Assessing spatio-temporal changes in forest cover and fragmentation under urban expansion in Nanjing, eastern China, from long-term Landsat observations (1987–2017)

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ABSTRACT

Assessing changes in forest cover and fragmentation under urban expansion and the correlation analysis between these changes can provide decision support for urban forest managers. In this study, forest cover and morphological spatial patterns (cores, islets, perforations, edges, loops, bridges, and branches) were firstly mapped by the vegetation change tracker (VCT) algorithm and morphological spatial pattern analysis (MSPA) respectively in Nanjing from 1987 to 2017. Next, the visible red and near-infrared-based built-up index (VrNIR-BI) was derived to extract urban impervious surface (UIS) areas, and the neighbourhood-based urban expansion model was proposed to describe the expansion types (edge-expansion, infilling and outlying). Finally, the relationships among the forest cover, fragmentation changes and urban expansion were determined using the Pearson correlation coefficient (r). The results showed that the distribution of forest cover in Nanjing was relatively scattered and it decreased by 94 km², while the UIS area increased by 893 km² from 1987 to 2017, resulting in some forests being gradually surrounded or encroached upon by UIS areas. The main forest morphological spatial pattern was identified as cores, with many small-area cores. Moreover, islets exhibited a higher proportion of 0.18, and these suggested that the fragmentation of Nanjing’s forests was severe. Forest net changes had the higher correlation with cores, edges and branches. In addition, there were strong correlations between edge-expansion and cores, edges, branches with the r values greater than 0.75, which meant that most of the urban areas extended to core regions from the forest edges or branches. The derived information will help forest managers monitor forest dynamics in response to urban expansion and achieve sustainable development.

1. Introduction

Forests, as an important part of urban ecosystems, contribute greatly to environmental improvement and biodiversity protection, including absorbing carbon dioxide and air pollutants, relieving the urban heat island effect, and providing habitat conservation (Bowler, Buyung-Ali, Knight, & Pullin, 2010; Chen, Jim, Carreiro, Song, & Wu, 2008; Estoque, Murayama, & Mynt, 2017; Hall, Skakun, Arsenault, & Case, 2006). However, rapid urban expansion is producing disturbances globally by changing forest cover and its connectivity (Hernando, Velázquez, Valbuena, Legrand, & García-Abril, 2017), such as by encroachment on local vegetation (Gong, Yu, Joesting, & Chen, 2013; Mckinney, 2002) and the division of unbroken forests into small and isolated fragments (Lord & Norton, 1990). This process has been especially noticeable in Nanjing city of eastern China as it vigorously develops land to meet people’s demand for housing and infrastructure driven by rapidly increasing population over the past several decades (Chen, Gao, & Chen, 2016; Nanjing Statistics Bureau, 2018). Long and dense time series of forest cover and fragmentation changes and the related disturbance events (such as urban expansion) are still not currently available for governmental managers to make decisions for urban planning in Nanjing. Traditional methods for detecting changes in forest cover are based on national forest resource inventory data conducted every five years in China (Zeng, Tomppo, Healey, & Gadow, 2015), which are usually limited by the small spatial and temporal scales, resulting in inadequate land management information for urban planners.
Multiple remote sensing techniques have been increasingly used to detect forest cover changes and to monitor forest fragmentation (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Da Ponte et al., 2017; Dadashpoor, Azizi, & Mohgadasi, 2019; Gong et al., 2013; Hansen, Stehman, & Fung, 2010; Paul & Nagendra, 2015; Zhou, Zhang, Yu, Wang, & Wang, 2017). Many studies have mapped forest changes and fragmentation based on coarse-resolution datasets (Hansen, Defries, Townshend, & Sohldberg, 2000; Jin & Sader, 2005; Verbesselt, Hyndman, Newnham, & Culvenor, 2010), and these products are not suitable for the application of local scales. High-resolution images can capture more subtle forest changes (Pu & Landry, 2012; Zhu, Shen, Diao, Li, & Zheng, 2019), but most high-resolution images are confined to small areas with short time spans due to high costs and limited availability on the urban area scale, thereby limiting their role in urban planning. Thus, time series of Landsat data with proper spatial and temporal information and free access have been widely used in forest cover change detection (Huang et al., 2010; Kennedy, Cohen, & Schroeder, 2007; Masek et al., 2008; Shen et al., 2019; Zhu & Woodcock, 2014), especially for some highly automated algorithms such as LandTrendr (Kennedy et al., 2007), vegetation change tracker (VCT) (Huang et al., 2010) and continuous changes and detection and classification (CCDC) (Zhu & Woodcock, 2014). Compared with LandTrendr and CCDC, the input and implement of VCT is simple and straightforward, and it only takes only 2–3 h to complete the generation of forest change maps, while LandTrendr and CCDC require more time and/or data storage.

Moreover, many efforts have been made to characterize forest fragmentation. Early studies on fragmentation used landscape metrics, such as edge density, connectivity index, to express the degree of fragmentation through statistical values across the study area, and they did not provide the locations where the different types of pattern occurred (Dadashpoor et al., 2019; Gong et al., 2013). Unlike landscape metrics, morphological spatial pattern analysis (MSPA) (Soille & Vogt, 2009), based on edge width and neighbourhood analysis, divides all forest pixels into 7 categories (core, islet, loop, bridge, edge, perforation and branch) representing a clear distribution map of the forest landscape, markedly improving the spatial decision process in urban decision-making and urban forest management. Additionally, some studies have examined the analysis of forest fragmentation in the context of changing forest cover. Specially, Gong et al. (2013) found that Shenzhen’s forest cover recovered to 85.5%, accompanied by the appearance of small and isolated forest patches. However, the lack of analysis on the correlation between forest cover and fragmentation is evident. Thus, the combination of VCT and MSPA helps to analyze the spatio-temporal changes of forest cover and fragmentation, and it also contributes to providing diverse spatially explicit data for us to understand the relationships between these changes.

Urban expansion, as a threat to forest cover and fragmentation, is always associated with area increases and expansion of urban imperious surface (UIS) regions. UIS areas are defined as natural or man-made materials that prevent the infiltration of surface water into the soil, and they are commonly extracted from the UIS index (Arnold & Gibbons, 1996; Estoque & Murayama, 2015). In general, urban expansion includes three types proposed by Liu et al. (2010): (1) edge-expansion; (2) infilling; and (3) outlying. The division of these three types of expansion is mainly based on buffer analysis and the landscape expansion index. To be consistent with the neighbourhood analysis of MSPA and to consider the connectivity between the expanded patch and the original patch, a neighbourhood-based idea was proposed to classify the three types of expansion. Currently, several studies have successfully investigated the impact of UIS areas on forest loss and fragmentation (Dadashpoor et al., 2019; Miller, 2012; York et al., 2011; Zhou et al., 2017; Zhou & Wang, 2011). However, these studies focused on bi-temporal or triple-temporal images to emphasize the areas and locations of forest loss caused by urban expansion or to explore the relationships between forest changes and urban expansion. Few studies have examined a comprehensive relationships between forest changes and morphology-based fragmentation induced by urban land expansion in a long-term manner.

The purpose of this article was to characterize the changes in forest cover and fragmentation in the context of urban expansion. The specific objectives were as follows: (1) assessing annual changes in forest cover and fragmentation using dense time series Landsat data from 1987 to 2017 and analyzing the relationships between forest cover changes and fragmentation; (2) proposing a neighbourhood-based urban expansion model and revealing how urban expansion affects forest cover and fragmentation from 1987 to 2017 at 3–4 year intervals; and (3) discussing how to apply current results to urban planning and providing reasonable suggestions for urban managers to achieve sustainable forest development.

2. Materials and methods

2.1. Study sites

Nanjing (118°22′–119°14′E, 31°14′–32°37′N, covering an area of 6597 km²), the capital of Jiangsu Province in eastern China, is located on the Yangtze River and is a state-level megacity (Fig. 1). Nanjing has a subtropical monsoon climate with four distinct seasons. The annual precipitation is 1200 mm, and the annual average temperature is 15.4 °C (Li et al., 2016). The forest type in this region is now deciduous and evergreen broad-leaved mixed forests and the main types of crops are rice, wheat and corn. In recent decades, Nanjing has experienced rapid urbanization, which has brought about large increases in the population and gross regional product from 4.80 million residents and 10.92 billion RMB in 1987 to 8.34 million residents and 1171.51 billion RMB in 2017, respectively (Nanjing Statistics Bureau, 2018). There are 11 administrative districts in Nanjing, divided into downtown (Xuanwu, Qinhuai, Jianye, and Gulu districts) and suburban regions (Pukou, Qixia, Yuhuatai, Jiangning, Liuhe, Lishui, and Gaochun districts) (Fig. 1).

2.2. Study data

The satellite data used in this study included Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) scenes from 1987 to 2017 with Path/Row numbers of 120/038. The images for 1996, 2004, 2008, and 2012 were not available in this work due to their extremely poor quality. Because our goal was to map forest changes with sufficient accuracy from Landsat observations, the acquisition dates of most images had to fall into the growing reason (mid-May through mid-September for the mid-latitude regions). Forests always maintain stable spectral characteristics (Dodge & Bryant, 1976; Huang et al., 2010), while the spectrum of some crops, similar to forests in a certain season, will obviously fluctuate due to harvest. For all satellite images, surface reflectance and brightness temperature datasets, with no cloud contamination or few clouds in the images, were directly obtained from the United States Geological Survey (USGS) (https://glovis.usgs.gov). Two dates in a year were used to synthesize a clear and cloudless image for one year. The details of Landsat data used in this analysis are summarized in Table 1.

2.3. Mapping forest cover changes

Huang et al. (2010) developed the VCT algorithm to track vegetation change. The VCT consists of two steps to identify forest cover changes, i.e., individual image analysis and time series analysis. Individual image analysis mainly involves the masking of noise, (such as clouds, shadows and snow), recognition of forest samples and calculation of the integrated forest z-score (IFZ) (Huang et al., 2010). During the time series analysis, we mainly used the value of adjacent year to replace the noise area. After filling the noisy areas, the temporal profile of IFZ was used to determine the forest change. Specifically, forest pixels have low IFZ values, and non-forest pixels have high IFZ values. If the IFZ of a pixel is
always low throughout the time series, then it may be a persistent forest (value 2 in Table 2). If the IFZ remains very high throughout the time series, then it may be a persistent non-forest (value 1 in the table). If a pixel has consecutive low IFZ values at the beginning, but the value suddenly increases in a particular year, and the increase lasts for a period of time (because the forest recovery is unlikely to be completed in a short time), then the pixel is likely to experience disturbance events in this particular year (value 6 in Table 2). If the increasing IFZ returns to consecutive low IFZ again, then it is marked as “Probable forest with recent disturbance” (value 5 in Table 2), otherwise it is marked as “Post-disturbance” (value 7 in Table 2). More details of VCT are described in the work made by Huang et al. (2010).

Finally, we generated 27 annual disturbance map with seven classes and their definitions are shown in Table 2. Then we reclassified the annual disturbance map into forest and non-forest product and 27 forest cover maps were obtained. According to the definition of each category of an annual disturbance map, value 2 (persistent forest) and 5 (probable forest with recent disturbance) were grouped into a new forest class. The remaining five classes were reclassified into the non-forest class.

### 2.4. Mapping forest fragmentation

MSPA applies mathematical morphological principles, such as erosion, expansion, and anchoring skeletons, to describe the spatial composition of forests. The input data for MSPA must be a binary raster map (referring to forests and non-forests in this study). There are two key and user-speciﬁed parameters in MSPA: (1) connectivity and (2) edge width. The connectivity can be set to 4 or 8 neighbor. 4 neighbor defines the connectivity as a center pixel at only four pixel borders. 8 neighbor defines the connectivity as a center pixel at four pixel borders and four corners. Edge width deﬁnes the distance (at the pixel level) between cores and non-forest and the thickness of non-core classes of forest. In general, the default values for connectivity and edge width are 8 and 1 pixel width (Soille & Vogt, 2009). Lastly, MSPA, based on the given connectivity and edge width, divides all forest pixels into seven categories, namely, cores, islets, bridges, loops, edges, perforations and branches.

The cores are defined as the interior of the forests, located at a certain distance from non-forest areas, and represent non-fragmented habitats.
Islets are small and isolated forests that are not connected to other forests, and wildlife is less likely to communicate with the outside. Bridges and loops are connector forests that represent pathways for material exchange and energy flow within the core areas. Bridges connect different core areas, whereas loops connect the same core areas. Edges and perforations refer to external and internal boundaries of forests, respectively, and have obvious edge effects. One side of the branches is connected to a connector or boundary, and the other side is connected to the non-forest areas (Vogt et al., 2007). A schematic diagram of these definitions is shown in Fig. 2.

In this study, we first converted the VCT-based forest disturbance products into binary images of forest and non-forest and then used the free software package GUIDOS (http://forest.jrc.ec.europa.eu/download/software/guidos) to implement the MSPA on each binary image using 8-pixel neighbourhoods and an edge width of 30 m.

2.5. Mapping UIS areas and urban expansion types

2.5.1. Mapping UIS and water areas

The one-year urban expansion in Nanjing did not have a profound impact on forest cover and fragmentation, especially during the period from 1987 to 1990 when the area of urban expansion was relatively small (Nanjing Land and Resources Bureau, 2012). To emphasize the impact of urban expansion on forests, we decided to map UIS areas at 3–4 year intervals from 1987 to 2017.

A variety of UIS indices have been proposed to extract UIS areas. Estoque and Murayama (2015) proposed the VrNIR-BI, conducted a comparison of multiple UIS indices and found that the accuracy of VrNIR-BI was highest, which allowed for the accurate separation of UIS and non-UIS areas. We extracted UIS from VrNIR-BI images in 1987, 1990, 1994, 1997, 2000, 2003, 2007, 2010, 2013, and 2017. To generate four land cover categories for subsequent accuracy assessments (water, UIS, forest, other), the modified normalized difference water index (MNDWI) (Xu, 2006) was used in this study to extract water bodies because previous studies have shown that it achieves a more accurate classification (Ji, Zhang, & Wylie, 2009; Xu, 2006).

First, the thresholding operation was applied to MNDWI images and the generated index images simultaneously, the optimal thresholds were accordingly determined to extract water and UIS distribution information for 10 images. The water body index and VrNIR-BI used in this study were obtained using Equations (1) and (2):

\[ \text{MNDWI} = \frac{\rho_{\text{Green}} - \rho_{\text{SWIR1}}}{\rho_{\text{Green}} + \rho_{\text{SWIR1}}} \]  \hspace{1cm} (1)

\[ \text{VrNIR} - BI = \frac{\rho_{\text{Red}} - \rho_{\text{NIR}}}{\rho_{\text{Red}} + \rho_{\text{NIR}}} \]  \hspace{1cm} (2)

Where, \( \rho_{\text{Green}}, \rho_{\text{SWIR1}}, \rho_{\text{Red}}, \rho_{\text{NIR}} \) refer to the atmospherically corrected surface reflectance values of the green, shortwave infrared 1 (SWIR1), red and NIR bands.

2.5.2. Mapping urban expansion types

Based on Liu’s theory (2010), urban expansion is divided into three types: (1) edge-expansion, (2) outlying, and (3) infilling. If only a portion of the expanded patch is connected to the original UIS, then it is considered edge-expansion; if the expanded patch is not connected to the original UIS at all, then it is considered outlying; and if the expanded patch is completely surrounded by the original UIS, then it is considered infilling (Fig. 3).

Unlike the buffer analysis from Liu et al. (2010), we classified urban expansion based on the structural connectivity of the urban landscape. First, UIS binary images of all years were obtained, where value 1 represented UIS and value 0 represented non-UIS. We compared the UIS binary images of adjacent dates to obtain the urban expansion areas. Subsequently, on the original UIS binary image (the previous year image), the urban expansion regions were set to null. For an expanded patch, calculating the maximum and minimum values of the central pixel in the 8-pixel neighbourhood and assigning them to the central pixel respectively. If the maximum value in each expanded patch was 1 and the minimum value was 0, then the expanded patch was edge-expansion; if both the maximum and minimum values were 1, the expanded patch was infilling; and if the maximum and minimum values were both 0, then the expanded patch was outlying.

2.6. Statistical analysis

For the correlation between forest cover and fragmentation, and the correlation between urban expansion and fragmentation, we used different analysis scales. 26 images of forest change products were obtain based on VCT, and such a sample size was enough for the correlation analysis. However, we only had 9 maps of urban expansion. To get more accurate results, we decided to increase the sample size and analyzed the relationships between urban expansion and fragmentation at the districts scale. Specifically, we calculated the total net change area of VCT-based forest cover and MSPA-based fragmentation for the entire study area in the adjacent years at the pixel level. Using the net change areas of forest cover as an independent variable and the net change areas of each morphological spatial pattern as a dependent variable, the linear regression model and Pearson correlation coefficient (r) were used to analyse the relationships between forest cover change and
5

obtain the actual category of each point; and (4) we counted the number overlaid onto the Landsat original images or Google earth maps to Accuracy assessment of classification results.

Table 3

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<td>93.3</td>
<td>91.1</td>
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<td>89.1</td>
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<tr>
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<td>90.4</td>
<td>91.0</td>
<td>90.5</td>
<td>84.3</td>
<td>89.0</td>
<td>85.2</td>
<td>85.1</td>
<td>82.7</td>
</tr>
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3.2. Spatio-temporal changes in forest cover and fragmentation

The forest distribution of Nanjing was spatially scattered, and large areas of forest were mainly distributed in scenic forest areas and forest parks, such as the Purple mountain scenic forest area in Xuanwu district, the Laoshan national forest park in Pukou district and Niushou mountain forest park in Jingning districts (Fig. 4, number 1, 2, and 3). From 1987 to 2017, it could be seen that the forests became increasingly surrounded or encroached upon by UIS or other land cover types. Specifically, the forests in the east of Qixia district were obviously replaced by UIS. Some UIS areas appeared in the western forests of Laoshan mountain from 2007 to 2017. However, some other land cover types have been restored to forests. The most apparent place was the Mufu mountain in Qixia district (Fig. 4, number 4). It used to be a mining site, and the forest coverage increased after a series of greening projects. The forest cover areas have fluctuated over the past 30 years, with a maximum area of 946.1 km² in 2007 and a minimum area of 833.2 km² in 2017 (Fig. 5(a)). From 2013 to 2016, the forest areas showed substantial increases, similar to the trend from 1998 to 2007, except for a slight decline in 2002 (Fig. 5(a)).

During the past 30 years, cores were the dominant morphological spatial pattern, followed by islets and edges, whereas the perforations were the least common. The core area proportion (the area of each morphological spatial pattern divided by the total area of the forest in the current year) consistently increased to 0.47 in 1990, after which the proportion started to decrease to 0.45 in 1997. Subsequently, the core area proportion increased again to 0.47 in 2002, and finally, the cores remained stable at approximately 0.45 after 2002. The change trends of the loops, bridges, and branches were roughly the same as that of the cores (Fig. 5(b)). The spatial patterns of forest fragmentation are shown in Fig. 6 using the first year and last year as examples. There were many very small areas of cores and islets, and forest fragmentation was pervasive in Nanjing (Fig. 6). In particular, the forests of Gaochun and Liuhe districts were almost entirely in the form of islets, and there were almost no large-area cores. Over time, large-area cores became divided into multiple small-area cores, and small-area cores became islets. Some bridges, loops, branches and islets disappeared (Fig. 6). Here we took the core summary statistics of 10 images as examples, only a small percentage of the core areas have been isolated (not connected to the other core by bridges), and most of the cores are connected (Table 4). From 1987 to 2000, the connected cores showed fluctuating changes, after
which the connected cores remained basically increasing and reached its peak at 72.8% in 2017. Besides, most core forests (about 80%) were less than 1ha in size, and there were a small amount of cores (about 3%–4%) whose areas were over 10 ha (Table 4).

3.3. Relationships between forest net changes and forest fragmentation

There were significant positive linear correlations between forest net changes and all morphological spatial patterns (p-value<0.05) (Fig. 7). The branches, edges and bridges had strong correlations with forest net changes, with the r greater than 0.80, while perforations had the
weakest correlation with forest net changes, with a r of 0.40. The r of cores, islets, and loops with forest net changes, although not as high as that of branches, were between 0.72 and 0.77 (Fig. 7).

3.4. Impact of urban expansion on forest cover and fragmentation

The UIS area continuously increased from 703 km$^2$ in 1987 to 1596 km$^2$ in 2017 (Table 5). The UIS area slowly increased at a rate of 1.7% from 1987 to 1990 and then accelerated to a rate 5.2% during 2003–2007. After 2007, the rate of increase slowed (Table 5). A much larger area of UIS was observed east of the river than west of the river (Fig. 4). Over time, the UIS expanded from the downtown to the suburbs, such as Jiangning, Pukou, and Qixia districts (Fig. 4). Relatively few forests (13.3 km$^2$) were converted into UIS from 1987 to 1990 (Table 5). The largest area of forest converted into UIS was 34.9 km$^2$ from 2007 to 2010, after which there was a slight decrease in the forest loss caused by UIS (Table 5).

The most common type of urban expansion was edge-expansion, and the least common type was infilling (Fig. 8(a)). The p-values in Fig. 8(b) were all less than 0.01, which indicated that all correlations were significant. The edge-expansion areas had the highest correlation with each morphological spatial pattern among the three urban expansion types. The correlations were the higher between the cores, edges and branches and the edge-expansion, with the r value greater than 0.75 (Fig. 8(b)). In general, infilling areas had the lowest correlation with the seven morphological spatial patterns, with r less than 0.40. The r between outlying and all morphological spatial patterns were between 0.50 and 0.70, with the branches having the strongest correlation with the outlying areas.

4. Discussion

4.1. Assessments and application of forest cover and fragmentation

The VCT model has been used in many studies (Huang et al., 2010; Li et al., 2016). For example, Li et al. (2016) characterized forest cover changes in the Ning-Zhen Mountains of Nanjing and used visual interpretation to attribute the forest disturbance types (e.g., mining and urbanization). We not only extended the areas of forest cover to the entirety of Nanjing but also combined VCT with VrNIR-BI to automatically determine the areas forest cover changes resulting from urban expansion during the past 30 years, which provided a good perspective on the forest dynamics. Based on the forest cover maps from the VCT model, we used a morphology-based approach to further characterize the forest fragmentation. Previous studies have mainly used various landscape metrics to characterize forest fragmentation (Dadashpoor et al., 2019; Gong et al., 2013; Zhou et al., 2017). These results were only expressed quantitatively, and their practical utilities were limited in contrast to our spatially explicit fragmentation maps based on MSPA (Fig. 6).

The MSPA can also be used in forest management planning, such as the construction of an ecological network. Two important components of ecological networks are hubs and links (Benedict & Mcmahon, 2002). Cores can be identified as hubs, and bridges can be identified as links (Wickham, Ritter, Wade, & Vogt, 2010). Additionally, all development and utilization activities in the large areas of cores can be strictly prohibited for ecological protection to some extent. The width of the existing corridors (bridges and loops) can be increased appropriately to increase forest areas. In addition, planting vegetation on the non-forest side of branches and forming multi-level branches will increase the connectivity between forest and non-forest areas (Ostapowicz, Vogt, et al., 2010).
Simultaneously, forest boundaries increased as a result of forest fragmentation. Thus, an in-depth understanding of the scope and intensity of the boundary effects has a direct impact on the conservation of biodiversity in nature reserves (Harper et al., 2005). Obviously, these actions derived from MSPA can be used to help promote sustainable advancements in urban environments and urban management.

### 4.2. The relationships and their implications among forest change, fragmentation and urban expansion

In this study, we examined the relationships between forest changes and fragmentation, and found that the r between forest net changes and perforations was only 0.40, indicating that forest loss or gain had poor correlation with perforations and was unlikely to take place inside the forest. The r between forest net changes and islets was 0.72, which meant that the increases in forest cover also led to an increase in islets, making forests look more fragmented. Kozak et al. (2018) also found that an increase in the forest area did not always lead to a decrease in fragmentation by linear regression. The forest net changes had stronger linear relationships with core, edges and branches, with the r greater than 0.80, and these relationships showed that narrow edges and branches were the most likely to lose and gain, only resulting in the decrease or increase in the forest connectivity at the edge of forest.

Urban expansion had significant correlations with seven forest morphological spatial patterns (p-value < 0.01), and the three types of urban expansion had different effects on all morphological spatial patterns. The main type of expansion in our results was edge-expansion, and the correlation between edge-expansion and fragmentation was strongest. Therefore, the urban edge expansion was most likely to cause forest fragmentation in Nanjing. Among the seven morphological spatial patterns, cores, edges and branches were highly correlated with edge-expansion, suggesting that UIS expand outward and invaded the core regions from the forest edges or branches. Additionally, the effect of new patches (outlying) on fragmentation should not be underestimated. The correlations between infilling and all morphological spatial patterns were low, indicating that the internal expansion of UIS had little impact on fragmentation. Zhou et al. (2017) concluded that the UIS areas had a stronger negative correlation with mean patch size of forests in the Yangtze River Delta (including Nanjing, but not limited to Nanjing), which was consistent with our results. Thus, expansion of UIS areas should be cautiously assessed by jointly using ecological, environmental and economic measures to achieve the balance between economic prosperity and environmental protection.

### 4.3. Major drivers of forest cover changes and fragmentation in Nanjing

An increase in UIS was associated with a decrease in forest area and resulted in increased fragmentation, such as the expansion of the Lukou international airport in Pukou district, the constant establishment of university and villa residential areas in Qixia district, and the development of the high-technology industry and the construction of talent centres in Jiangning district. Especially in recent years, the establishment of the new Jiangbei districts in 2015 (Pukou and Liuhe districts) and the fact that Nanjing became the only megacity in the Yangtze River Delta in 2016 further facilitated the improvement of urban service functions and attracted more talent. The associated construction and development activities have considerably altered the urban land use and led to the replacement of forests by UIS, which has further contributed to

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**Table 5**

<table>
<thead>
<tr>
<th>Year</th>
<th>UIS area (km²)</th>
<th>Period</th>
<th>Annual change rate (%)</th>
<th>Conversion of forest to UIS (km²)</th>
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<tbody>
<tr>
<td>1987</td>
<td>703</td>
<td>1987–1990</td>
<td>1.7</td>
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<tr>
<td>1990</td>
<td>739</td>
<td>1990–1994</td>
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<td>2000</td>
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<td>2010</td>
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<td>2013</td>
<td>1548</td>
<td>2013–2017</td>
<td>0.8</td>
<td>24.7</td>
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<tr>
<td>2017</td>
<td>1596</td>
<td>–</td>
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the severe fragmentation of urban forests. For example, small and isolated islets have remained a high proportion, and the narrow bridge and loop components in Nanjing are vulnerable to fragmentation and have changed into islets or even vanished.

Despite the continuous increase in UIS, the total area of forest sometimes increased (Fig. 5(a)), suggesting that the government also paid more attention to the ecological function of forests during the urbanization. Balancing the conflicts between the demand for development and forest protection, the government proposed the “Green Nanjing” strategy in 2002 and began a series of forest recovery projects, such as planting shelter forests, afforestation of barren hills, construction of country parks, and greening of villages, which achieved remarkable outcomes. From 2002 to 2007, the forest area increased constantly (Fig. 5(a)).

4.4. Limitations of this study

Some low-precision land cover maps could be explained by poor quality images. In addition, we did not investigate the impact of the geographical location of urban expansion on fragmentation. In the future, the performance of multi-source remote sensing data in land cover mapping should be fully explored.

5. Conclusions

This paper aims to characterize the spatio-temporal patterns of forest cover and fragmentation under urban expansion using dense time series Landsat data from 1987 to 2017 and proposes a neighbourhood-based expansion model to investigate the relationships among forest cover, fragmentation and urban expansion. During the period of 1987 and 2017, the forest cover in 2017 was less than that in 1987, and a high proportion of small-area cores and islets represents the severe fragmentation. The impacts of forest net changes on fragmentation varied by morphological spatial patterns, with the branches being most relevant to net changes. In addition, the UIS area gradually expanded to consume forest cover and increase fragmentation on the landscape scale. In the three urban expansion models, the r value between the edge-expansion and morphological spatial patterns were relatively high, indicating that the outward expansion of the original UIS had the greatest impact on fragmentation. These findings can provide suggestions for urban development and can help managers understand forest changes associated with urban expansion. Future research could be combined with geostatistical knowledge to consider the role of UIS location in forest landscapes.

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Declaration of competing interest

None.

CRediT authorship contribution statement


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