Changes of Forestland in China's Coastal Areas (1996-2015): Regional Variations and Driving Forces

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Abstract

Coastal forests play a critical role in the defence of natural disasters like typhoons and tsunamis. The deforestation and forest degradation due to rapid urbanization has presented great challenges (e.g. debris flows and floods) to China's coastal areas. Using a unique national land-use survey dataset and geographical information system (GIS)-based spatial analytics, including local Moran's I and geographically weighted regression (GWR), this paper investigates the regional variations and associated driving forces of forestland changes in China's coastal areas across three periods: 1996-2000, 2000-2008 and 2009-2015. The results suggest that the forestland has generally increased until 2008 and has decreased since 2009. Particularly, some counties in the south coast have higher degree of forestland loss during 1996-2008 and the growth of forestland after 2009 was only found in a few counties in the north and east coast. Also, the results indicate that the initial proportion of forestland in each period and the changes of arable-land have significant positive associations with the forestland changes across all the three periods, where the former mainly affects the northern coast while the latter has a primary influence in the southern coast. The findings suggest that government policies for increasing forestland such as the "Grain for Green" project were highly effective in China's coastal areas before 2008 but have shown less impact ever since. This research provides insights into the dynamics of forestland in China's coastal areas and can assist with future decision-making regarding forest resources protection and management.

Keywords: Forestland; Spatial Analysis; GWR; China; Coastal areas

1 Introduction

The land resources of China have undergone tremendous changes during the rapid urbanization over the last few decades, largely due to the massive urban construction involving transforming agricultural land (e.g. arable land, grassland and forestland) to other land-uses such as industrial and property developments. For example, the arable land in China has been reduced by about 8.27 million hectares ("ha") during 1996-2005 when the urbanization rate has increased from 30.5% to 43.0% (National Bureau of Statistics of China (NBSC), 2006). In particular, the deforestation and forest degradation has seen serious consequences for the physical environment and ecosystem, including increased carbon dioxide emissions, growth of endangered species, reduced biodiversity, intensified soil degradation as well as many natural disasters like debris flows, droughts and floods. For instance, the flow regimes (e.g. magnitude, return periods and duration) of the Meijiang watershed, China, had been significantly altered by deforestation and the recovery from such changes through reforestation took much longer than expected due to consequent soil erosion (Liu et al., 2015). Deforestation was considered as one of the major factors resulting in the devastating debris flow on 8th August 2010, in Zhouqu – a small county in Gansu province, China (Ren, 2014). Given the ecological and economic value of forestry, enhancing forest management and construction is of great importance to both sustainable development and general well-being.

Since the 1990s, a range of laws and regulations, such as the New Land Administration Law (1998) and the Forestry Law of the People's Republic of China (1998), have been proposed and implemented for reinforcing forest protection and management (Wang et al., 2012). Meanwhile, several major ecological construction projects were initiated for afforestation and restoration of forests, such as the "Grain for Green" program beginning in 1999 with the primary goal of restoring the desertification, salinization, soil erosion or low-yield farmland to forests and pasture (Feng et al., 2005). As a result, the area of forestland gradually increased, particularly in Western China. For example, the overall restored farmland was about 6.51 million ha during 2000-2008 (Wang et al., 2018a). The forestland area (% of total land area) of China has increased from 18.0% in 1996 to 26.7% in 2015 (NBSC, 2016). However, the changes of forestland and forest-coverage have varied across space and time. Brandt et al. (2012) found that the clearing of old-growth forest had accelerated during 1999-2009 despite the increase of forest-cover rate in

northwest Yunnan, China. Wang et al. (2018b) indicated that although the national forestland has an overall growth of 8.49 million ha during 1996-2008, it has declined in some regions such as Tibet, Xinjiang and Inner Mongolia while expanding in some big cities like Beijing, Shanghai and Chongqing, which could be attributed to the local physical environment, economic growth and land-use policies. Therefore, clearly understanding regional variations in forestland changes can better inform future decisions and improve policy-making pertaining to forest resource management and development.

Most studies on forest dynamics have relied upon remote sensing images, such as those from Landsat MultiSpectral Scanner (MSS)/Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) sensors, to extract forest-cover information and detect the changes between different periods (e.g. Clement et al., 2009; Brandt et al., 2012; Alix-Garcia et al., 2016; Mas and Cuevas, 2016; Zhang et al.; 2016; Shirvani et al., 2017). Although such data are easy to acquire and can cover a long-time period (for example, the Landsat images have been available from 1972), the results are often subject to the resolution of the sensors and the uncertainty of image interpretation. In comparison, detailed land survey data collected by fieldwork are of higher accuracy and thus can better reflect the actual forestland changes. However, this type of land survey is both expensive and time-consuming particularly for large countries and regions. Over the last three decades, China has completed two national land surveys in 1996 and 2009 respectively, covering around 2,800 counties, 43,000 towns and 740,000 villages (Wang et al., 2018a). The survey contains information about the amount and location of each land-use type, as well as the land ownership in each county, which have provided valuable land resources details in China. Based on such data, Wang et al. (2012, 2018a) examined the changes of various land-uses in China and the relationships with land policies and socio-economic activities.

When investigating the impact of potential driving forces on forestland/forest-cover changes, many studies have employed global models such as multiple linear regression (e.g. Wimberly and Ohmann, 2004; Brandt et al., 2012; Alix-Garcia et al., 2016). This type of approach, however, cannot capture spatial variations of the relationships between the response variable (e.g. land-use changes) and potential influencing factors (e.g. population, slope and rainfall), which is usually the case for the changes of land resources like forestland. In recent years, many scholars have attempted to analyze forest changes using GWR, a local spatial modelling technique that accounts for varying spatial

relationships. It has been used in a variety of applications (e.g. Fotheringham et al., 2015; Yao and Fotheringham, 2016) since the seminal work by Brunsdon et al. (1996), and has been found in several studies on forestland/forest-cover changes to have a greater explanatory power than global models like ordinary least squares (OLS) regression (e.g. Clement et al., 2009; Jaimes et al., 2010; Mas and Cuevas, 2016; Shirvani et al., 2017).

As the interface between land and oceansphere, coastal areas are resource-rich but ecologically fragile. Coastal forests play a critical role in the defence from natural disasters like typhoons or tsunamis. Also, the coastal zone, especially in the Southeast China, is the most rapidly developed and intensely urbanized area in China which has several economic hubs such as the Yangtze River Delta (YRD) and the Pearl River Delta (PRD) urban agglomerations. Thus, the assessment of forestland changes can provide evidence to support sustainable development and urbanization in China's coastal areas.

The aim of this research is to explore regional variations of forestland changes in China's coastal areas as well as to investigate the underlying driving forces. Specifically, using the datasets from national land surveys and national land-use change surveys, GIS-based spatial analyses including exploratory spatial data analysis (ESDA) and GWR are employed to investigate the spatially varying patterns of forestland changes and associated relationships with potential drivers across coastal provinces. Knowledge of regional differences in forestland changes and driving forces can help develop region-specific policies for future forestland management and development. To the best of our knowledge, only Wang et al. (2012, 2018a, 2018b) used national land survey data to investigate the land-use changes in China, but the analyses of forestland changes as well as the influencing factors were essentially descriptive. In this regard, this research is the first effort to quantify the spatially varying relationships between the forestland changes in China and the potential drivers with a focus on the coastal areas.

2 Materials and Methods

2.1 Data and Study Area

The study area is located on China's coast, including eight provinces (Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Guangxi) and two municipalities (Tianjin and Shanghai) (Figure 1) and covering an area of about 124.12 million ha (13.1%

of the total area of China). With the advantages of geographic location for foreign trade and abundant natural resources, as well as driven by various preferential policies for urban development, the coastal zone has led the urbanization and economic development of China since the "reform and opening-up" in late 1970s and has attracted a large number of migrant workers from the inland part of the country (Wu et al., 2007). In 2015, the total population in the coastal zone was about 586.15 million (about 42.6% of China's total population) and contributed 57.1% of the national overall gross domestic product (GDP) (NBSC, 2016). Meanwhile, the coastal region has been facing the challenges presented by rapid urbanization such as metal contamination, water pollution and landscape fragmentation (Lin et al., 2013; Wang et al., 2013). As important ecological and economic resources, forestland and forests are crucial to the long-term sustainability of China's coastal areas.

<Figure 1 about here>

The forestland data used in this research come from two sources: national land survey and national land-use change survey (Wang et al., 2012, 2018a), which were collected by the Ministry of Land and Resources of China (known as China State Land Administration Bureau before 1998). The land use information in the national land survey was mainly extracted from high-resolution satellite images and aerial photographs, and then verified and corrected by field surveys and paper maps produced using photogrammetric methods. Comparatively, the national land-use change survey primarily relied upon field survey.

Specifically, the dataset used here covers five years: 1996, 2000, 2008, 2009, 2015. The data of 1996 and 2009 are from the first and second national land survey, respectively, and the data of the other years are from the national land-use change survey. The information of forestland and its changes was summarized for each county – the third-level administrative division of China following provincial-(first) and prefectural-(second) levels. Accounting for the time of the two national land surveys and the "Grain for Green" project, the changes of forestland were considered over three periods here: 1996-2000 (period I, abbreviated as P-I), 2000-2008 (P-II) and 2009-2015 (P-III). Further, due to the administrative division adjustment in 2009, two sets of spatial units were adopted in this study, one for the first two periods including 720 counties and the other for the last

period containing 969 counties. Figure 1 shows the proportion of forestland within each county in the study area in 2015. It can be observed that the areas on the north (eastern Liaoning and northern Hebei) and south coast (Zhejiang, Fujian, Guangdong and Guangxi) have relatively higher ratios of forestland than the other regions. Particularly, most counties in Zhejiang, Fujian and Guangdong have over 50% land occupied by forests or woods.

In terms of potential driving forces of forestland changes, a variety of socioeconomic, geographical and policy factors have been examined by previous research (e.g. Clement et al., 2009; Jaimes et al., 2010; Brandt et al., 2012; Mas and Cuevas, 2016; Shirvani et al., 2017). For instance, it was found that topography (e.g. elevation and slope) could significantly affect deforestation (Mas and Cuevas, 2016). The growth of other types of land-uses like residential and cultivated land were considered closely related to the decline of forestry (Shirvani et al., 2017; Wang et al., 2018a). Accounting for previous findings as well as the reality of China, such as the changes of arable land associated with the "Grain for Green" project (Wang 2018a), and after an initial exploratory analysis of correlation and collinearity between variables, six factors were selected in this research. The data for the selected covariates were obtained from local statistical yearbooks for the study periods, as described in Table 1.

<Table 1 about here>

2.2 Spatial Analysis

ESDA and spatial regression were utilized in this research. First, regional variations of forestland changes were explored by choropleth mapping – a straightforward way to visualize spatial data, followed by spatial cluster analysis using Local Moran's I. Then, the spatial relationships of forestland changes and potential drivers was investigated by the GWR approach. Those analyses were implemented with several software tools. Local Moran's I was calculated using GeoDa, a free opensource software for spatial data analysis (Anselin and Rey, 2014). GWR analysis was carried out in GWR4 (http://gwr.maynoothuniversity.ie/gwr4-software/). The commercial GIS software, ArcGIS (version 10.3, ESRI, Redlands, California, USA), was used for data management, processing and visualization.

2.2.1 ESDA

The choropleth maps were generated to show the spatial distribution of forestland changes across the counties in the study area. The value mapped for each county is the average annual proportion of forestland change, which can be derived by (1):

$$\Delta p_i = (p_{i,t_{END}} - p_{i,t_{BEG}})/(t_{END} - t_{BEG}) \tag{1}$$

where i denotes a county, t_{BEG} and t_{END} are the first and the last years of a period, respectively, and $p_{i,t_{END}}$ and $p_{i,t_{BEG}}$ are percentages of the forestland in county i for years t_{BEG} and t_{END} accordingly. Thus, Δp_i was calculated for every county within the study area and for every period under concern. It should be noted that although the forestland changes are averaged over a certain period here, such changes could have occurred in only one year or a few years of the period under concern.

Instead of the entire coastal region, of particular interest are the areas with statistically significant forestland changes. This was achieved with the Local Moran's I, which is an indicator of spatial association and usually applied in spatial cluster analysis to examine patterns of observation distribution over geographic space. It was utilized in this study to identify spatial clusters of areas (i.e. counties) with significantly high growth or loss of forestland. The Local Moran's I associated with county i, I_i, is calculated by the formula in (2) (Anselin, 1995):

$$I_i = \left(\frac{nz_i}{\sum_i z_i^2}\right) \sum_j w_{ij} z_j \qquad \text{with} \qquad z_i = x_i - \bar{X} \tag{2}$$

where n is the total number of counties in the study area, x_i is the forestland change (%) within a period (calculated as, take P-I as an example, the percentage of forestland in 2000 minus that in 1996), $\bar{X}$ is the average of all x_i s, and w_{ij} is a spatial weight representing the spatial relationship between counties i and j. As there are many islands in the coastal region, the K-nearest-neighbors method was adopted to construct spatial weights so that every county would have the same number (K) of neighbors. If only considering the contiguous counties, both the average and median number of neighbors defined by spatial contiguity is five and therefore adopted as the value of K in the spatial weight calculation. Similar to Δp_i, I_i was calculated for each period for county i.

2.2.2 GWR

The GWR model can be defined as in (3) (Fotheringham et al., 2002):

$$y_i = \beta_{i0} + \sum_k \beta_{ik} x_{ik} + \varepsilon_i \tag{3}$$

where again for county i, y_i is defined same as the x_i in (2), β_{i0} is the constant, x_{ik} is the value of the kth covariate, β_{ik} is the regression coefficient associated with x_{ik}, and ε_i is the random error. Unlike the parameters in global regression models, β_{ik} (also β_{i0}) in (3) is a function of the geographic location of county i, allowing the relationships between forestland changes and potential drivers to vary over geographic space. Specifically, a local model is fitted for each county with a subset of proximate counties which are weighted using a spatial kernel function. The local estimates for county i, are calculated by (4) if using matrix representation (Fotheringham et al., 2002):

$$\widehat{\boldsymbol{\beta}}(i) = (\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{W}(i)\boldsymbol{X})^{-1}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{W}(i)\boldsymbol{Y} \tag{4}$$

where $\boldsymbol{W}(i)$ is a diagonal matrix with the element w_{ij} indicating the weight of county j with regards to county i (i.e. the regression point).

Considering the varying size of different counties, an adaptive spatial kernel was used in this research where the nearest K counties (neighbors) would be included in local model calibration. The optimal bandwidth (i.e. K) was selected by the small-sample-size corrected version of Akaike information criterion (AICc) (Fotheringham et al., 2002). Specifically, the bi-square function expressed in (5) was used to define the spatial kernel:

$$\text{Bi-square weighting function:} \quad w_{ij} = \begin{cases} \left[1 - (d_{ij}/b)^2\right]^2 & \text{if } d_{ij} < b \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where b is the distance to the Kth nearest county and d_{ij} is the distance between counties i and j. The function in (5) is preferred here as it is reasonable to consider the influence of the counties beyond the bandwidth negligible given the spatial extent of the study area.

The statistical significance of local estimates was determined with the adjusted critical t-value proposed by Byrne et al. (2009) to address the multiple hypothesis testing problem*. Further, the local variability of each covariate was tested by comparing the interquartile range (IQR) of local estimates and the standard errors (SE) of global estimates from the OLS regression. In other words, the relationship between forestland changes and a covariate can be considered spatially nonstationary if the associated IQR is larger than 2*SE (Fotheringham et al., 2002).

Considering the high skewness of data distribution, the absolute value of forestland changes (either gain or loss of forestland), i.e., the degree or level of forestland changes, was used here as the dependent variable (denoted by $|y_i|$ in (6)), and accordingly, the absolute changes of population density and arable land were used here. The natural logarithm transformation was employed to improve the linearity of the relationships between the forestland changes and potential influential factors, as well as to meet the assumptions on the error term in linear regression. As a result, the GWR model adopted in this research was formulated as in (6):

$$\ln|y_i| = \beta_{i0} + \beta_{i1}\ln(FL\_BASE) + \beta_{i2}\ln(POPDEN) + \beta_{i3}\ln(ELEV) + \beta_{i4}\ln(SLOPE) + \beta_{i5}\ln(RAIN) + \beta_{i6}\ln(ARABLE) + \varepsilon_i \quad (6)$$

Similarly, in total three GWR models were fitted with one for each period. For the comparison purpose, the corresponding OLS regression models were also implemented with the same set of data and variables.

3 Results

3.1 Regional Variations of Forestland Changes

Considering the overall changes of forestland in the entire coastal region over the three periods, the forestland has been increased by 39,600 ha in P-I and 267,400 ha in P-II, while has been reduced by 314,000 ha in P-III. However, the changes within each county varied over both space and time, as shown in Figure 2. For all three periods, the growth of forestland was largely within 0.5%, and most decline was within 0.1%. Compared to

* The adjusted t-values were calculated based on the Fotheringham-Byrne procedure using the function gwr.t.adjust in the R package GWmodel (https://www.rdocumentation.org/packages/GWmodel/versions/2.1-4/topics/gwr.t.adjust).

the first two periods, P-III only saw a few counties with an increase of forestland, largely located in Jiangsu, Shandong, Hebei and Liaoning. Further, more spatial variations in forestland changes can be observed in P-II than in P-I and P-III, with more counties having a higher degree of forestland gain (e.g. as high as 8.0%) or loss (e.g. as low as -6.7%) particularly in Zhejiang, Guangdong and Guangxi. In contrast, the counties in Fujian had become more similar in terms of forestland changes over time.

<Figure 2 about here>

Further, four categories of local clusters with significant (p-value < 0.05) forestland changes are presented in Figure 3. The first two types consist of the counties with similar values of forestland changes, which in Figure 3 are denoted by high-high (in red) and low-low (in blue) areas, respectively. That is, a county within a high-high (or low-low) cluster has a relatively high (or low) proportion of forestland change, and so are the surrounding counties (neighbors). In contrast, the other two types include the counties with very different forestland changes from the proximate counties, which in Figure 3 are indicated by high-low (in pink) and low-high (in light-blue) areas. In other words, a county within a high-low (or low-high) cluster has a relatively high (or low) ratio of forestland change while the value of which is relatively low (or high) for its neighbors.

<Figure 3 about here>

As seen in Figure 3, the spatial distribution of local clusters has varied across the three periods. Across the study area, there were much fewer clusters on the east coast (Jiangsu, Zhejiang and Fujian) in P-III compared to the previous two periods. The locations of local clusters also vary across time. For example, the high-high clusters were mainly located in the south in P-I, in the east in P-II and in the north in P-III. The low-low clusters were largely situated in the south in P-I and P-III, but in the northeast and southeast in P-II. Local clusters also have varied over space and time within several provinces. Take Liaoning province as an example, few clusters were found for the first two periods, but all four types of clusters were observed for the last period. In contrast, for Zhejiang and Fujian, several clusters were found for P-I and P-II, but less or no clusters were identified for P-III. There are no significant local clusters found for the two municipalities Tianjin and Shanghai. Also, a county can belong to different types of clusters in different periods.

For instance, the low-high cluster in east Liaoning in P-I became a high-low cluster in P-III, implying different patterns of forestland change in the two periods.

3.2 Spatially Varying Relationships between Forestland Changes and Driving Forces

First, the coefficient estimates for the global regression models are presented in Table 2. According to the R^2, the performance of the model for P-III is better than those for P-I and P-II, in which the covariates explain about 60% of the variations in the dependant variable (i.e. the degree of forestland change). The significance of the covariates varies across the three models. Only the coefficient estimates for FL_BASE and ARABLE are significant and both positive, implying that the degree of forestland changes and the forestland at the beginning of a period (also the changes of arable land - in absolute value) will vary in the same direction, *ceteris paribus*. That is, if a county had a larger percentage of forestland in 1996, it would have a higher degree of forestland change (either increase or decline) in P-I. Similarly, if a country had a higher level of arable-land change during 1996-2000, it would also have a higher level of forestland change in P-II, where the changes for both types of land can be either an increase or a decline. The elevation (ELEV) does not have a significant impact on the forestland changes in all the three models. The rest of the covariates demonstrate a significant affect in one or two periods but not the other(s). For example, both slope (SLOPE) and average precipitation (RAIN) show a negative association with the forestland changes only in P-III.

<Table 2 about here>

Further, the statistics of local estimates for the GWR models, as well as the results of geographical variability tests, are given in Table 3. For each covariate, instead of a single coefficient estimate from a global model, a set of local estimates varying with the geographical locations of the counties were derived from GWR. For example, the global estimate for ARABLE is 0.15 for P-I while the local estimates for the same period ranges from 0.05 to 0.44. Also, the geographical variability of the covariates varies across the three periods. For example, all the covariates except RAIN have significant local variability in P-I, but only two variables, FL_BASE and ARABLE, consistently have significant spatially varying relationships with forestland changes over time. Again, compared to the OLS regression, the differences of the AICc values for the two types of models at the bottom of Table 3 suggest that GWR performs better in explaining the

relationships between forestland changes and the associated covariates, although the advantage of GWR over OLS is weaker for the two models of P-I and P-II.

<Table 3 about here>

As both of them have significant global estimates and geographical variability, FL_BASE and ARABLE are selected for further exploration of the spatial distribution of their local estimates, which are depicted by Figures 4 and 5, respectively. As can be seen in Figure 4, the significant local estimates of FL_BASE have distinct spatial patterns for the three periods, which are primarily located in the north in P-I and P-II, and covers most of the study area except Fujian and Guangxi in P-III. Also, although all the significant local estimates of FL_BASE indicate a positive association between the level of forestland changes and the initial proportion of forestland in each period, the strength of that relationship varies across space. For example, the ratio of forestland in 1996 has a stronger impact on the forestland change in P-I for the counties in Tianjin and central Hebei. But in P-III, more impact of the proportion of forestland in 2009 was found in east Shandong. Compared with P-I and P-III, P-II has fewer significant local estimates of FL_BASE for which there is also less variation in the values, indicating that in P-II the forestland (%) in 2000 does not have a significant impact on the forestland changes in most counties.

<Figure 4 about here>

In terms of the impact of arable-land changes, Figure 5 indicates that P-I and P-II have a similar spatial distribution of the significant local estimates of ARABLE, with higher values mainly located in the south and lower values in the north. Similar to FL_BASE, the levels of forestland and arable-land changes are positively correlated, which implies that a higher (or lower) degree of forestland change is associated with a higher (or a lower) level of arable-land change. Compared with P-I and P-II, only a few counties show a significant relationship between the changes of forestland and arable-land, which are located in Liaoning, Jiangsu and Guangxi – very different from the patterns in the previous two periods. Among the coastal zones, it seems only the foreland changes in some counties in Guangxi have been consistently affected by the arable-land changes across the three periods.

<Figure 5 about here>

4 Discussion

The above results indicate that both forestland changes and the relationships with associated driving factors demonstrate spatially varying patterns. The forestland has generally increased until 2008 and has decreased since 2009. Particularly, some counties in the south coast have higher degree of forestland loss during 1996-2008 and the growth of forestland after 2009 was only found in a few counties in the north and east coast. Also, two factors, the initial proportion of forestland in each period and the changes of arable-land, show significant positive associations with the forestland changes across all the three periods, where the former mainly affects the northern coast while the latter has a primary influence in the southern coast.

In general, the changes of forestland can be considered as a response to the national policies in recent years. For example, the overall increase of forestland between 1996-2008 could be attributed to the strong enforcement of relevant laws and regulations on agricultural land protection (Wang et al., 2012; Song and Pijanowski, 2014; Feng et al., 2015). There has been massive growth of forestland nationwide since the "Grain for Green" project (Feng et al., 2015; Wang et al., 2018a), and the overall forestland in China increased by 15.97 million ha during 2000-2008 (NBSC, 2009). The decrease of forestland after 2008 could be related to the Cultivated Land Balance programs where forestland was converted to arable land to maintain the quantity of the latter (Song and Pijanowski, 2014; Wang et al., 2018a).

Local policies at the province level also have played an important role in forestland changes in different regions. For example, the strong policies on forestland protection and afforestation of Zhejiang province can help explain the significant increase of forestland between 2000 and 2008 (see Figure 2). In 1999, Zhejiang first started the construction of key non-commercial forests through afforestation, replanting and converting farmland to forests, which has effectively protected the forests within the region (Ministry of Land and Resources, 2016). Meanwhile, a green belt of ten thousand kilometres has been promoted in Zhejiang since 2000 (Ministry of Land and Resources, 2016). As a result, the overall area of forestland restored from farmland in Zhejiang was nearly 30 times that of the Fujian province and six times that of the Guangdong province

in that period (2000-2008) (Ministry of Land and Resources, 2016). The growth of forestland in Hebei during 2009-2015 (see Figure 3) can be attributed to the reform of collective forest property beginning in 2006 in the province, which has greatly encouraged local farmers to participate in forest management and construction and produced an afforestation area of 253 km^2 in 2010 (Xinhua News Agency, 2010).

Further, the spatial heterogeneity of the roles of various influencing factors can be linked to national policies and local topographical conditions. For instance, the arable-land changes during 2000-2008 had strong association with the forestland changes (mainly in Guangdong and Guangxi) in the same period (see Figure 5), which became less significant during 2009-2015, probably indicating a reduced impact of the "Grain for Green" project in the coastal region after ten years since its introduction. This is also reflected by an overall decrease of forestland in P-III (see Figure 2). In particular, Figure 5 suggests that the changes of arable-land and forestland between 1995 and 2008 in Guangxi province were significantly correlated. The main reason could be that Guangxi is a mainly mountainous region and a large amount of sloping cultivated land that is not suitable for farming has been converted to forestland, leading to the reduction of arable land and the increase of forestland in Guangxi particularly since 2002. For example, about 2,327 km^2 arable land was restored to forestland in Guangxi during 2001-2010 (Ministry of Land and Resources, 2016). In contrast, in some coastal provinces such as Zhejiang and Fujian, some restored farmland was also converted to lakes and other land uses in addition to forestland (Ministry of Land and Resources, 2016). As a result, little significant association between the changes of arable land and forestland was observed in those provinces (see Figure 5).

Regarding policy implications, some suggestions can be derived from the findings of this research. First, given the different values of ecological service functions of forestland in different coastal regions, which are higher in the south and lower in the north, there is an urgent need to develop and implement distinct regional ecosystem management strategy customized for different coastal regions. Similarly, the national eco-compensation schemes should develop region-specific policies, accounting for the spatial heterogeneity in the ecological service functions of forest land. Finally, the legislation of eco-compensation is necessary for providing a fixed source of funds through environmental and carbon taxes, therefore promoting the sustainability of forestland.

There are several areas worth of further research. First, more variables can be incorporated into the GWR analyses to account for other factors contributing to the forestland changes, such as the investment in forestry construction and governmental subsides for the "Grain for Green" project if the data are available. Second, instead of all forestland changes, separate regression analysis can be run for afforestation and deforestation, respectively, which can involve different set of driving forces. Third, further analysis can be carried out for different types of forestry (e.g. shrubs and trees) separately rather than all of them as done in this work. Fourth, in addition to its area, how the functionality, particularly the ecosystem service capacity of forestland, as well as its role in regional ecosystem, has changed over space and time deserves further investigation. Finally, the temporal dimension can be integrated into the regression analysis to account for the temporal associations of forestland changes between different years if more data can be collected.

5 Conclusions

Using detailed land survey data, this research explored the regional variations of forestland changes in China's coastal areas over three periods during 1996-2015 and investigated the potential driving forces using GIS-based spatial analysis. The results suggest that there were significant spatial variations in the forestland changes across the twenty-year period of study, and the relationships between forestland changes and possible influencing factors also varied over space and time. In particular, the initial proportion of forestland in each period and the changes of arable-land were found to have significant positive associations with the forestland changes across all the three periods, although with very different spatial patterns. The findings suggest that government policies for increasing forestland such as the "Grain for Green" project were highly effective in China's coastal areas before 2008 but have shown less impact ever since.

Sustainable use and management of various land resources like forestland is central to addressing the conflict between the limited natural resources and the demand from economic development. As a primary type of ecological land-use, forestland is of fundamental importance to long-term sustainable development. Given the spatial inequality in forestland distribution, understanding regional variations of forestland changes and the potential drivers remains crucial for developing region-specific policies

for effective forestland management and protection, for which spatial analysis techniques like ESDA and spatial regression can be powerful tools.

Conflicts of Interest: The authors declare no conflicts of interest.

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Figure 1 Study area and the percent of forestland in 2015

Figure 2 Average annual change of forestland (in %)

Figure 3 Local cluster maps of forestland changes

Figure 4 Significant local estimates of FL_BASE

Figure 5 Significant local estimates of ARABLE

Table 1 Description of covariates in the GWR models

Covariates	Description
FL_BASE	Proportion of forestland in the beginning year of a period (in %)
POPDEN	Change of population density within a period (e.g. 1996-2000) (in 1,000 people/km^2)
ELEV	Proportion of land with an elevation higher than 100 *m* (in %)
SLOPE	Proportion of land with a slope larger than 25 degree (in %)
RAIN	Average annual rainfall within a period (ranging from 0 to 20 with higher values indicating more rainfall)
ARABLE	Change of proportion of arable-land within a period (in %)

Table 2 Global estimates from OLS regression

Covariate	P-I	P-II	P-III
Constant	-4.09*	-2.37*	-1.67*
FL_BASE	0.87*	0.46*	0.63*
POPDEN	0.15*	0.03	0.11*
ELEV	-0.02	-0.05	0.03
SLOPE	-0.13	0.02	-0.13*
RAIN	-0.15	0.26	-0.62*
ARABLE	0.15*	0.12*	0.07*
R^2	0.28	0.21	0.57

*: p-value < 0.05

Table 3 Local estimates from GWR and geographical variability of the covariates

Covariate		P-I				P-II				P-III			
		Min	Max	Median	Geographical Variability	Min	Max	Median	Geographical Variability	Min	Max	Median	Geographical Variability
Constant		-7.87	3.60	-2.57	√	-11.07	39.35	0.04	√	-60.60	95.23	-3.12	√
FL_BASE		0.52	1.29	1.00	√	-1.12	1.23	0.45	√	-0.26	2.70	0.72	√
POPDEN		-0.08	0.74	0.13	√	-0.15	0.15	0.02		-0.44	0.85	0.06	√
ELEV		-0.47	0.23	-0.10	√	-2.18	0.42	-0.05		-2.48	0.66	0.00	
SLOPE		-0.73	0.33	-0.09	√	-0.54	2.07	0.01		-1.48	1.22	-0.20	
RAIN		-3.39	1.95	-0.52		-13.72	4.67	-0.82	√	-41.68	28.01	-0.73	√
ARABLE		0.05	0.44	0.15	√	-0.02	0.70	0.20	√	-0.19	0.90	0.10	√
Bandwidth		234				157				91			
R^2	**OLS**	0.28				0.21				0.57			
	GWR	0.36				0.41				0.81			
AICc	**OLS**	3456.86				3297.05				4180.24			
	GWR	3445.89				3204.32				3838.63			
Difference of AICc (GWR - OLS)		-10.97				-92.73				-341.61			

Figure 1 Study area and the percent of forestland in 2015

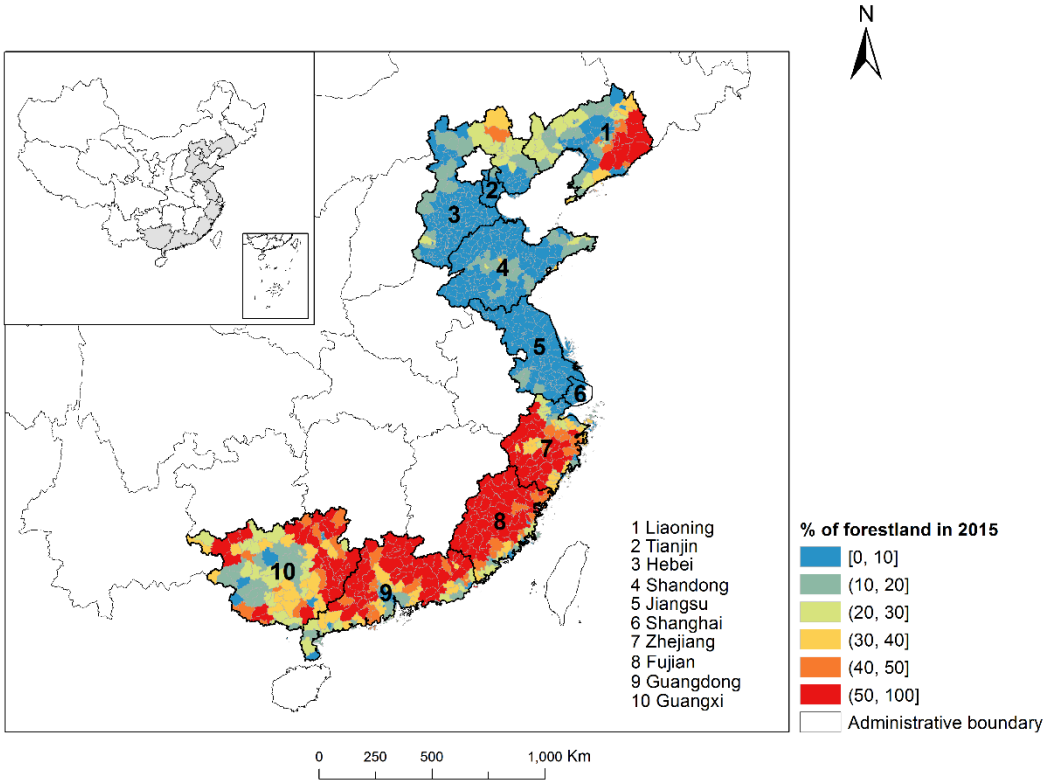

Figure 2 Average annual change of forestland (in %)

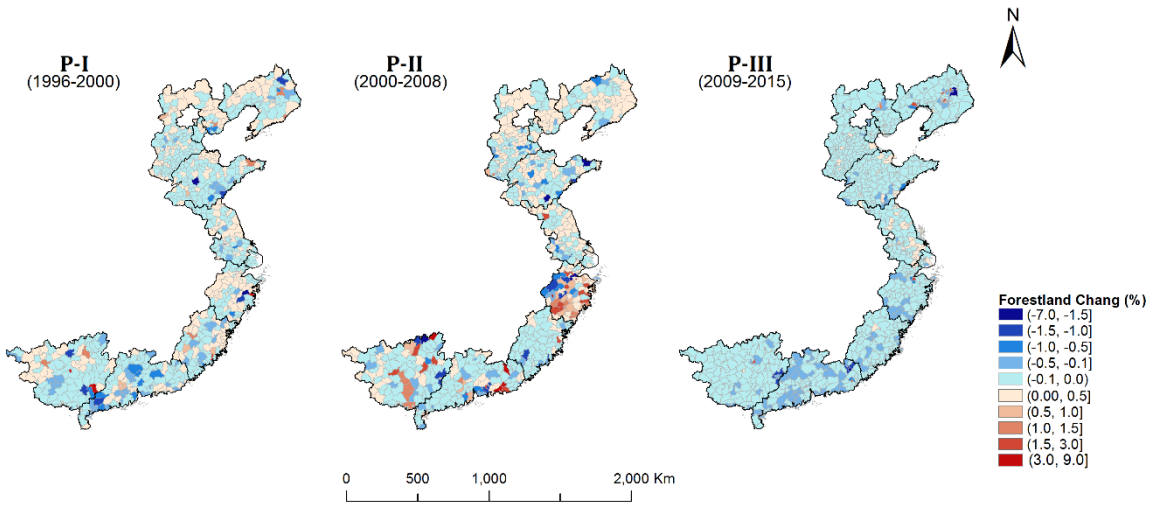

Figure 3 Local cluster maps of forestland changes

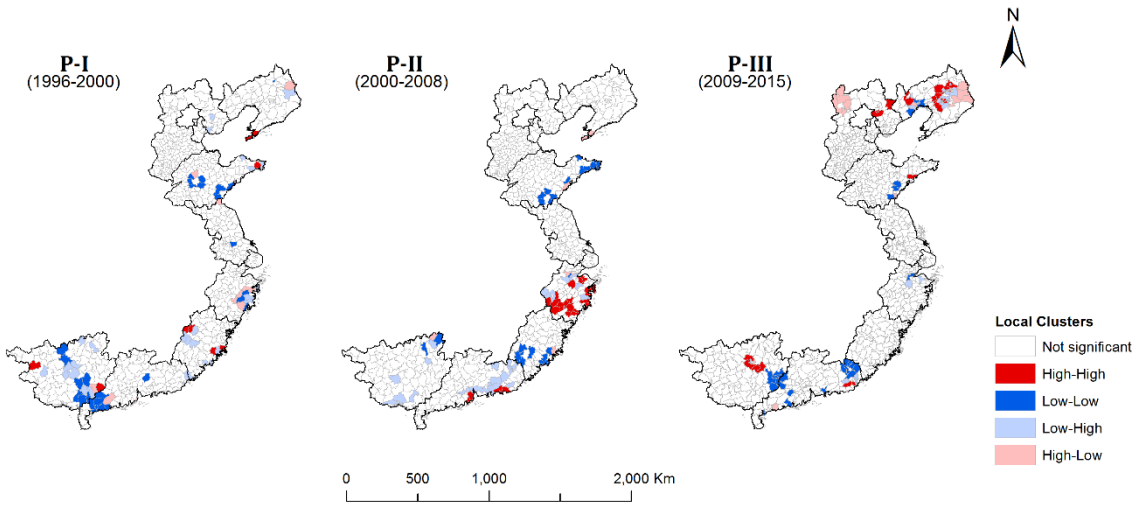

Figure 4 Significant local estimates of FL_BASE

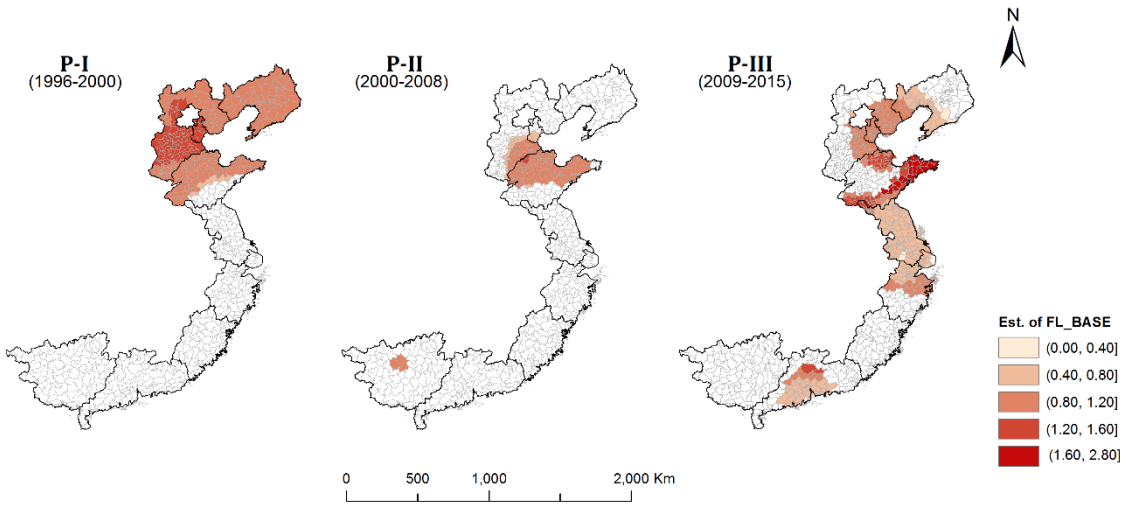

Figure 5 Significant local estimates of ARABLE