetrics*. Chichester: John Wiley & Sons, 1135–1142.

McGarigal K, 2015. *Fragstats Help*. Amherst: University of Massachusetts.

Miller M D, 2012. The impacts of Atlanta's urban sprawl on forest cover and fragmentation. *Applied Geography*, 34: 171–179. doi: 10.1016/j.apgeog.2011.11.010

NBSC (National Bureau of Statistics of China), 2010. *China Compendium of Statistics*. Beijing: China Statistics Press. (in Chinese)

NBSC (National Bureau of Statistics of China), 2013. *China Compendium of Statistics*. Beijing: China Statistics Press. (in Chinese)

NDRC (National Development and Reform Commission of China), 2014. *National New-type Urbanization Plan*. Available at: http://www.gov.cn/zhengce/2014-03/16/content_2640075.htm (accessed on 16 March 2014)

Reddy C S, Sreelekshmi S, Jha C S et al., 2013. National assessment of forest fragmentation in India: landscape indices as measures of the effects of fragmentation and forest cover change. *Ecological Engineering*, 60: 453–464. doi: 10.1016/j.ecoleng.2013.09.064

Setiawan Y, Yoshino K, Prasetyo L B, 2014. Characterizing the dynamics change of vegetation cover on tropical forestlands using 250 m multi-temporal MODIS EVI. *International Journal of Applied Earth Observation and Geoinformation*, 26: 132–144. doi: 10.1016/j.jag.2013.06.008

Seymour F, 2020. Seeing the forests as well as the (Trillion) trees in corporate climate strategies. *One Earth*, 2(5): 390–393. doi: 10.1016/j.oneear.2020.05.006

Shen W J, Wu J G, Grimm N B et al., 2008. Effects of urbanization-induced environmental changes on ecosystem functioning in the phoenix metropolitan region, USA. *Ecosystems*, 11: 138–155. doi: 10.1007/s10021-007-9085-0

Song D X, Huang C, Sexton J O et al., 2014. Size and frequency of forest loss and gain in China during 2000–2005. In: *American Geo-physical Union*, *Fall Meeting 2014*. San Francisco: AGU, Tao R, Su F B, Liu M X et al., 2010. Land leasing and local public finance in China's regional development: evidence from prefecture-level cities. *Urban Studies*, 47(10): 2217–2236. doi: 10.1177/0042098009357961

Trac C J, Schmidt A H, Harrell S et al., 2013. Environmental reviews and case studies: is the returning farmland to forest program a success? three case studies from Sichuan. *Environmental Practice*, 15(3): 350–366. doi: 10.1017/S1466046613000355

Turner II B L, Lambin E F, Reenberg A, 2007. The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, 104(52): 20666–20671. doi: 10.1073/pnas.0704119104

Van Den Hoek J, Ozdogan M, Burnicki A et al., 2014. Evaluating forest policy implementation effectiveness with a cross-scale remote sensing analysis in a priority conservation area of Southwest China. *Applied Geography*, 47: 177–189. doi: 10.1016/j.apgeog.2013.12.010

Wahyudi A, Liu Y, Corcoran J, 2018. Combining landsat and landscape metrics to analyse large-scale urban land cover change: a case study in the Jakarta Metropolitan Area. *Journal of Spatial Science*, 64(3): 515–534. doi: 10.1080/14498596.2018.1443849

World Bank, 2015. World bank database. http://data.worldbank.org. Cited 13 May 2015.

Wu Z, Dai E, Wu Z F et al., 2019. Future forest dynamics under climate change, land use change, and harvest in subtropical forests in southern China. *Landscape Ecology*, 34(4): 843–863. doi: 10.1007/s10980-019-00809-8

Xie H L, Kung C C, Zhao Y L, 2012. Spatial disparities of regional forest land change based on ESDA and GIS at the county level in Beijing-Tianjin-Hebei area. *Frontiers of Earth Science*, 6(4): 445–452. doi: 10.1007/s11707-012-0338-7

Xie H L, He Y F, Zhang N et al., 2017. Spatiotemporal changes and fragmentation of forest land in Jiangxi province, China. *Journal of Forest Economics*, 29(1): 4–13. doi: 10.1016/j.jfe.2017.08.004

Xu G L, Huang X J, Zhong T Y et al., 2015. Assessment on the effect of city arable land protection under the implementation of China's national general land use plan (2006-2020). *Habitat International*, 49: 466–473. doi: 10.1016/j.habitatint.2015.06.017

Yang C, Wu G F, Ding K et al., 2017b. Improving land use/land cover classification by integrating pixel unmixing and decision tree methods. *Remote Sensing*, 9(12): 1222. doi: 10.3390/rs9121222

Yang C, Li Q Q, Hu Z W et al., 2019a. Spatiotemporal evolution of urban agglomerations in four major bay areas of US, China and Japan from 1987 to 2017: Evidence from remote sensing images. *Science of the Total Environment*, 671: 232–247. doi: 10.1016/j.scitotenv.2019.03.154

Yang C, Wu G F, Chen J Y et al., 2019b. Simulating and forecasting spatio-temporal characteristic of land-use/cover change with numerical model and remote sensing: a case study in Fuxian Lake Basin, China. *European Journal of Remote Sensing*, 52(1): 374–384. doi: 10.1080/22797254.2019.1611387

Xu G, Zhou Z, Jiao L et al., 2020. Compact urban form and expansion pattern slow down the decline in urban densities: a global perspective. *Land Use Policy*, 94: 104563. doi: 10.1016/j.landusepol.2020.104563

Yang C, Zhang C C, Li Q Q et al., 2020. Rapid urbanization and policy variation greatly drive ecological quality evolution in Guang-dong-Hong Kong-Macau greater bay area of China: a remote sensing perspective. *Ecological Indicators*, 115: 106373. doi: 10.1016/j.ecolind.2020.106373

Yang J, Sun J, Ge Q S et al., 2017a. Assessing the impacts of urbanization-associated green space on urban land surface temperature: a case study of Dalian, China. *Urban Forestry & Urban Greening*, 22: 1–10. doi: 10.1016/j.ufug.2017.01.002

Yu Sisi, Sun Zhongchang, Guo Huadong et al., 2017. Monitoring and analyzing the spatial dynamics and patterns of megacities along the maritime Silk Road. *Journal of Remote Sensing*, 21(2): 169–181. (in Chinese)

Yu Z W, Yao Y W, Yang G Y et al., 2019. Strong contribution of rapid urbanization and urban agglomeration development to regional thermal environment dynamics and evolution. *Forest Ecology and Management*, 446: 214–225. doi: 10.1016/j.foreco.2019.05.046

Zengin H, Değermenci A S, Bettinger P, 2018. Analysis of temporal changes in land cover and landscape metrics of a managed forest in the west black sea region of northern Turkey: 1970-2010. *Journal of Forestry Research*, 29: 139–150. doi: 10.1007/s11676-017-0423-6

Zhang J, Zhou Y K, LI R Q et al., 2010. Accuracy assessments and uncertainty analysis of spatially explicit modeling for land use/cover change and urbanization: a case in Beijing metropolitan area. *Science China Earth Science*, 53: 173–180. doi: 10.1007/s11430-009-0199-4

Zhang L, Weng Q H, 2016. Assessment of urban growth in the Pearl River Delta, China, using time series Landsat imagery. In: Weng Q H (ed). *Remote Sensing for Sustainability*. London: CRC Press.

Zhang Z X, Wen Q K, Liu F et al., 2016. Urban expansion in china and its effect on cultivated land before and after initiating "reform and open policy. *Science China Earth Sciences*, 59(10): 1930–1945. doi: 10.1007/s11430-015-0160-2

Zhong T Y, Mitchell B, Huang X J, 2014. Success or failure: evaluating the implementation of China's national general land use plan (1997-2010). *Habitat International*, 44: 93–101. doi: 10.1016/j.habitatint.2014.05.003