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Influences of Topographic Factors on Outcomes of Forest Programs and Policies in a Mountain Region of China: A Case Study

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In China, the successive government has implemented ambitious programs and policies to reverse the decline in forest cover. As an essential source of freshwater and an ecological barrier for Beijing, Zhangjiakou City has implemented several forest expansion strategies. Topographic conditions in this mountainous area have generated spatially heterogeneous afforestation outcomes. Quantifying the impact of these conditions on implemented forest programs could improve ecological restoration strategies of Chinese mountain areas. Using remotely sensed data from the Landsat 5 Thematic Mapper and the Landsat 8 Operational Land Imager, we generated land cover data to identify forest cover changes in Zhangjiakou City in 1989, 2000, and 2015. Forest cover data, topographic information (elevation, slope, aspect, land relief, and terrain niches), and spatial statistical models (geographically weighted regression [GWR]) were used to analyze re- and afforestation over 2 periods (1989–2000 and 2000–2015). The results show that forest cover in Zhangjiakou City increased by one third from 1989 to 2015. The rate of afforestation from 2000 to 2015 was 4 times the rate observed between 1989 and 2000. A trend toward gradual afforestation of higher-elevation and gentler-slope areas and land relief and terrain niche zones was observed between the 2 periods. Expansion mostly occurred in grasslands, arable lands, and unused lands. Elevation, slope, and land relief were the dominant topographic factors influencing forest cover change. Such factors influenced afforestation directly through their effect on microclimates and local biophysical conditions and indirectly by limiting the geographic area where forest programs could be implemented. Terrain niche was also an important predictor of forest cover change under complex topographic conditions. The GWR results indicate heterogeneous forest cover change processes across the study area. Our analysis could guide the implementation of effective forest expansion programs and policies, particularly for degraded mountain ecosystems.

Keywords: *forest programs; forest policies; forestland change; restoration; topographic factors; geographically weighted regression; spatial heterogeneity.*

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Introduction

Land use and land cover change is regarded as a basic component of global environmental change (Turner et al 2007), and its pace and intensity have accelerated over the last 3 decades (Lambin and Veldkamp 2005). With urbanization and industrialization, land use change reflects changes in the human–nature relationship. Forestland change is an important issue in the science of land use and land cover change, because forest ecosystems are fundamental for the biosphere due to their provision of multiple ecosystem services (Bottalico et al 2016) that are critical for the human–nature system (Rammer and Seidl 2015). There have been large forestland changes in many areas of the world, triggering many studies conducted to assess the global consequences of such changes (Fu and Gulinck 1994; Mather et al 1998; Gerhardt and Foster 2002; Rudel et al 2005; Zhang et al 2006; Lambin and Meyfroidt 2010; Barbier and Tesfaw 2015; Jachowski et al 2016).

Mountain areas account for two thirds of the total land area of China (Li et al 2017) and provide vital ecosystem goods and services to the population. However, socioeconomic development accompanied by inappropriate land use, such as clear-cutting or deforestation, has had catastrophic effects. Widespread soil erosion and flood disasters at the end of the last century (Liu and Diamond 2005) had a tremendous influence on the socioecological system, especially in mountain areas. To promote environmental conservation and afforestation, the Chinese government has been implementing a series of ecological restoration programs and policies since 1978, such as the Key Shelterbelt Construction Program (beginning 1978), Beijing–Tianjin Sandstorm Control Program (beginning 2002), Wildlife Conservation and Nature Reserve Development Program, Forest Eco-Compensation Program, Forest Conservation Program, and Grain to Green Program (beginning 2000) (Liu et al 2008). Yeh (2009) has argued that the preceding programs have favored differential interventions through processes of internal territorialization. According to Zinda (2012), many collaborators have provided resources to promote such projects, the performance of which has depended on the responses of local officials and residents (Zinda et al 2017). Earlier research revealed that the area of forestland in China began to grow in approximately 1980 (Mather 2007). However, there were also some challenges, including lack of appropriate technical practices and neglect of market-based approaches (Xu et al 2006), as well as potential damage to the ecosystem when forest cover increase is achieved with nonnative trees (Xu 2011).

Van Den Hoek et al (2014) have argued that the spatially different forest cover change in Southwest China illustrates the highly differentiated effectiveness of policy implementation. Zhang et al (2017) report that larger vegetation gains appeared in high-elevation communities in 2000–2010, whereas low-elevation communities had larger gains in Yunnan after the Grain to Green Program in 2010–2014. As a natural parameter, topography is one of the most important land attributes of a landscape (Zonneveld 1989) and is usually considered when identifying land management units (Gercek 2017), land use suitability and patterns (Allen et al 1995; Li et al 2006; Liu and Li 2015; Gao et al 2016), and ecological units (Silva et al 2006). Some studies about mountain areas have reported that topographic factors can influence forest type distribution (Van-Kesteren 1996), forest fragmentation and recovery (Galicia et al 2010), and forest-cutting areas (Ikemi 2017) through both biophysical and socioeconomic processes. In mountain regions in particular, special and complex topographic features may directly influence patterns and processes of forestland change by affecting biophysical conditions; this in turn affects the patterns and trends of natural vegetation regeneration, which may determine the effectiveness of forest regeneration policies (Sun et al 2014; Zhang et al 2017). In addition, topographic conditions may indirectly influence the choice of the implementation area—such as by determining whether an area is fit for planting trees by hand. Although topographic factors may influence the outcomes of forest programs in mountains, existing studies do not clearly explain what these influences may be.

Zhangjiakou City is an ecological restoration area with rugged mountain terrain and various topographic factors that influence land use. It is also an extremely important source of freshwater and a vital ecological barrier for Beijing, the capital of China. Agriculture and animal husbandry have always been the main land use types. Because of policies encouraging agriculture and animal husbandry but disregarding the impact of overgrazing and expansion of cultivation upslope, soil erosion and deforestation seriously affected the local environment and the lives of communities living there. Expansion of construction land and indiscriminate mining also damaged the environment. To promote environmental protection and in response to the country's ecological restoration policies, Zhangjiakou City undertook unprecedented afforestation and reforestation engineering measures: the Key Shelterbelt Construction Program as of 1978, the Grain to Green Program as of 2002, and the Beijing–Tianjin Sandstorm Control Program as of 2000 (Liu et al 2017). Currently, Zhangjiakou City is implementing the second stage of the Beijing–Tianjin Sandstorm Control Program (from 2013 to 2022) and of the Grain to Green Program (from 2014 to 2022). Policies for prohibiting extension of grazing and encouraging stable feeding, the declaration of a national and provincial natural reserve zone, and restrictions on the expansion of construction land were also implemented after 2000. These forest programs and policies have resulted in a major increase in forest ecosystem services. However, most afforestation sites are characterized by poor natural conditions, with occasional geological hazards and difficult conditions for road construction, and poor climate conditions, such as uneven rainfall, cumulative temperature, and frequent strong winds, leading to drought, the need for replanting, and higher reforestation costs to ensure the preservation rate. The current understanding of forest change dynamics and of the impact of topographic factors on forest change in Zhangjiakou City is poor, although both factors are relevant and crucial to reforestation and afforestation policies. Thus, it is essential to better understand the influence of topographic factors on forestland change processes.

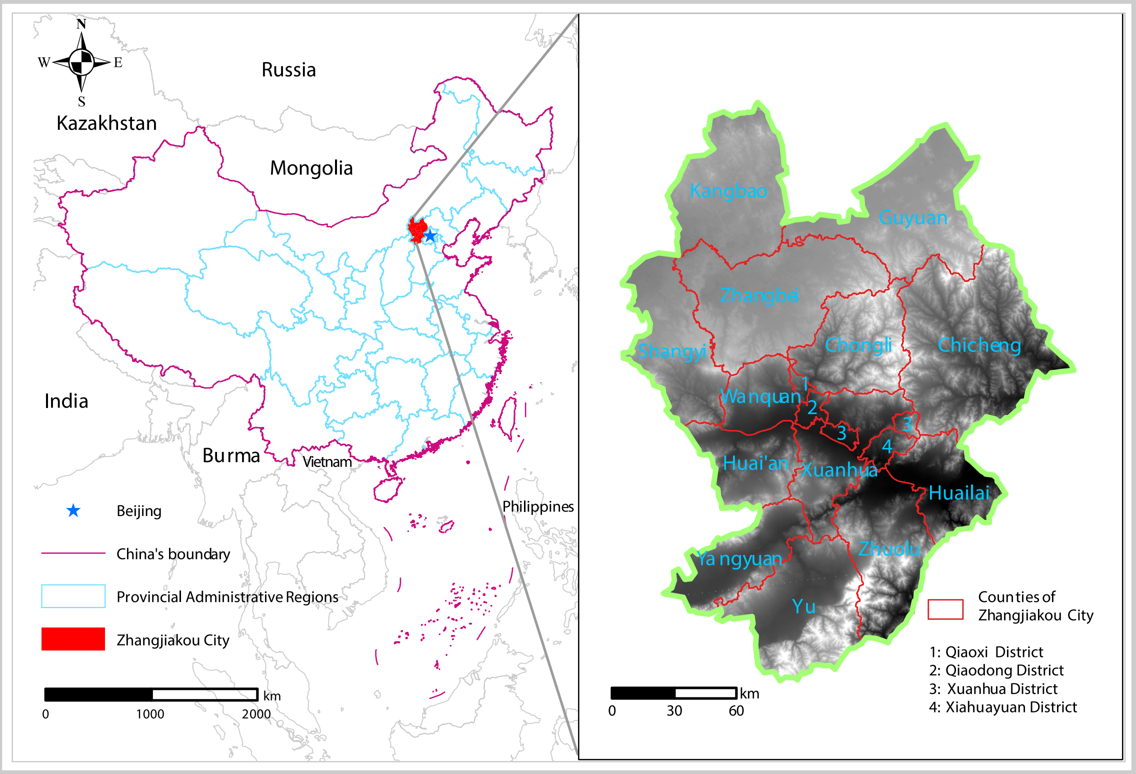
The aim of this study was to quantify the spatial and temporal patterns of forestland change and the relationship between topographic factors and forestland change after forest programs and policies started to be implemented 25 years ago in Zhangjiakou City. Unlike classical statistics and qualitative analysis methods conducted in previous studies (Gerhardt and Foster 2002; Galicia et al 2010; Mu et al 2015; Peng et al 2016; Ikemi 2017), this study both adopted a spatial statistical approach and developed a spatially explicit model to explain the relationship between forestland changes and topographic factors. By providing results from a case study, the present paper could provide theoretical support for the practical implementation of reforestation and afforestation programs and policies in similar areas.

Material and methods

Study area

Zhangjiakou City, located in the northwest of Hebei Province, is situated at the junction of Beijing and Inner Mongolia and includes 4 administrative districts and 13 counties (Figure 1). The total area of Zhangjiakou City is approximately 36,800 km^2 (Sun et al 2016). The northwest region is part of the Mongolian Plateau, with high terrain that is mainly grazing land. In the southeast, hills, valley, and plains result in complex terrain that is used for agriculture. The elevation of Zhangjiakou City ranges from 320 m in the lowest river valley to 2841 m at the highest point. The region has benefited from the Reform and Open Door policy of China, which has promoted extensive socioeconomic development. Zhangjiakou City has experienced rapid urbanization, with an urban population of 46.94% by 2015 and with about US$ 2 billion of gross domestic product generated in 2014 (Liu et al 2017). The geographic features of the study area, situated in both the Yanshan Mountains and the Taihang Mountains, are mostly typical mountain

FIGURE 1 Location of the study area (39°30′–42°10′N, 113°50′–116°30′E). (Map by Longhui Lu)



characteristics. Because of the proximity of Beijing City and Tianjin City (2 metropolises in China) and its high elevation, this area is both an important water source region and a wind channel for both cities.

Forests in the region consist mainly of trees (72%), with only 27% of the forests consisting of shrubs. The main tree species include *Prunus armeniaca* (21%), *Betula platyphylla* Sukaczev (18%), *Ulmus pumila* L. (9%), and *Quercus suber* L. (9%); shrubs are mainly *Corylus ferox* Wall. (27%), *Caragana microphylla* (21%), and *Hippophae rhamnoides* L. (15%). In these forested lands, 60% of the area was planted for soil and water conservation, 19% was planted for windbreaks and sand fixation, and 9% was planted for orchards. Other forest uses are road protection, firewood, and pharmaceutical and chemical industries, but with lower percentages. Although 45% of the trees are natural forests, 48% were planted as seedlings. According to official data, the increase in forest cover in Zhangjiakou City since 2000 was 39% by the end of 2016. Forest planning for 2019–2035 foresees that this increase will reach 55% by 2035.

The Key Shelterbelt Construction Program started in 1978, focusing on windbreak and sand fixation. The program will continue until 2050. The area is mainly distributed in the western and northern regions of Zhangjiakou. The Beijing–Tianjin Sandstorm Control Program and the Grain to Green Program have been implemented in all counties since 2002 and will continue until 2022. The Beijing–Tianjin Sandstorm Control Program integrates many smaller programs, such as the Forest Program for Regions beyond the Great Wall, the Beijing–Hebei Ecological Water Sources Conservation Forest Program, the Green Program for Main Road, and the Green Program Around the Counties, all of which aim to control sandstorms and soil erosion. The Grain to Green Program and the subsequent Consolidating Program for Grain to Green provide direct subsidies for farms that convert cultivated land on slopes to forests or its natural state. All programs have adopted artificial afforestation, which requires enormous manpower and seeding efforts. In addition, the Beijing–Tianjin Sandstorm Control Program and the Grain to Green Program adopted afforestation through aerial seeding and closing of hillsides to facilitate afforestation. Compulsory annual public planting of trees is also implemented. The main species planted are evergreen species (eg *Platycladus orientalis,* Chinese pine) and deciduous species (eg *Populus alba* L.). Tasks are assigned in a top-down process annually and evaluated each year by the government. The first phase of these programs focused on the expansion of the forest area, and the second phase focuses on the quality of forest growth.

The areas where the different measures were implemented by forest programs and policies during 2000–2015 is shown in Figure S1 (*Supplemental material,* https://doi.org/10.1659/MRD-JOURNAL-D-18-00050.1.S1). Before 2007, the Grain to Green Program (both cultivated land converted to forest and cultivated land reverted to its natural state) produced the largest reforested and afforested area. After 2007, reforestation became the main measure. The main afforestation measures were hill closure to facilitate afforestation before 2009 and artificial plantation and nurturing and management of base construction after 2008. When applying these measures, topographic factors were considered in cultivated land converted to forest and cultivated land reverted to its natural state. According to the plan, cultivated land on slopes steeper than 25° had to be converted to forest or its natural state. However, in many cases, implementation did not consider slope, and a lot of

TABLE 1 The 5 topographic factors considered in this study.

Category	Land relief (m)	Slope (°)	Elevation (masl)	Aspect (°)	Terrain niche
1	0–20	Very gentle: 0–6	320–400	Plane: −1.0	0.23–0.24
2	20–40	Gentle: 6–15	400–600	N: 0–22.5	0.24–0.43
3	40–60	Steep: 15–25	600–800	NE: 22.5–67.5	0.43–0.64
4	60–80	Very steep: >25	800–1000	E: 67.5–112.5	0.64–0.84
5	80–100		1000–1200	SE: 112.5–157.5	0.84–1.05
6	100–324		1200–1400	S: 157.5–202.5	1.05–1.25
7			1400–1600	SW: 202.5–247.5	1.25–1.46
8			1600–2841	W: 247.5–292.5	1.46–1.67
9				NW: 292.5–337.5	1.67–1.87
10				N: 337.5–360.0	1.87–2.01
11					2.01–2.28
12					2.28–2.49
13					2.49–2.70
14					2.70–2.98

cultivated land that farmers no longer wanted to plant was converted as well. Because of the significant amount of compensation for farmers who returned farmland to forestland and the high amount of investment for planting trees, investment activity in the Grain to Green Program was highest before 2007 (Figure S2, *Supplemental material,* https://doi.org/10.1659/MRD-JOURNAL-D-18-00050.1.S1). After 2007, most investment went into forest replantation, artificial plantation, and engineering work on steep slopes to enable forest planting. Investment for hill closure to facilitate afforestation before 2007 and afforestation by aerial seeding after 2007 was also significant.

Data

Landsat data products were used to classify land use and detect land use changes (Cohen and Goward 2004): 2 remote sensing images for 1989 and 2000 were acquired at a spatial resolution of 30 × 30 m from the Landsat 5 Thematic Mapper and 1 sensing image for 2015 were acquired from the Landsat 8 Operational Land Imager via China's Geospatial Data Cloud (CAS-CNIC 2015).

The topographic data—elevation, slope, aspect, land relief (LRE: the difference between maximum and minimum elevation; Sun et al 2014), and terrain niche (TNI: a terrain index integrating slope and elevation; Guo et al 2013)—were obtained from a digital elevation model (DEM) coming from the Shuttle Radar Topography Mission 30-m DEM, downloaded with a spatial resolution of 30 × 30 m from China's Geospatial Data Cloud (CAS-CNIC 2015).

Methods

Land use classification and calculation of topographic factors: The preprocessing of remote images and supervised classification were produced by ENVI 5.0 (for concrete steps, see the user's handbook for ENVI 5.0; Exelis Visual Information Solutions 2012). No cloud masking was necessary, because our images had low cloudiness. For atmospheric correction of the images, we used Top of Atmosphere Reflectance. The classification algorithm used the maximum likelihood estimation method. We then applied the land cover classification system of China (Liu et al 2017) (Figure S3, *Supplemental material,* https://doi.org/10.1659/MRD-JOURNAL-D-18-00050.1.S1). The classification included arable land, forestland, grassland, orchard land, built-up land, roads, water areas, and unused land. According to national standards, forestland refers to the area where the canopy density is above 0.2, including trees, shrubs, and bamboo. The classification results were tested and verified. The training data consisted of ground samples collected in July 2014, November 2015, and August 2016, which were then expanded to 307 samples using Google Earth aerial photos. Among the preceding samples, 30% were randomly selected for validation to assess the accuracy of classification.

Elevation, slope, and aspect data were calculated using the raster surface tool of ESRI ArcGIS 10.2 (see concrete steps in the user book of ArcGIS 10.2; ESRI 2013). The LRE and TNI data were calculated using the raster calculator tool according to Sun et al (2017).

Classification of topographic factors: To determine the characteristics of multiple topographic factors and to ensure they were appropriate for analysis, the values of the topographic factors were classified into various terrain zones (Table 1). The elevation map was classified into 8 terrain zones with intervals of 200 m to express the decrease in temperature and precipitation with elevation. The slope map was classified into 4 terrain zones by considering standards for the classification and gradation of soil erosion in China. The aspect map was classified into 10 terrain zones covering all aspects. The LRE map was classified into 6 terrain zones (used quantiles were reclassified). The TNI map

TABLE 2 Temporal variations in forestland changes from 1989 to 2015.

Forestland	Area (ha)	Change (%)
Change by specific year		
1989	914,900	24.86
2000	971,100	26.38
2015	1,218,900	33.12
Change per period		
1989–2000	56,200	6.14
2000–2015	247,800	25.52

was classified into 14 terrain zones, in which each level represented a 100-m increase in elevation and a 2° increase in slope (Sun et al 2014).

Grid cells and spatial statistics: To explicitly quantify the relationship between topographic factors and forestland changes, the grid-cell method was used because of its advantages for spatial analysis (Maimaitijiang et al 2015). To measure the change in forestland, a 2-km grid-cell net of vector polygons was built using the fishnet tool in ArcGIS. The percentage of forestland in 1989, 2000, and 2015 and the percentage changes of forestland in all cells within the 1989–2000 and 2000–2015 periods were calculated. The average values of the topographic factors within cells were calculated using the zone statistic in ArcGIS.

Spatial regression method: The geographically weighted regression (GWR) model can investigate the various spatial relationships originating from location and distance and can calculate spatial autocorrelation (McMillen 2004). The GWR model was used to analyze heterogeneous spatial relationships at the local scale; the model equation was as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \qquad i = 1, 2, \ldots, n \quad (1)$$

where Y_i is the dependent variable that denotes the percentage change of forestland in each cell; x_i is the independent variable that denotes the average value of the topographic factors (elevation, slope, aspect, LRE, and TNI) in each cell; β_0 is the intercept parameter of sample i; (u_i, v_i) are the coordinates of the location of sample i; $\beta_k(u_i, v_i)$ is the local regression coefficient k for sample i; x_{ik} is the independent variable k of sample i; β_k is the error of variable k; and ε_i is the ransom error of sample i.

Results

Accuracies of the classification

The accuracy assessments showed that the global accuracy in 1989, 2000, and 2015 was 86.82, 88.92, and 86.38%, respectively. The producer's accuracy for forestland in 1989, 2000, and 2015 was 82.82, 87.80, and 84.78%, and the user's accuracy was 86.17, 90.34, and 89.09%, respectively. Meanwhile, all producer accuracies and user accuracies for other land cover types were between 80 and 94%. The Kappa statistic coefficient in 1989, 2000, and 2015 was 0.84, 0.87, and 0.83, respectively, which sufficiently satisfied the recommended value (Ellis et al 2010) and was available for further analysis.

Spatial distribution and temporal variation of forestland changes

From 1989 to 2015, the forestland area in Zhangjiakou City experienced unprecedented growth of about 33%, with an increase of 304,000 ha (Table 2). There was slight growth of 56,200 ha from 1989 to 2000, representing an increase from 24.86 to 26.38% of the total area (+6.14%), and a significant rise of 247,800 ha from 2000 to 2015, representing an increase from 26.38 to 33.12% of the total area (+25.51%). This represents a 4.4-fold increase between the 2 periods.

The spatial distribution of forestland changes between the 2 periods was also distinctly different (Figure 2). From 1989 to 2000, both forestland increase and decrease occurred, but the ranges of forestland changes were small (−10 to +10%) in most areas of Zhangjiakou, except for some obvious increases in some areas (eg Kongbao, Zhangbei, and Yu counties, 20–40%). From 2000 to 2015, there was a major increase in forestland in many areas of Zhangjiakou, especially in the northeastern, central, and southeastern counties. Almost all of the study area experienced such growth, except for some areas in Huailai and Zhuolu counties and the southeastern part of the urban area. Forestland increase was significant in almost half of Zhangjiakou City (21–40%); in the other half, it was lower (<10%). On the county scale, all counties experienced unstable forestland changes, and both afforestation and deforestation took place from 1989 to 2000, especially in Guyuan and Yu counties, where forestland decreases were more frequent than increases. But from 2000 to 2015, all counties experienced forestland growth. During this period, the dominant contribution (60%) took place in 4 counties: Chicheng County (+710 km^2), Zhangbei County (+295 km^2), Chongli County (+263 km^2), and Guyuan County (+217 km^2).

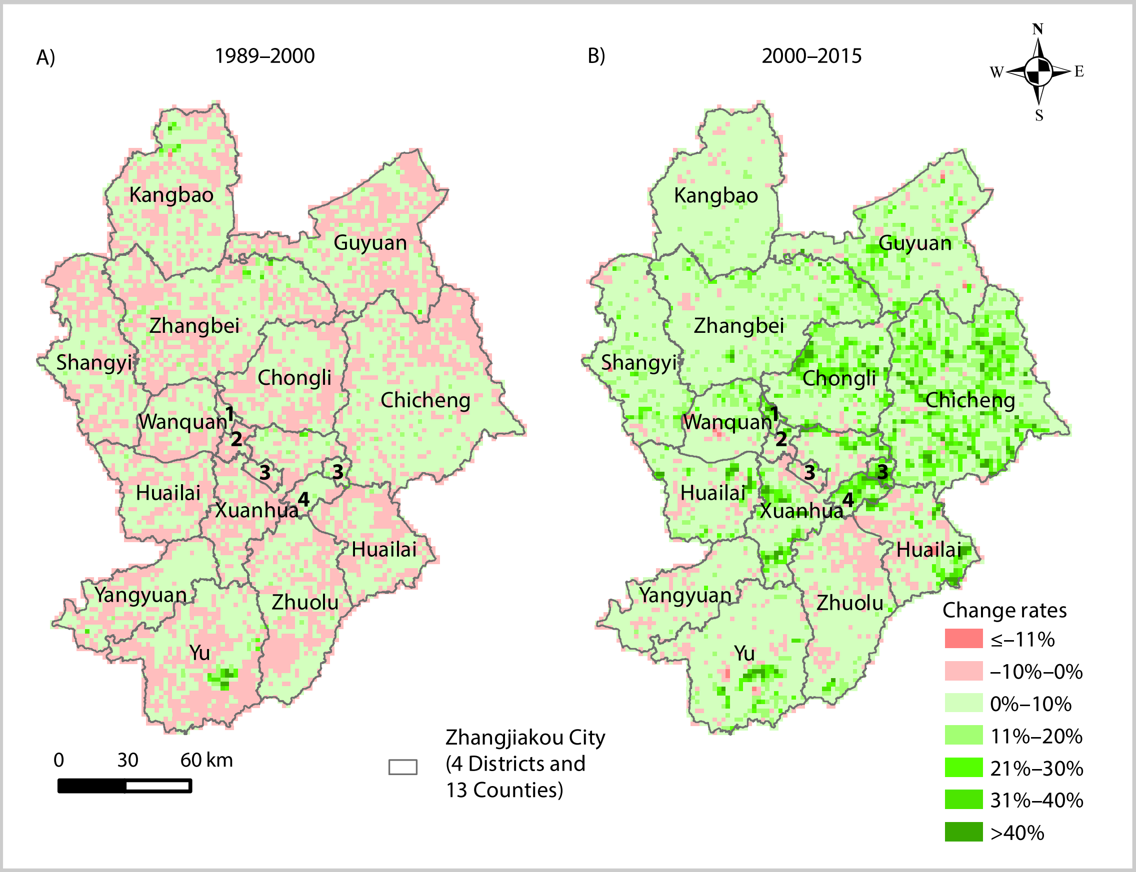
Variations in the land cover change matrix

From 1989 to 2015, the land cover types that were mostly converted into forestland were grassland (60%), arable land (24%), and unused land (13%) (Table 3). The increase in built-up land and roads resulted in a decrease of forestland in these categories; however, this forestland decrease in Zhangjiakou City was well managed, because it was restricted to a small area compared with the area where increases took place.

Analysis of the land cover change matrix during the 2 periods clearly shows that the main land cover change process was conversion to forestland (Table 4). All land cover types experienced a higher conversion into forestland in the second period. Generally, little transformation from forestland to other land cover types took place. From 1989 to 2000, increases in grassland, roads, built-up land, and arable land were the main cause of a decrease in forestland in some areas. From 2000 to 2015, increases in grassland, arable land, unused land, built-up land, and orchards caused local decreases in forestland. The amounts of forestland that were changed to other types during the latter 15 years were higher than those in the first period.

The spatial distribution of the land cover types converted into forestland shows that spatial factors affected forestland

FIGURE 2 Spatial distribution of forestland changes and change rates in the 2 periods.



increase (Figure 3). Grassland converted to forestland was mainly located in the eastern mountain area, whereas arable land converted to forestland was mainly located on the northwestern plateau and unused land converted to forestland was mainly located in the southern area. From 1989 to 2000, the area converted to forestland was fragmented; however, from 2000 to 2015, changes from grassland and unused land to forestland display an intensive and continuous trend, whereas the conversion of arable land remained sporadic. At the same time, most existing forestland remained unchanged (9540 km^2).

Influence of multiple topographic factors on land cover changes

The topographic factors analyzed in this study—elevation, slope, aspect, LRE, and TNI—were divided into a maximum of 14 levels of influence on forestland changes and land cover change, as well as on forest programs and policies (Table 1). From 1989 to 2015, the increase in forestland mainly occurred within specific ranges with regard to elevation (800–1600 m, 87% of total changes), slope (0–25°, 84% of total changes), LRE (0–80 m, 86% of total changes), and TNI (0.64–1.87, 88% of total changes) (Figure S4, *Supplemental material*, https://doi.org/10.1659/MRD-JOURNAL-D-18-00050.1.S1). The distribution of forestland changes with different topographic factors was similar in the 2 periods, illustrating how natural topographic conditions can influence forestland changes at a basic level. However, there was a subtle difference: comparatively, in the last decade, the distribution of areas where forestland increased tended to be at higher elevations (1000–1400 m) and LRE values (20–60 m), on gentler slopes (6–15°), and at lower TNI values (0.64–1.05). The results of this analysis indicate that elevation, slope, and LRE were the dominant topographic factors influencing forestland changes. With regard to aspect, the areas where forestland increased were mainly located in zones at levels 3–7, indicating that increase on south-facing slopes was greater than increase on north-facing slopes.

When considering the impact of different topographic factors on conversion of land cover types into forestland, we found that conversion from grassland, arable land, and unused land accounted for 97% of the total changes (Figure 4). Different patterns among these land use conversions were based on multiple topographic factors, and they occurred over different periods, which influenced the general trend in the increase in forestland area. The conversion of grassland was the dominant contributor to the increase in forestland in the higher-elevation and LRE zones and in gentler-slope and lower-TNI zones, such as elevation zones at levels 5–7, slope zones at levels 2–3, LRE zones at levels 2–4, and TNI zone at levels 5–9. The conversion of arable land contributed significantly in the higher-elevation zones (such as the zones at levels 6–7), the gentler-slope zones (level 1), and the lower LRE zones (level 1). Generally, the land cover types converted into forestland also mainly occurred at the specific ranges of topographic features.

An obvious result was that the conversion of grassland to forestland around existing forest areas was by far the main afforestation and reforestation process. Although grassland has an important ecological service value, in mountain areas

TABLE 3 Percentage conversion of land cover types into forestland from 1989 to 2015.

Conversion	Change (%)
Grassland to forestland	60.0
Arable land to forestland	24.0
Unused land to forestland	13.0
Water area to forestland	1.0
Orchards to forestland	1.0
Built-up land to forestland	0.7
Roads to forestland	0.3
Total conversion to forestland	100.0

at high elevations, this value is not as high as the need for windbreak and sand-fixing functions, as well as water resource protection. Indeed, grassland in mountain areas is of poor quality and grows on thin soil. China's forestry programs and policies had clear objectives and mission requirements each year. The objectives were to transform the previous sandstorm-strengthening zone into a sandstorm-weakening zone and effectively control desertification, degradation, salinization, and soil erosion, especially in situ sand (dust) accumulation, with a view to mitigating wind and sand damage. Therefore, the grassland around the existing forest became the main target area of conversion to forest. This led to the most obvious growth around existing forest, and the most important land type converted to forestland was grassland.

Explicit spatial relationship between forestland changes and topographic factors

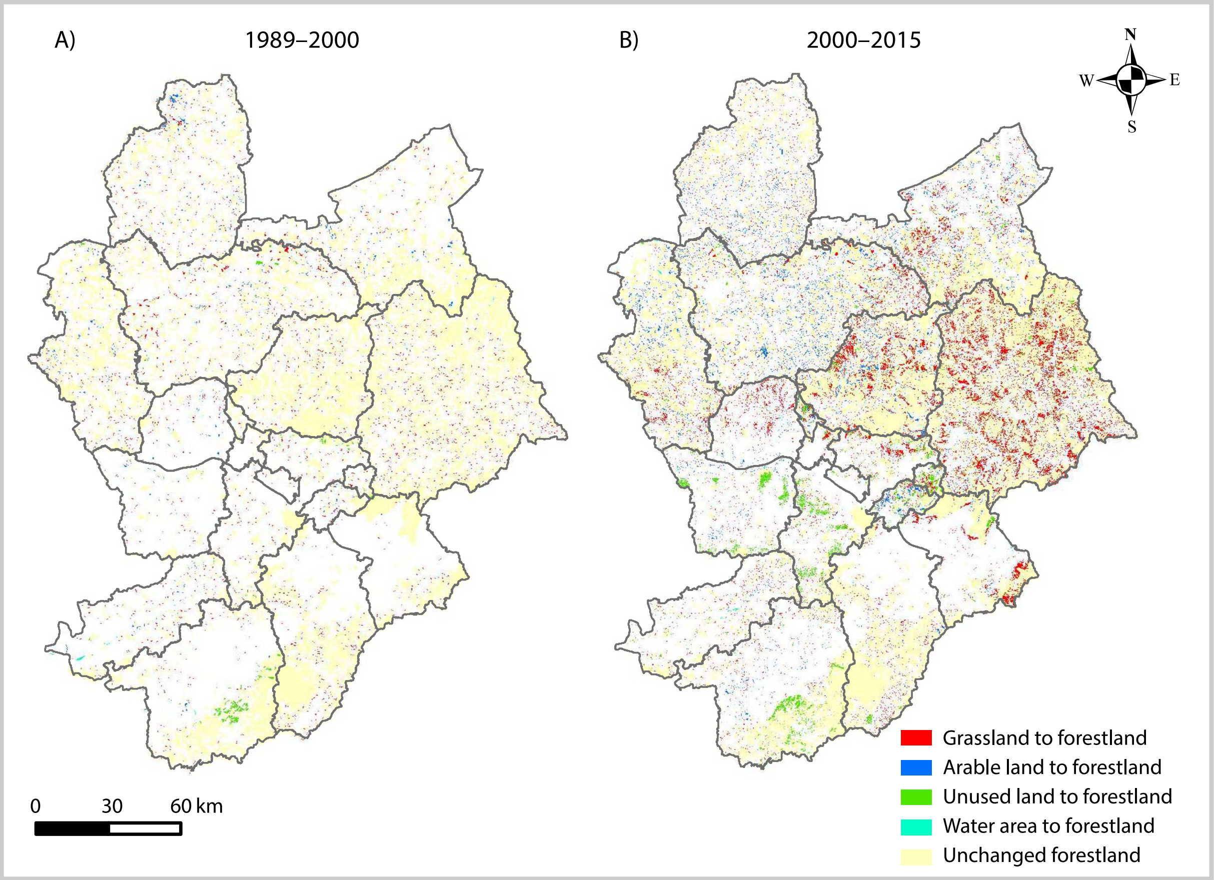
A GWR model containing a parameter of adaptive kernel density and a bandwidth parameter with number of neighbors set at 30 was used to determine the detailed spatial patterns of correlation coefficients between forestland changes (percentage change of forestland) and topographic factors (Figure 5). But the GWR models showed that only the coefficients characterizing the correlations between forestland changes and TNI were significant enough to predict the relationship. The adjusted R^2 value for the period 1989–2000 was 0.29, indicating a medium modeling effectiveness. For the period 2000–2015, it was 0.56, indicating a preferable modeling effectiveness.

Both significantly positive and significantly negative correlations were estimated from the GWR model results during the 2 periods. From 1989 to 2000, significant

TABLE 4 Land cover change matrix for 1989–2000 and 2000–2015.

Land type	Arable land	Orchards	Forestland	Grassland	Built-up land	Roads	Water area	Unused land	Total changed from...
Change from 1989 to 2000 (ha)									
Arable land	—	5990	8913	17,042	7285	1732	33	181	**41,176**
Orchards	2	—	671	50	456	25	0	6	**1210**
Forestland	103	64	—	266	130	185	0	1	**749**
Grassland	221	1569	38,748	—	2520	503	9	95	**43,665**
Built-up land	0	0	0	0	—	3	0	0	**3**
Roads	0	0	0	0	0	—	0	0	**0**
Water area	4001	489	1023	2624	655	100	—	500	**9392**
Unused land	3922	1039	7544	4691	910	36	2	—	**18,144**
Total changed into...	**8249**	**9151**	**56,899**	**24,673**	**11,956**	**2584**	**44**	**783**	—
Change from 2000 to 2015 (ha)									
Arable land	—	40,840	53,732	35,820	19,981	3835	1475	3767	**159,450**
Orchards	5082	—	4686	8134	3850	441	107	518	**22,818**
Forestland	3579	2156	—	5385	2366	636	415	2440	**16,977**
Grassland	8268	3965	164,349	—	9716	714	1491	2750	**191,253**
Built-up land	506	121	230	419	—	76	41	98	**1491**
Roads	184	57	112	90	96	—	11	12	**562**
Water area	5972	4355	2218	3423	1679	472	—	3072	**21,191**
Unused land	3151	1725	39,350	70,541	4808	176	1667	—	**121,418**
Total changed into...	**26,742**	**53,219**	**264,677**	**123,812**	**42,496**	**6350**	**5207**	**12,657**	—

FIGURE 3 Spatial distribution of the different types converted into forestland in the 2 periods.



correlations occurred mainly in the northwestern area of Zhangjiakou City, such as in Zhangbei and Guyuan counties. From 2000 to 2015, there were strong positive correlations primarily in the northeastern, central, and southern counties, whereas negative correlations only occurred in relatively few areas in Chongli and Chicheng counties.

The prediction efficiency of GWR models showed that significant coefficients with an absolute value of more than 0.4 accounted for only 0.68% and those with an absolute value of more than 0.2 accounted for 2.68% of the total study area in the period 1989–2000 (Table 5). A negative correlation accounted for 5.24%, and a positive correlation accounted for 6.33%. But in the period 2000–2015, the significant coefficients with an absolute value of more than 0.4 accounted for 9.34%, those with an absolute value of more than 0.2 accounted for 17.17%, and those with an absolute value of more than 0.1 accounted for 20.27% of the total study area. The negative correlation accounted for 15.41%, and the positive correlation accounted for 32.38%. The percentage of the coefficients over 0.1 in the 2 periods increased from 11.57 to 47.79%. This shows that the GWR model was more efficient at predicting the relationship between TNI and forest changes during the period of rapid forest growth after increased implementation of the forest programs and policies. When TNI was within the range of 1.18 to 1.21, it was positively correlated with forest changes: forest increased more with the increase in the TNI index. By contrast, when TNI was within the range of 1.37 to 1.44, it was negatively correlated with forest change: forest increased more with the decrease in the TNI index. The topographic nature had the most significant effect on forest change (above 0.4) when the TNI coefficient was around 1.18 (significant forest increase) and 1.41 (significant forest decrease). The spatial distribution of positive and negative correlation coefficients could thus provide guidance for the selection of locations and allocation of investment in future forest programs and policies.

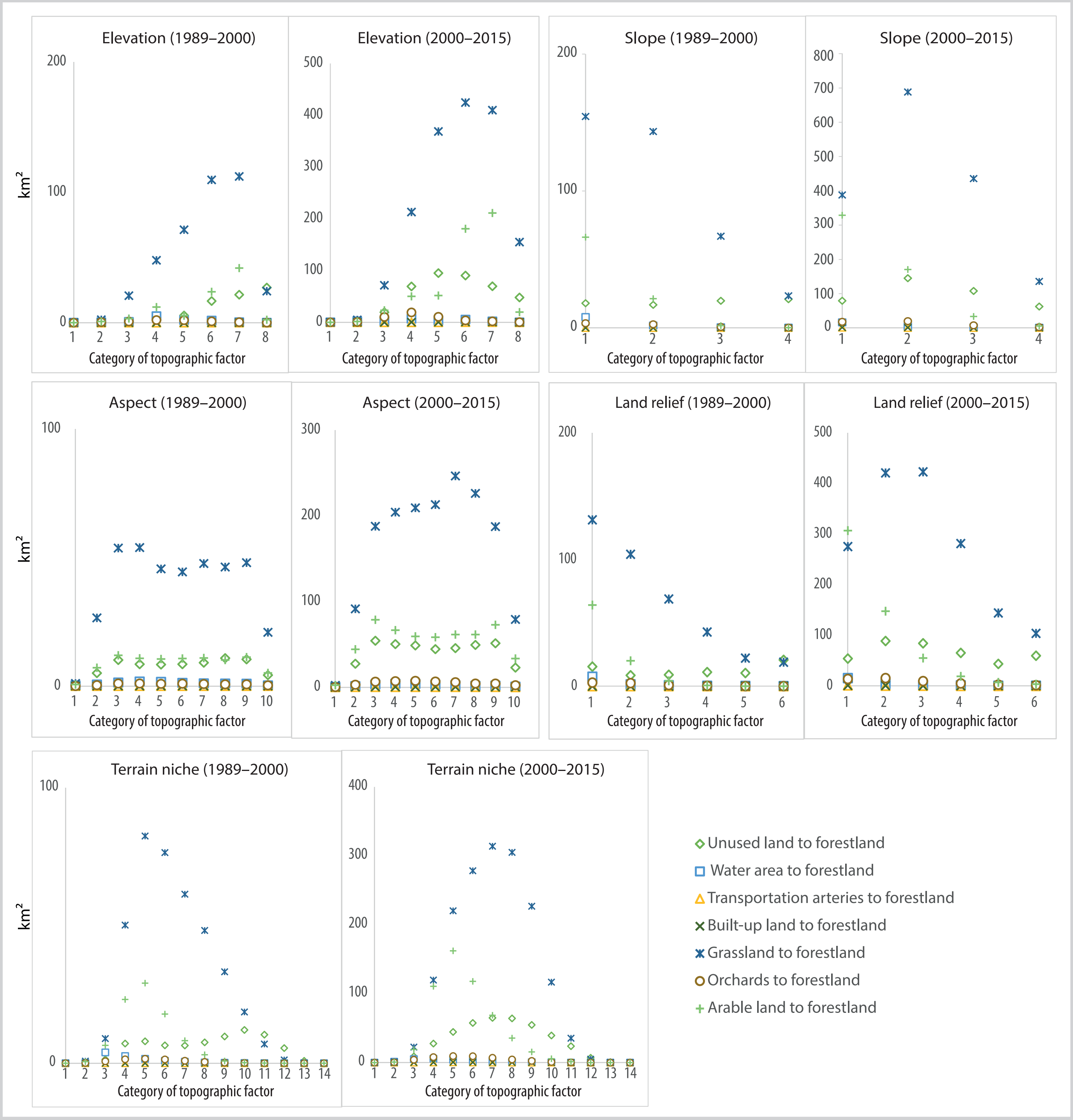
Discussion

Main drivers of forestland growth: forest programs and policies

The analysis of forestland changes in Zhangjiakou City revealed an enormous increase in the spatial extent of forestland from 1989 to 2015. This increase was particularly rapid from 2000 to 2015. The forest programs and policies were the main driving forces. These programs and policies aimed to effectively control desertification, degradation, salinization, and soil erosion, with a view to mitigating wind and sand damage. The Key Shelterbelt Construction Program was implemented mainly in the agropastoral transitional zone in the western and northern parts of Zhangjiakou. The Beijing–Tianjin Sandstorm Control Program and the Grain to Green Program were implemented in all counties, with clear tasks for every year.

Based on large amounts of guaranteed funds, a series of combined measures was implemented: artificial plantation and afforestation through aerial seeding, as well as hill closure to facilitate afforestation; forest replantation;

FIGURE 4 Distribution of land cover types converted into forestland based on different topographic factors for the 2 periods. See Table 1 for the categories for each topographic factor.



engineering work on steep slopes to enable forest planting; nurturing and management of base construction; traditional Chinese medicine plantation; conversion of cultivated land to forest; and reversion of cultivated land to its natural state. By the end of 2016, the forest coverage rate reached 39%. With these programs, Zhangjiakou City established wind- and sand-blocking forest, water resources conservation forest, protective forest for cultivated land, and protective forest along rivers. These combined measures constitute the region's ecological protection system. The higher rate of increase in forestland area in the later period indicates the synergetic impact of the Grain to Green Program and the Beijing–Tianjin Sandstorm Control Program, together with other ecological engineering initiatives.

Forestland mainly emerged from grassland, arable land, and unused land, meaning that the return of grain-growing land to forestland in the southeast and the return of grazing land to forestland in the northwest, along with afforestation

FIGURE 5 Spatial heterogeneity from the GWR models, showing the correlation coefficients between forestland changes and TNI in the 2 periods.

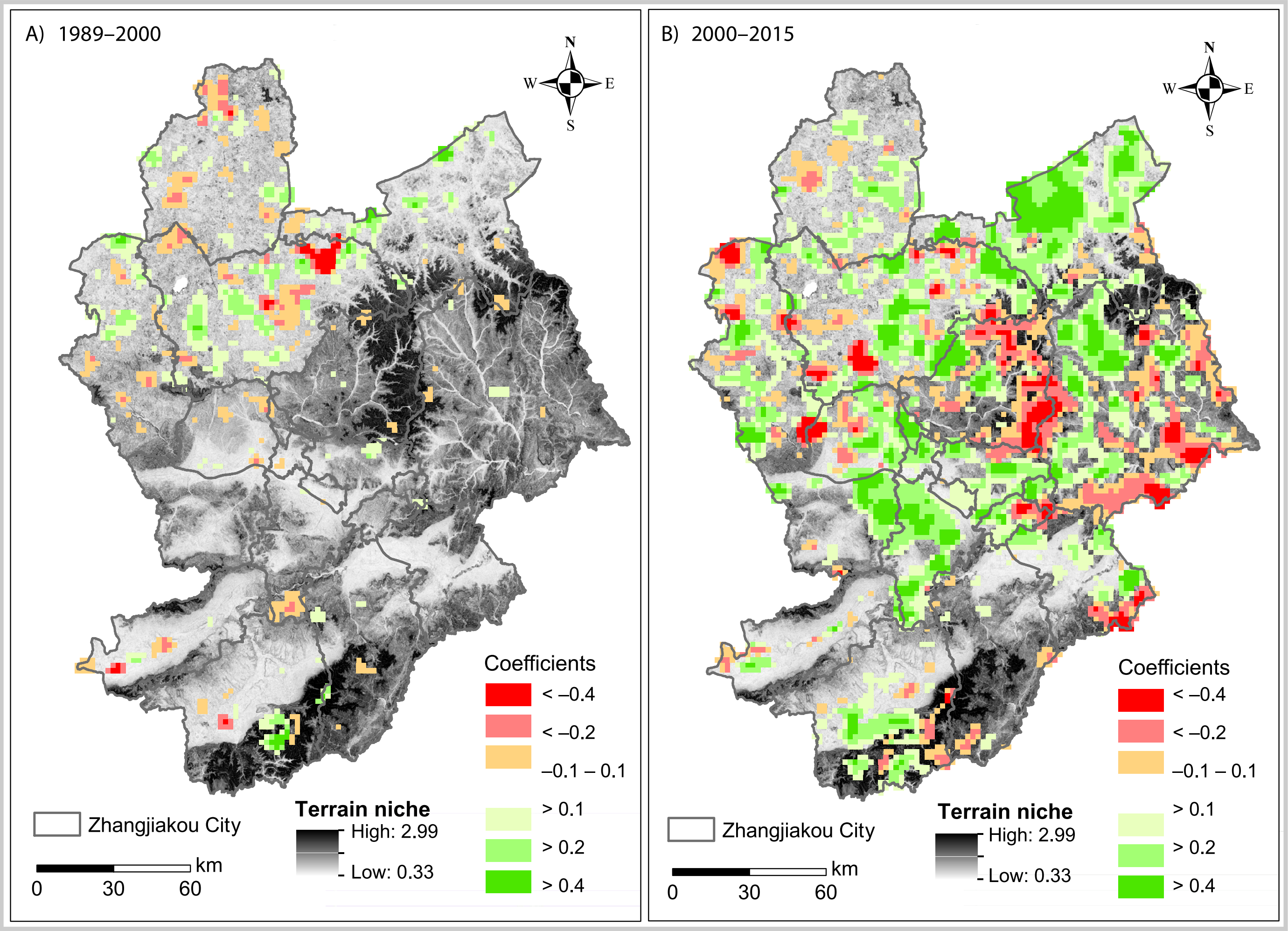


TABLE 5 Efficiency of GWR models and prediction horizon of coefficients between terrain niche and forestland changes.

Coefficient	GWR 1989–2000 (%)	GWR 2000–2015 (%)	Terrain niche, 1989–2000	Terrain niche, 2000–2015
<−0.4	0.36	2.42	0.87	1.41
<−0.2	0.96	5.43	0.95	1.44
<−0.1	3.92	7.57	1.09	1.37
−0.1> <0.1	88.43	52.21	1.20	1.23
>0.1	4.30	12.70	1.06	1.21
>0.2	1.72	12.75	1.05	1.19
>0.4	0.31	6.92	1.17	1.18
Coefficient level 3 (>0.4/<−0.4)	0.68	9.34	1.17/0.87	1.18/1.41
Coefficient level 2 (>0.2/<−0.2)	2.68	18.17	1.05/0.95	1.19/1.44
Coefficient level 1 (>0.1/<−0.1)	8.22	20.27	1.06/1.09	1.21/1.23
−	5.24	15.41	0.87–1.09	1.37–1.44
+	6.33	32.38	1.05–1.17	1.18–1.21

on unused land, have jointly contributed to the increase in forestland. By December 2014, the government had invested US$ 2.9 billion to implement these policies over an area of 13,472.7 km^2 in Zhangjiakou City. In addition, socioeconomic development from 2000 to 2015 led to urbanization and industrialization and resulted in a decrease in land use pressure, because many famers moved to the city for better employment prospects due to limited economic outcomes from agriculture. Overall, the rate of increase in forestland area has been accelerated by high investment in reforestation engineering and decreasing land use pressure induced by socioeconomic development.

Influence of topographic factors on implementation of programs and policies

The relationship between topographic factors and forestland changes and transfer can explain the impact of topographic factors on the implementation of forestry programs and policies to a certain extent. In the study area, the increase in forestland area tended to occur at high elevation, high LRE, gentle slope, and low TNI, which demonstrates the effectiveness of reforestation and afforestation engineering projects. Indeed, when the local forestry sector practiced reforestation and afforestation engineering, the area not classified as prime cropland for the protection of food security was the first to be used for reforestation and afforestation. Such areas were usually located at high elevations. With the implementation of the Grain to Green Program in the study area, there was a policy of returning farmland on slopes steeper than 25° to forestland. This was achieved by offering subsidies to convert the farmland on slopes steeper than 25°, whereas farmland on slopes under 25° could be voluntarily returned to forestland. Topographic factors affected the distribution of human activities and indirectly affected the choice of areas of forestry and policies implementation.

To ensure the effectiveness of forestry programs, various operable and practicable areas were selected because of the heterogeneity of social and economic conditions affected by the topographic factors. The voluntary conversion of arable land to forestland made a large contribution to the increase in forestland area in gentle-slope areas, such as zone 1. The increase in forestland area in locations with a high LRE provides evidence that the abandoned cropland in high-relief areas resulted from a decrease in land use pressure induced by socioeconomic development. The increase in forestland area on southern-facing slopes was larger than that on northern-facing slopes, which could result from the greater rainfall received on the southern-facing slopes. Therefore, topographic factors also affected the effectiveness of forestry programs because of resulting biophysical conditions.

Support for future forest programs and land use management

Compared with other topographic factors, TNI was the best index for predicting the spatial relationships between topographic factors and forestland changes. The GWR model indicated both positive and negative correlations between TNI and forestland changes, suggesting that the topographic factors had spatially explicit influences on the efficiency of afforestation programs and policies. Zhangjiakou City's future development strategy aims to support ecocity development by protecting the Beijing–Tianjin water source area and offering a sandstorm control area. The coordinated development of Beijing–Tianjin–Hebei (transfer of high-tech industries to Zhangjiakou City) with the upcoming Beijing–Zhangzhou Winter Olympic Games and a planned renewable energy development area require Zhangjiakou City to maintain forest protection and sustainable economic development. Apart from continuing to implement the previously mentioned forest programs and policies, the local government is beginning to pay attention to vegetation restoration in mining areas, afforestation in difficult lands, and tending of young forest.

The efficiency of these future forest programs and policies can increase if suitable topographic sites are chosen based on the findings of the present study. In particular, the GWR result that topographic factors had the most significant effect on forest changes (above 0.4) when TNI was around 1.18 and 1.41 should lead forest programs to prefer sites in the range that is expected to be most effective. However, the noteworthy finding that TNI was positively correlated with forest changes when it was within 1.18–1.21 and negatively correlated with forest changes when it was within 1.37–1.44 should also be taken into account. Sites should also be situated as high as possible when TNI is within 1.18–1.21 but should be as low as possible when TNI is within 1.37–1.44.

Among the limitations of the present study, the classification of forestland according to the national standard referred to an area where the canopy density was above 0.2; this does not discriminate between plantations and natural forests. A future study will improve the accuracy of classification and distinguish between plantations and natural forests. There are many potential influences on land use change, including both natural and socioeconomic factors, and the land use system is the result of human interactions with the natural environment (Verburg et al 2015). The complex interactions between human and natural systems makes it difficult to fully understand forestland change. In this study, similar factors (eg topographic factors) influenced the forestland changes in the 2 time intervals of 1989–2000 and 2000–2015, but other unknown factors may also have had an influence. The topographic factors might also have influenced these factors, adding to the complexity. We recommend the use of high-resolution datasets of grid-cell measurements when possible for generating metrics using multiple neighborhood sizes to both minimize and characterize potential unknown biases (Theobald et al 2015). However, a modifiable areal unit problem, which could emerge because of scaling effects, would still be present in the calculation of the GWR model and might hinder the further research.

Conclusions

Zhangjiakou City, as a typical policy-induced afforestation and reforestation area, has experienced a major increase in forestland over the past 25 years, especially in the period 2000–2015. The main driving forces were forest programs and policies. This study investigated the spatial distribution and temporal variation of forestland changes and their relationship with topographic factors at the grid-cell scale for the periods 1989–2000 and 2000–2015. A spatially integrated analysis method for modeling the spatial heterogeneity of the relationship was developed. There was clear evidence of a temporal variation, with a major increase in the second period. Forest increase was also significant in the northeastern, central, and southern counties.

Compared with other studies, this study not only explained the status of implementation of forestry programs and policies in Zhangjiakou City but also conducted a statistical analysis of the impacts of topographic factors on the implementation of these programs and policies and quantitatively calculated the specific range and positive or negative effects of these impacts. Slope, LRE, and elevation were the primary topographic factors indicating a forestland increase. Grassland and arable land were the dominant land use types that were converted into forestland, with an increasing trend in land conversion in locations with a high elevation and gentle slope. Topographic factors affected the effectiveness of forestry programs, because they affected both biophysical conditions and choice of implementation area for socioeconomic reasons. GWR predicted both explicit spatial and significantly positive and negative correlations and can be used for predicting the influence of topographic factors on the implementation of effective local afforestation and reforestation programs and policies. Based on these results, we suggest developing a mapping system for forest programs to predict best reforestation and land use management in China.

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Supplemental material

FIGURE S1 Areas of forest programs implemented in Zhangjiakou City for 2000–2015.
FIGURE S2 Investment in forest programs in Zhangjiakou City for 2000–2015.
FIGURE S3 Land cover changes in Zhangjiakou City for 1989, 2000, and 2015.
FIGURE S4 Forestland changes based on multiple topographic factors for 1989–2000 and 2000–2015.

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