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Quantifying the Compound Factors of Forest Land Changes in the Pearl River Delta, China

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Abstract: Forestland has been a focus of urbanization research, yet the effect of urbanization on forest land change on an urban agglomeration scale still remains unclear. Screening and quantifying the main factors affecting forest land changes have practical significance for land planning and management. Considering the characteristics of the region and referring to related studies, 26 natural, social, and economic factors were screened in the Pearl River Delta (PRD), where land-use changes are intense. Geographically weighted regression and the relative importance were used to quantify the spatial heterogeneity of these main factors. There was still a large area of deforestation evident in the PRD with its afforestation area of 604.3 km^2 (mainly converted from cropland) and a deforestation area of 1544.6 km^2 (mainly converted from built-up land). The effects of socio-economic factors were the main factors for these forest land changes, especially the rural population and migration. Deforestation mainly occurs in urban growth boundaries, which will be the focus area for further land management. These main factors have the potential to provide a methodological contribution to land-use changes, and the results of this study can provide a solid theoretical basis for forest land management and urban planning (e.g., balancing expansion of built-up land and ecological protection that advances forest land protection and restoration).

Keywords: urbanization; forest land change; driving factor; Geographically Weighted Regression; relative weight

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1. Introduction

Urbanization has been an increasing global phenomenon during the past century [1]. China, in particular, is experiencing an important stage of urbanization, with its urban population rapidly increasing from 17% in 1978 to 61% in 2019. This rapid urbanization has caused dramatic changes in regional land use, the most significant of which are the increase in urban built-up land and the significant decrease in forest land and grassland [2,3]. The area of forest land and grassland in China had decreased by nearly 16.4 × 10^3 km^2 from 2010 to 2015 [4]. The reduction and degradation of forest land directly affected the composition of ecosystems' species, increased ecological risks, and decreased the quality of human settlements [5]. The absence of green space affects humans' health and their human well-being [6]. As China's urbanization rate continues to grow, pushing the rural population to the cities, forest disturbance has become more serious as it is further occupied and degraded [7]. For the promotion of humans' well-being and sustainable development, the government is changing its concept of forest land management by focusing mainly on conservation and restoration. The government has issued a series of forest land protection policies, for example, nature reserves, ecological redlines, and returning cropland to the forest land [8–10]. The range of forest land decrease areas has gradually decreased, but this was mainly concentrated in the low urbanization areas. In the highly urbanized areas, due to the expansion of population, the area of forest land still in decline [4,11]. The main reason is a misunderstanding of the factors of forest land changes, current forest land management lags, and the uncertainty in balancing urbanization expansion and forest protection by decision-makers [12].

Land change is the result of humans' interactions with the natural environment [8]. Profound differences in natural, social, economic, and cultural situations can mean that different drivers vary in importance and impacts [13]. Many studies have elaborated on the factors of land changes and explored the response mechanisms of different factors to these land changes. Socio-economic factors, such as population density, market, resident income, and policies, were generally believed to result in land-use changes [14–16]. Research methods have been mainly based on mathematical modeling or spatial correlation analyses [17–19]. Regional socio-economic factors have spatial agglomeration, exhibit spatial non-stationarity, and have distinct temporal signatures [20]. However, global-level statistical approaches are not enough to explain the main mechanism within the region, especially on the scale of urban agglomerations. Geographically weighted regression (GWR) can establish a series of local regressions over multiple observation points within a certain distance to capture variations of the independent variable and dependent variable [21]. GWR can also be used to visualize the spatial response relationship between land changes and main factors, as well as to measure the positive and negative effects of these factors on land-use changes [8]. GWR has been extensively used in landscape changes and environmental heterogeneity on a regional scale [20,22,23].

Urban agglomerations are an advanced form of spatial organization in urban development [24]. In China, the regional integration pattern of the development of urban agglomerations by central cities has emerged since 2000. The rapid growth of urban agglomerations has resulted in significant changes in forest land. Quantifying the compound factors of forest land changes can contribute to policy formulation and land-use management [25]. Based on this situation, this study took the Pearl River Delta (PRD) urban agglomeration as the case study, as it is one of the most densely populated and highly urbanized areas in China. The goals of this study were to (1) identify the factors of forest land changes through literature research and investigation, (2) quantify gross forest land losses and gains under the urban agglomeration from 2000 to 2018, and (3) identify the determining factors of forest land changes by GWR and the relative importance analysis. This study is a novel attempt to establish the relatively perfect factors and explore the variations of the relationships between forest land changes and the factors in a spatially explicit way. Decision-makers can use this knowledge for better management and land planning, both in China and in countries experiencing this same situation.

2. Materials and Methods

2.1. Study Area

The PRD urban agglomeration is one of the most dynamic economic spaces in the Asia-Pacific region [26], consisting mainly of nine cities: Guangzhou (GZ), Zhaoqing (ZQ), Foshan (FS), Zhongshan (ZS), Zhuhai (ZH), Jiangmen (JM), Dongguan (DG), Shenzhen (SZ), and Huizhou (HZ) (Figure 1). With the rapid growth of urban agglomerations and the rapid expansion of cities in the PRD, land use has greatly changed since 2000. From 2000 to 2017, built-up land areas increased by 61%, and developed lands occupied 2356 km^2 of ecological space [22]. The total area of forest land in PRD accounted for 54% of the urban agglomeration areas. The spatial distribution of forest land is a natural ecological security barrier for urban agglomeration, which is particularly important for regional ecological security. Currently, the impacts of these factors on forest land changes under this urbanization development remains unclear, and decision-makers still lack a quantitative evaluation, resulting in uncertainty of land-use simulation scenarios.

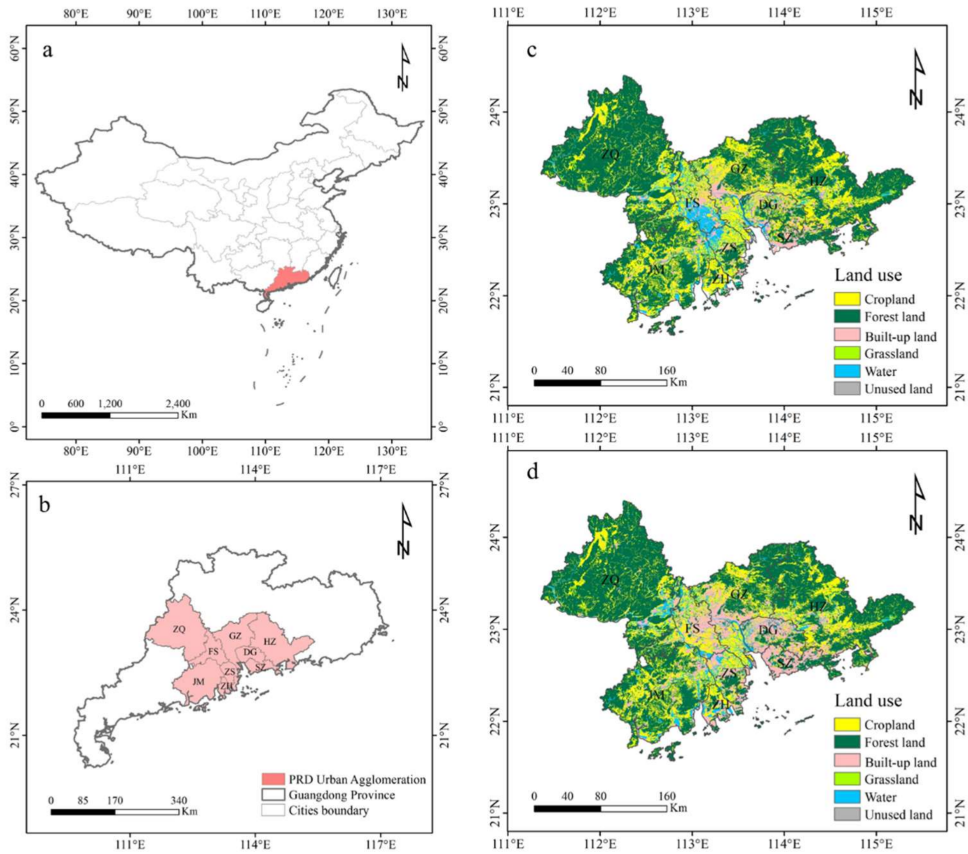

Figure 1. The study area of the Pearl River Delta (PRD) urban agglomeration: (**a**) Guangdong Province in China; (**b**) PRD urban agglomeration in Guangdong Province; (**c**) Land-use of PRD urban agglomeration in 2000; and (**d**) Land-use of PRD urban agglomeration in 2018. DG: Dongguan, FS: Foshan, GZ: Guangzhou, HZ: Huizhou, JM: Jiangmen, SZ: Shenzhen, ZH: Zhuhai, ZQ: Zhaoqing, ZS: Zhongshan.

2.2. Data

2.2.1. Land-Use Data

The land-use data were retrieved from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/, accessed on 13 June 2020) with a spatial resolution of 30 m, which Landsat TM/ETM and Landsat 8 remote sensing images were used as data sources to interpret land-use data in 2000 and 2018 [12,27]. Through outdoor investigations and random sampling inspections, the accuracy rates of land-use classifications were more than 94% (Table S1), which can be used to explain the land changes. Land-use types were divided into six broad types: forest land, cropland, built-up land, grassland, water, and unused land (Figure 1). According to the classification of land use in China (GBT 21010-2017), forest land (canopy density ≥10%) was referred to as the growth of trees, shrubs, bamboo, as well as coastal mangrove land and other forest lands. Afforestation represented the conversion of other land use into forest land, and deforestation represented the conversion of forest land into other land use. To identify the hotspots of forest land changes, we used the *Getis-Ord Gi** analysis technique in ArcGIS 10.2. This technique identifies statistically significant spatial clusters of high (hot spots) and low (cold spots) values of changes [28].

2.2.2. Selection of Factors

Currently, the factors consist mainly of natural and socio-economic factors, but their evaluation index systems are quite different on different scales [28,29]. Although knowing how to define drivers effectively and measurably is difficult, commonalities can be selected from relevant studies [30]. The main factors of land change in adjacent regions or countries of the PRD were systematically studied in China, Japan, Korea, Philippines, Laos, Myanmar, Thailand, and Cambodia. These areas were close to the study area; have similar physical, geographical, and cultural factors; and different levels of urbanization. The comprehensive related force of land change can be obtained through a research review of these regions. This study utilized an advanced search of the Web of Science and conducted a comprehensive investigation of the factors of land changes and degradation research for 1990 to 2019 (December).

We adopted these factors in the following ways. If the case study indicated that the main factor was the important force, we recorded it mentioned in each publication. Otherwise, we treated each of the mentioned factors (also in the discussion) as an alternative. We abandoned irrelevant factors, e.g., livestock, because the proportion of the breeding industry was very low in this region. Then we considered the characteristics of PRD, such as industrial characteristics, a large floating population, dense river networks, and most cities located along the coast. In addition, considering the availability of data, this study selected a total of 26 factors: twelve natural, eight social, and six economic (Table 1). Natural factors are geographical, meteorological, and disaster factors. Social factors are population and urbanization construction factors. Economic factors are economic development and market factors. The formulation and implementation of land policies in PRD were based on local natural conditions and social acceptability. Those related to forest land were the ecological redline policy, nature reserve policy, returning cropland to forest land policy, and urban development policy. The ecological redline policy and nature reserve policy were based on the comprehensive assessment of ecosystem services and ecological sensitivity. These two indicators were evaluated by natural factors, such as rainfall, evaporation, soil quality, DEM, all of which were included in the main factors. Returning cropland to forest land policy mainly considers DEM, soil quality, and ecological sensitivity. Urban development policy mainly considers population, GDP, DEM, and ecological carrying capacity. We can qualitatively analyze the effects of policies according to combinations of these factors. Because the socio-economic data were mostly counted by county administrative units, these units were the smallest evaluation unit used to evaluate the main forces quantitatively. If the main factors datasets did not change with time, we used them directly. Otherwise, we used the means and the rate of change. The data were standardized to eliminate dimensionality.

Table 1. Proxy variables of the compound forces.

Factors	Class	Measuring Indicators	Unit	Source
Natural factors	I Geographical	1 Digital elevation model (DEM)	m	ASTER's Global Digital Elevation Model [31].
		2 Relief amplitude	m	
		3 Soil chemical composition	%	The original soil data were produced from a series of soil maps covering the extent of China at a scale of 1:1 million based on the Harmonized World Soil Database [32].
		4 Soil carbon content	%	
		5 Distance to waterbodies	km	Calculated from land-use data.
		6 Distance to coastline	km	The coastline data were retrieved from the National Oceanic and Atmospheric Administration (NOAA).
	II Meteorological	7 Mean annual potential evapotranspiration	mm	The data were derived from the China Meteorological Data Center (http://data.cma.cn, accessed on 1 January 2021).
		8 Mean annual temperature	°C	
		9 Mean annual temperature change rate	%	
		10 Mean annual rainfall	mm	
		11 Mean annual rainfall change rates	%	
	III Disaster	12 Distance from soil erosion	km	Soil erosion was derived from the Resource and Environment Science Data Center (http://www.resdc.cn/, accessed on 1 January 2021).
Social factors	IV Population	13 Mean population density	inhabitants/km^2	Data were retrieved from the Statistical Yearbook and Statistical Bulletin on National Economic and Social Development of cities in PRD urban agglomeration.
		14 Population density change rates	%	
		15 Mean rural population density	inhabitants/km^2	
		16 Rural population density change rates	%	
		17 Population migration	%	
		18 Educational level	%	
	V Urban construction	19 Impermeable surface area	km^2	Calculated from land-use data.
		20 Impermeable surface area change rate	%	
Economic factors	VI Income	21 GDP density	million yuan/km^2	Data were retrieved from the Statistical Yearbook and Statistical Bulletin on National Economic and Social Development of cities in PRD urban agglomeration.
		22 GDP density change rate	%	
		23 Mean agriculture output value	million yuan/km^2	
		24 Proportion of tertiary industry	%	
		25 Disposable income of rural residents	yuan	
	VII Market	26 Road accessibility	km	Calculated from land-use data.

Table 1. *Cont.*

Factors	Class	Measuring indicators	Unit	Source
Natural factors	I Geographical	1 Digital elevation model (DEM) 2 Relief amplitude 3 Soil chemical composition 4 Soil carbon content 5 Distance to waterbodies 6 Distance to coastline	m m % % km km	ASTER's Global Digital Elevation Model [31]. The original soil data were produced from a series of soil maps covering the extent of China at a scale of 1:1 million based on the Harmonized World Soil Database [32]. Calculated from land-use data. The coastline data were retrieved from the National Oceanic and Atmospheric Administration (NOAA).
	II Meteorological	7 Mean annual potential evapotranspiration 8 Mean annual temperature 9 Mean annual temperature change rate 10 Mean annual rainfall 11 Mean annual rainfall change rates	mm °C % mm %	The data were derived from the China Meteorological Data Center (http://data.cma.cn, accessed on 1 January 2021).
	III Disaster	12 Distance from soil erosion	km	Soil erosion was derived from the Resource and Environment Science Data Center (http://www.resdc.cn/, accessed on 1 January 2021).
Social factors	IV Population	13 Mean population density 14 Population density change rates 15 Mean rural population density 16 Rural population density change rates 17 Population migration 18 Educational level	inhabitants/km^2 % inhabitants/km^2 % % %	Data were retrieved from the Statistical Yearbook and Statistical Bulletin on National Economic and Social Development of cities in PRD urban agglomeration.
	V Urban construction	19 Impermeable surface area 20 Impermeable surface area change rate	km^2 %	Calculated from land-use data.
Economic factors	VI Income	21 GDP density 22 GDP density change rate 23 Mean agriculture output value 24 Proportion of tertiary industry 25 Disposable income of rural residents	million yuan/km^2 % million yuan/km^2 % yuan	Data were retrieved from the Statistical Yearbook and Statistical Bulletin on National Economic and Social Development of cities in PRD urban agglomeration.
	VII Market	26 Road accessibility	km	Calculated from land-use data.

2.3. Geographically Weighted Regression Method (GWR)

GWR tests spatial heterogeneity by determining a specific bandwidth, and each evaluation unit can be used to construct an independent equation [33]. Through the multicollinearity analysis by SPSS, it was found that the variance inflation factors of 18 main factors were more than 10 [34]. There were multiple collinearities among these factors. To ensure the integrity of these factors more comprehensively, we have not performed stepwise regression. Principle component analysis (PCA) was used to eliminate multiple collinearities in the data. The factors with eigenvalue > 1 were extracted (Table S2). Then, an adaptive Gaussian kernel was used to determine the best bandwidth of GWR by the Akaike information criterion. The explanatory factors of GWR showed that the model had a certain accuracy and could explain the effect of the main forces on forest land changes (Table S3). The GWR formula in this paper is as follows:

$$y_i = \sum_k \left[\sum_n \beta_j(u_i, v_i) w_{kn}\right] Var_k + \varepsilon_i, \tag{1}$$

where y_i is the change area of forest land, $\beta_j(u_i, v_i)$ is the jth local parameter estimate coefficient, Var_k is raw data for main factors, w_{kn} is the coefficient of the kth variable for the nth PC, and ε_i is the error term. Because all the explanatory variables were standardized before the regression process, the coefficients of explanatory variables can be used to compare their relative contribution to the model fit [8].

2.4. Relative Importance Analysis

There was a certain correlation between the main factors as some had a combined impact, such as slope and soil conditions, which significantly affected the expansion of built-up land [28]. The class composed of various indicators can better explain the main factors of land-use changes and help provide technical support for decision-makers. Johnson's relative weight was used to quantify the relative importance of the main factors. Based on the contribution of these factors to R^2, they were ranked [28]. Johnson's relative weight was calculated as follows:

$$JRW_j(u_m, v_m) = \frac{\beta_i(u_i, v_i)^2 \times {w_{ij}}^2}{\sum_1^k \beta_i(u_i, v_i)^2 \times {w_{ij}}^2} \tag{2}$$

where $JRW_j(u_m, v_m)$ is the relative contribution of variable j in county unit, w_{ij} is the coefficient of the jth variable for the ith PC, $\beta_i(u_i, v_i)$ is the GWR coefficient of the ith PC at county unit, and k is the number of factors.

3. Results

3.1. Multi-Scale Forest Land Transformation

From 2000–2018, the area of forest land was reduced with an afforestation area of 604.3 km^2 and a deforestation area of 1544.6 km^2, resulting in a net decrease of 940.3 km^2 (Figure 2). Cropland and built-up land were the main land types converted to forest land. Deforestation was mainly occupied by built-up land, accounting for 62.9%, followed by cropland, which accounted for 19.3%. Deforestation was mainly concentrated in the urban growth boundaries of GZ and DG (Figure S1). Afforestation was mainly converted from cropland, accounting for 57.1%, built-up land accounted for 17.8%. Afforestation was distributed in a scattered pattern and was mainly concentrated in the west and south of the urban agglomeration. The forest land area of each city decreased at varying degrees (Figure 3). In terms of the total amount, deforestation was mainly concentrated in DG and JM, and afforestation was concentrated in JM and ZQ. However, in terms of unit area, deforestation and afforestation were both concentrated in DG and SZ (Figure S1). Except for SZ and ZH, where afforestation was mainly converted from built-up land, other cities converted cropland to forest land. Deforestation of all cities was mainly occupied by built-up land.

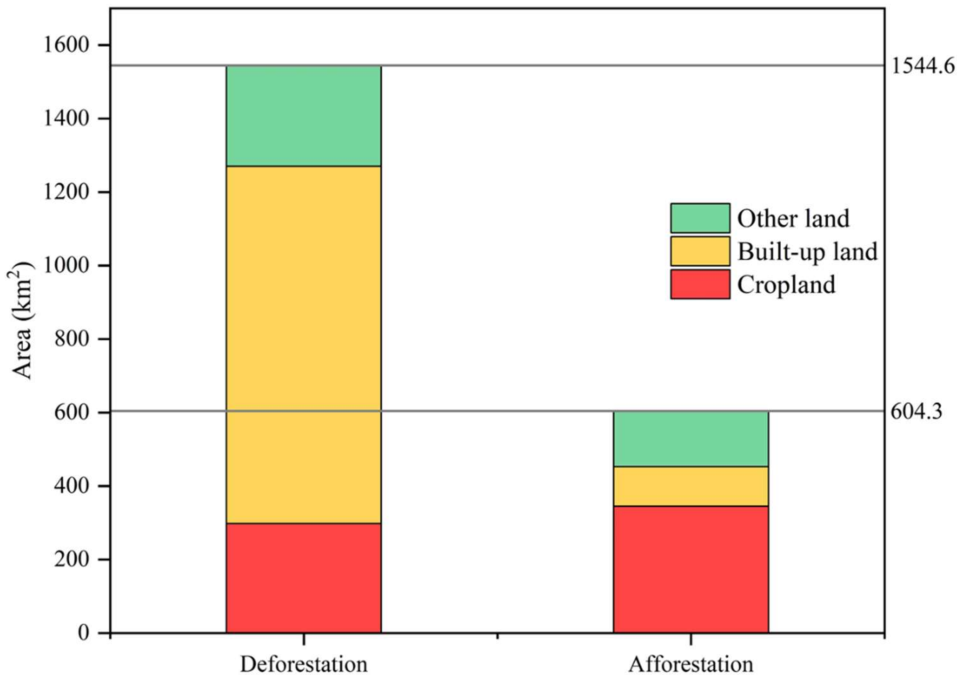

Figure 2. Conversion of forest land in the PRD urban agglomeration for 2000–2018.

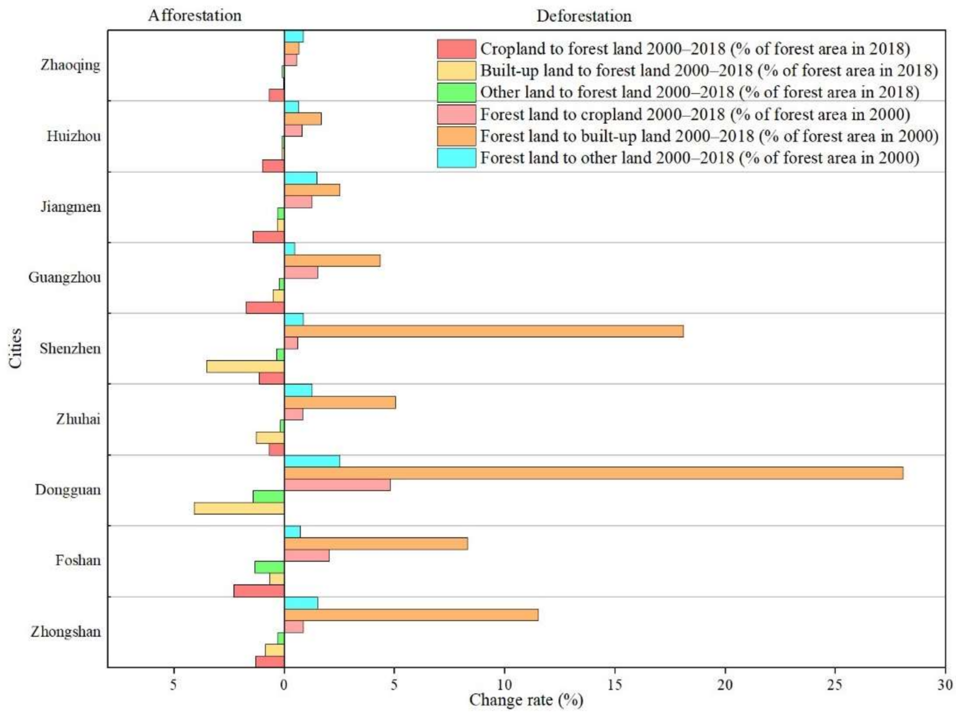

Figure 3. The estimated transformation between forest land to cropland, built-up land, and other lands from 2000 to 2018 among cities.

3.2. *Quantifying the Compound Main Factors of Deforestation*

There are some differences in the deforestation areas among cities in the PRD. However, the main factors in different cities had a consistent effect (16 factors in forest land to cropland and all factors in forest land to built-up land). The effect of forest land to cropland was more complex than to built-up land. Different effects were mainly reflected in the soil condition and the distance to water (Figure 4). The rural population change rate had a clearly positive effect on the conversion of forest land to cropland across cities (standardized coefficients >0.2). Especially in HZ, the standardized coefficient of the rural population change rate of >0.4 had a strong positive driving effect. Population migration, tertiary industry, and impervious surface area had a clearly negative effect on the conversion of forest land to cropland (standardized coefficients <-0.2). The geographical factors and market factors had a positive effect, whereas others had a negative effect on the conversion of forest land to cropland.

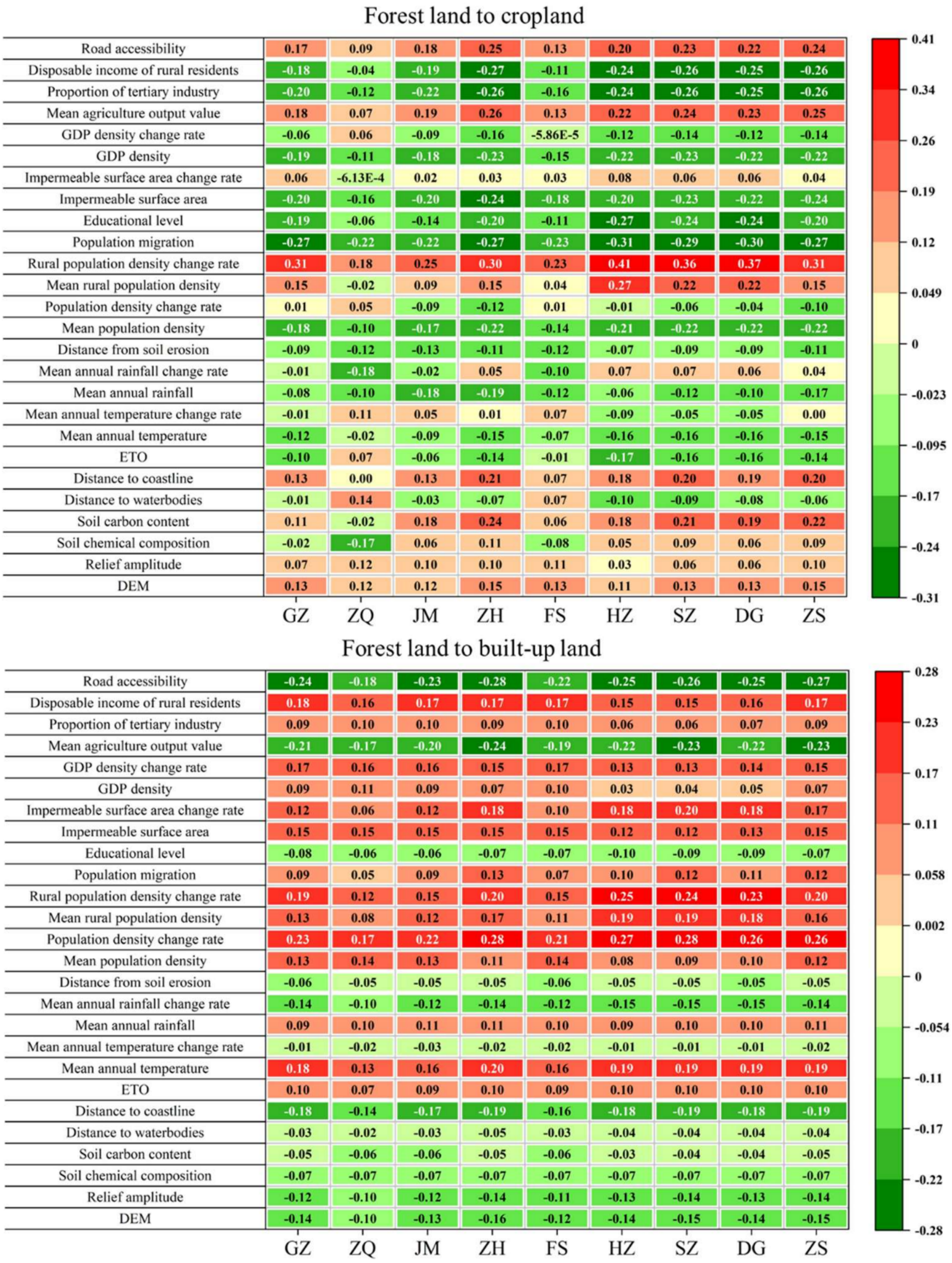

Figure 4. The Geographically weighted regression coefficients of each factor in different cities for deforestation. The numerical value represented the strength of the main force. The redder the color, the stronger the positive effect. The greener the color, the stronger the negative effect. GZ: Guangzhou; SZ: Shenzhen; ZH: Zhuhai; FS: Foshan; JM: Jiangmen; ZQ: Zhaoqing; DG: Dongguan; ZS: Zhongshan; HZ: Huizhou.

The effect of the conversion of forest land to built-up land showed no difference among cities (Figure 4). Population change rates had a clearly positive effect, whereas road accessibility and agriculture output value had a clearly negative effect on the conversion of forest land to built-up land across cities. The geographical factors and market factors had a negative driving effect, whereas others had a positive effect on the conversion of forest land to built-up land. The result was contrary to that of forest land to cropland. According to the analysis of relative importance, the effect of geographical and meteorological factors (29.4–47.6%) was still lower than that of socio-economic factors (52.4–70.6%). Population factors and income factors played a dominant role in deforestation (Figure 5). Geographical and meteorological factors exceeded population and income factors in ZQ in the conversion of forest land to cropland. The main reason is that the meteorological factors became more important. The conversion of forest land into built-up land was more affected by socio-economy.

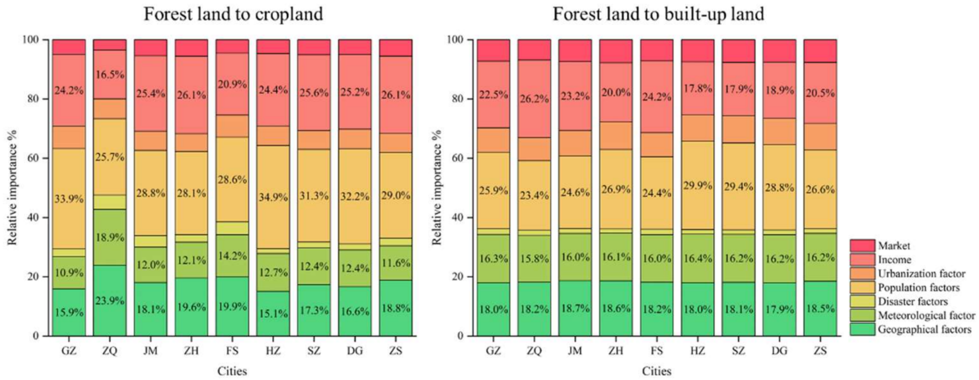

Figure 5. The relative importance of different factors in different cities for deforestation. GZ: Guangzhou; SZ: Shenzhen; ZH: Zhuhai; FS: Foshan; JM: Jiangmen; ZQ: Zhaoqing; DG: Dongguan; ZS: Zhongshan; HZ: Huizhou.

3.3. *Quantifying the Compound Factors of Afforestation*

Compared with deforestation, the main factors in different cities had a strong, consistent effect on afforestation (21 factors in cropland to forest land and 24 factors in built-up land to forest land) (Figure 6). Different effects were mainly reflected in the meteorological factors. The rural population change rate and the change in impervious surfaces had a clearly positive effect on the conversion of cropland to forest land. Population density, tertiary industry, and GDP had a clearly negative effect on the conversion of cropland to forest land across cities. The geographical factors, population factors, and urban expansion factors had a positive effect, and others had a negative effect on the conversion of cropland to forest land. The conversion of built-up land to forest land was driven by more factors, and their driving effect was stronger. GDP, population density, disposable income of rural residents, and tertiary industry had a clearly positive driving effect. In particular, the change rate of GDP had a strong positive driving effect. Soil conditions and distance to coastline had a clearly negative effect. The geographical factors, disaster factors, and market factors had a negative effect, and others had a positive effect on the conversion of built-up land to forest land. The effect of geographical and meteorological factors was still lower than that of socio-economic factors in afforestation, and the effect of natural factors was lower than that of deforestation (Figure 7). Population factors played a dominant role in cropland to forest land, and income factors played a dominant role in built-up land to forest land.

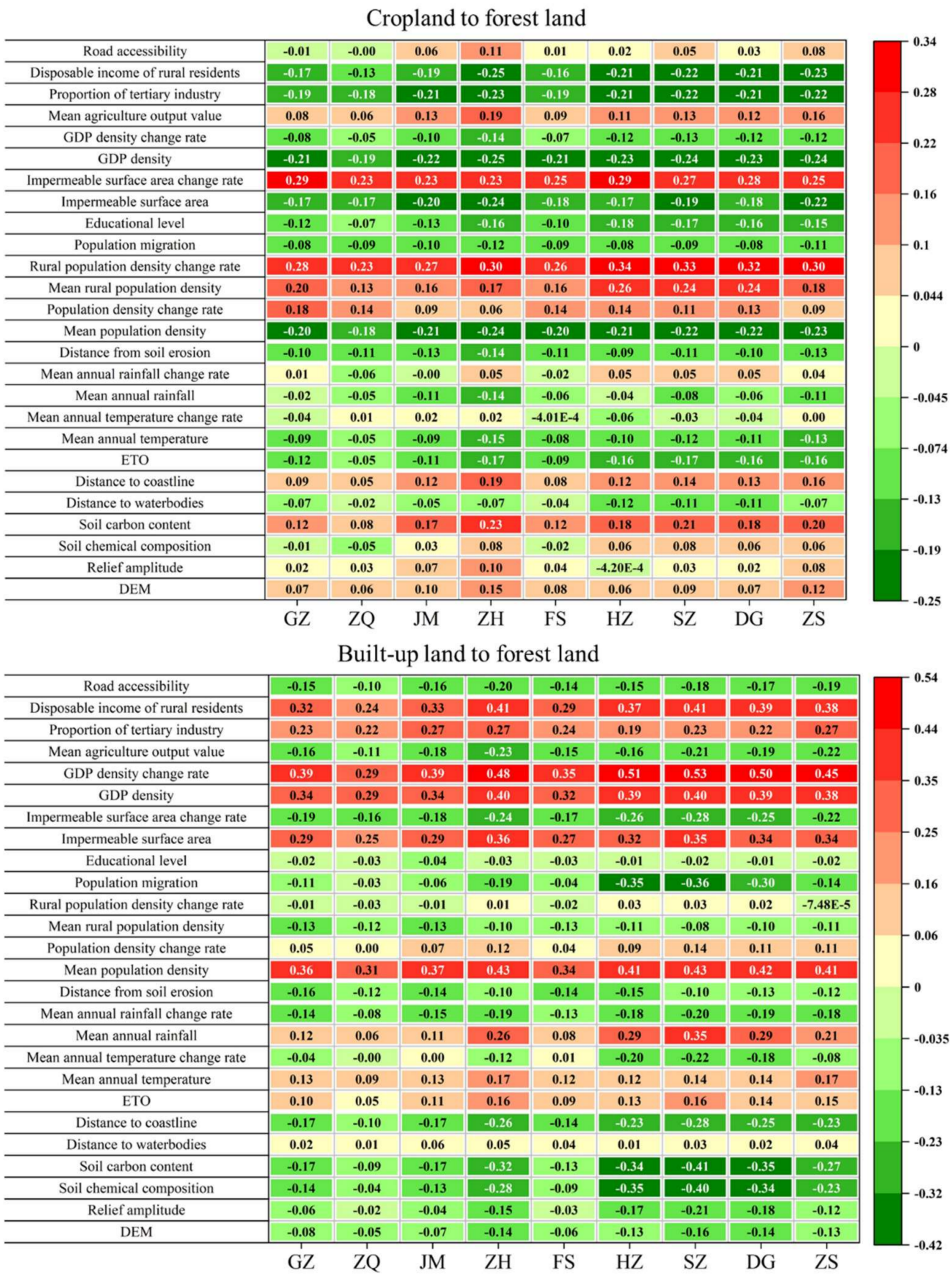

Figure 6. The Geographically weighted regression coefficient of each factor in different cities for afforestation. The numerical value represented the strength of the force. The redder the color, the stronger the positive effect. The greener the color, the stronger the negative effect. GZ: Guangzhou; SZ: Shenzhen; ZH: Zhuhai; FS: Foshan; JM: Jiangmen; ZQ: Zhaoqing; DG: Dongguan; ZS: Zhongshan; HZ: Huizhou.

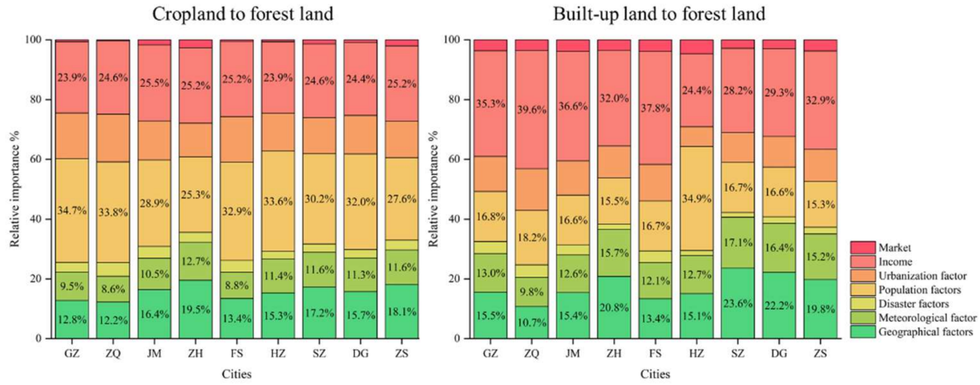

Figure 7. Relative importance of different factors in different cities for afforestation. GZ: Guangzhou; SZ: Shenzhen; ZH: Zhuhai; FS: Foshan; JM: Jiangmen; ZQ: Zhaoqing; DG: Dongguan; ZS: Zhongshan; HZ: Huizhou.

4. Discussion

This paper systematically summarized the forceful indicators of land-use changes and proposed how to quantify the difference compound factors at the urban agglomeration scale. Although our research is only in the PRD urban agglomeration, the goal of mapping land change was to identify factors that drive the land-use changes on a local scale and generalize this information to derive relevant information across scales [35]. Urban agglomeration is the future development trend of regional cities, and the PRD is the benchmark of China's urban agglomeration. The findings of this study will help reveal the mechanism of forest land changes under different urbanization factors in urban agglomeration. This paper has great significance in the studies of the land changes and their influence on urban development in East and Southeast Asia. Our analysis also confirmed that combined GWR methods and the relative importance can support further investigation and a clearer understanding of the forces of forest land changes. Traditional land-change modeling has been almost completely based on the global-level logistic regression, which does not effectively quantitative the socio-economic factors associated with the land change at a regional scale [8]. The GWR methods and the relative importance we proposed can be used to improve the performance of regional land-use change models. These methods focused on the forest land change processes on an urban agglomeration scale from both spatial and temporal perspectives and have suggested how to quantify natural and socio-economic forces.

The development of the urban agglomeration and the continuous growth of the population is bound to encroach on ecological space. Urban ecological policies only alleviate the speed and scale of this process, and the types and positions of encroachment have changed to some extent. Forest land showed a net decrease of 940.3 km^2 between 2000 and 2018. These outcomes were in line with the findings commonly reported in the literature at a regional scale and city scale [12,36,37]. In the PRD, the decrease in forest land was mainly due to the expansion of built-up land and mainly located within urban growth boundaries (e.g., DG, SZ). This was mainly because the region was a priority development area in land planning policy. In urban planning policy, the surrounding areas of urbanization have always been more likely to be occupied by residential, commercial, and industrial uses [12]. Neglect of the protection of ecological space in management, results in the reduction in forest land area. With the rapid development of urbanization and GDP growth, a lot of non-agricultural work has been provided in urban areas [38]. There have been many rural migrant workers in PRD in recent years, resulting in a sharp reduction in the rural labor force, and to a certain extent, the abandonment of cropland around the highly urbanized city [39], as rural migrant workers increased the conversion of forest land to built-up land in urban growth boundaries. At present, the pressure of deforestation caused by the growth of the rural population is gradually decreasing due to migrants, but this exacerbates the pressure of deforestation in highly urbanized areas. This is consistent with the findings of this study that show that deforestation in all cities was mainly caused by built-up land. The initial stage of urbanization is always accompanied by the occupation of ecological space by urban build-up land, resulting in a significant reduction in forest land area [40]. The government should strengthen monitoring and assessment of forest land in urban growth boundaries. We suggest strengthening the protection and construction of green space in this area rather than deforestation and replanting forests in remote areas. The green infrastructure can be built to meet the needs of residents through the combination of the development of centralized group green space and the increase in decentralized small green space. The government should also play a leading role in encouraging and guiding social forces, social capital, and private enterprises in participating in the construction and protection of urban forest land, establishing a diversified green space infrastructure construction and management mechanism, and advocating the decisive role of the market mechanism in resource allocation.

The impact of urbanization on afforestation was mainly reflected in the urban ecological policies, concentrated on natural factors [41]. Our results showed that the force of this transformation was the same in all cities, mainly due to the same planning standards being adopted in the planning process by the government (e.g., meet the needs of residents and solve the imbalance between supply and demand). The government policies, such as returning cropland to forest land, ecological restoration, and ecological redline policy, have important roles in the protection and construction of local forests [42]. As most studies have already shown, this study also concluded that the afforestation areas were mainly converted from cropland. This was closely related to the implementation of returning cropland to forest land in PRD. The results from GWR models further revealed the factors of this study can combine to explain the driving effect of some policies in afforestation. Soil carbon content, DEM, and relief amplitude had a positive effect on the conversion of cropland to forest land, and distance from soil erosion had a negative effect. This was mainly because returning cropland to forest land was based on cropland where soil erosion was serious, or the slope was more than 6 degrees or areas where soil quality was easy to restore to forest land. Cropland that met this standard was more likely to be converted to forest land. The results also showed that the distance to erosion and coastline had a negative driving effect on the conversion of built-up land to forest land. The main reason was the PRD carried out ecological restoration policies in ecologically sensitive areas, focused on ecological afforestation in the erosion area, and constructed coastal shelter forests. Because the formulation of the ecological policy was based on the evaluation of natural factors, the impact of ecological protection policies on afforestation was mainly reflected in natural factors. The GWR analysis also revealed that the rural population was a positive factor for the conversion of cropland to forest land. The loss of the labor force in rural areas has changed the agricultural management mode, and the government has implemented an ecological compensation policy to encourage the conversion of cropland to forest land [43]. We found that population density presented a positive effect on built-up land to forest land in highly urbanized areas. However, the increase in population density was the main reason for the decrease in forest land in many studied areas [8], which was also due to the PRD analyzing of ecological carrying capacity and delimiting of nature reserves. To satisfy ecological security and sustainable development, the government must construct ecological spaces by an ecological migration policy that meets the need of residents. The built-up area near the ecological protection area was restored as an ecological space. Yet, the conversion of built-up land to forest land was mainly concentrated in ecological protection and restoration areas, and the areas were small, so it was difficult to meet the needs of residents. The government needs to build ecological conservation spaces between cities and urban growth boundaries, increase forest areas, and improve forest quality. In short, build a network ecological corridor that parallel urban agglomeration and build a multi-level green infrastructure, improve green space systems, and create a differentiated ecological landscape.

This study was the first to quantify the natural, social, and economic factors of deforestation and afforestation in the PRD using spatial and temporal distribution characteristics. However, this study has some limitations and uncertainties. First, due to the difficulty of obtaining historical data, we only analyzed the forest land changes and factors from 2000 to 2018. As for choosing this period, this decision was mainly related to the development of PRD urban agglomerations. Since 2000, the scale of urban agglomeration has been initially realized. The analysis of forest land changes from 2000 to 2018 reflects the continuous mechanism of urbanization on forest land in PRD. However, due to a large amount of socio-economic data of urban agglomeration, we only analyzed the changing characteristics of these two periods, resulting in the lack of force that changed these characteristics, but the long-term gradient now better reflects the sustainable impact mechanism of socio-economic factors on forest land changes. Second, spatial inconsistencies existed between the main factor data and forest land change data. In light of the availability of statistical yearbook data, the county administrative units were used as an evaluation yardstick, and the average values reduced the importance of some factors. However, the distribution of forest land change patches was scattered, and considering the difference in data resolution, the value error after extraction was also large. The average processing could not only solve the error caused by different resolutions but also match with the socio-economic data. Therefore, the county-level administrative unit as the statistical unit had a certain scientific nature for the quantitative analysis at the urban agglomeration scale. Third, although important indicators of the main factors were selected according to previous studies, some indicators were not considered, and the policies were not considered as variables in the quantitative analysis. Considering that the policy cannot be quantified, this paper combined with the background of policy-making and qualitative analysis of the policy impact on forest land. At last, the combination of our indicators was mainly based on the characteristics of indicators. It is difficult to interpret the GWR model outputs thoroughly for mapping ecological management. A potential solution is to cluster or zone the factors with the help of machine learning and thus reducing the complexity of the model outputs. Establish a suitable local spatial clustering method may be a way for future additional investigations of geographical relations in order to reach the full potential of the GWR method.

5. Conclusions

Based on an extensive review of the relevant literature, we made new attempts to quantitatively evaluate the spatial effects of natural, social, and economic factors of forest land changes by utilizing the GWR model on an urban agglomeration scale, a deep understanding of the effects of urbanization, and an ecological policy on forest land changes. We made new attempts to at least partially fill in the knowledge gaps in urban forest land management. Reconstruction efforts to restore forest land did not offset human-caused forest losses, and the rate was found to be declining. Cropland and built-up land were the main types of forest land conversion. There is still a lack of reasonable planning of forest land, especially in urban growth boundaries of SZ, DG, and HZ. Population factors and income factors still have an important effect on the changes in forest land, but the impact is different. Many migrant workers are reducing the occupation of forest land by cropland, but increased built-up land occupied. Future forestry planning should be unified planning according to the development trend of urbanization degree and should strengthen the protection and construction of forest land in urban growth boundaries. This study can perhaps serve as an important resource for the formulation of environmental management measures and improve the accuracy of land-use planning models.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/rs13101911/s1, Figure S1. Hotspots distribution of forest land change. Table S1. The error matrix of classified and reference data for 2018. Table S2. Total variance interpretation of principal component analysis. Table S3. Explanatory factors of Geographically weighted regression.

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