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FACTORS AFFECTING THE PATTERN OF VEGETATION CARBON DENSITY IN A KARST REGION IN NORTHWEST GUANGXI, CHINA

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Abstract

The changing characteristics of vegetation carbon patterns in the karst region of northwest Guangxi, China and their impact factors were analyzed on the basis of vegetation inventory data from 2005 to 2010. A radial basis function network model (RBFN) was constructed using data from 1377 samples and 13 environmental factors. The results for the 5-year study period were as follows: (1) The total carbon storage of vegetation had increased with an annual growth rate of 1.84% and the carbon density of vegetation increased from 29.04 t hm^{-2} to 29.57 t hm^{-2}. The carbon density in the west (>40 t hm^{-2}) was greater than that in the Middle East (<25 t hm^{-2}). Hot spot analysis revealed a random distribution of vegetation carbon density in 2005, but a highly aggregated distribution in 2010. (2) The four most important impact factors on spatial distribution of vegetation carbon density in this area were land type, forest type, forest category, and vegetation type (significance <50%). The least important factors were location, slope, aspect, and elevation (significance of 2–11%). Vegetation carbon density increased significantly with the implementation of rocky desertification control measures. Factors changed by human activities had much greater impacts than topographic factors on the spatial distribution of vegetation carbon density. Therefore, the Ecological Immigration Program, returning farmland to forests, and rocky desertification control measures had an important effect on the pattern of vegetation carbon density.

Key words: Guangxi China, impact factors, karst, northwest, pattern characteristic, radial basis function network (RBFN), vegetation carbon

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1. Introduction

Estimation of vegetation carbon is one of the key steps in examining greenhouse gas CO_2 exchange between terrestrial ecosystems and the atmosphere (Dixon et al., 1994; Piao et al., 2009). Karst ecological systems are an important component of the terrestrial ecosystem (Cao et al., 2005) and the CO_2-H_2O-$CaCO_3$ system with biological and chemical active processes. Thus, karst systems play an important role in the global carbon cycle. There is relatively little carbon stored in karst soil because it is shallow and discontinuous. Consequently, the ratio of vegetation carbon to soil carbon is much higher in karst ecosystems than in other types of ecosystems (Cai et al., 2012). China has invested more than CNY 5 billion in rocky desertification control, and had implemented the following programs, beginning in the 1990's: the National Poverty Alleviation Plan, the Western Development Strategy, the Green for Grain Program, the Mountain Closure Program (to facilitate afforestation), and the Ecological Immigration Program. The focus of the Ecological Immigration Program was to help farmers in karst areas to move to non-karst areas where ecosystem conditions were deemed to be considerably better. During this

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campaign, 49,133 families (232,705 persons) were relocated in northwest Guangxi, China. The total area of the Green for Grain Program was up to 1,278.67 km^2 in Baise during 2001–2004 (Zhang et al., 2011). This included 605.33 km^2 of farmland that was restored to woodland and 673.33 km^2 of reforestation activities of barren hills. For example, in Duan County, the land area of rocky desertification had been reduced to 333,356.9 hm^2, and 45,333.33 hm^2 of land were converted from farmland to forest as part of the Green for Grain program by 2009. The comprehensive treatment of rocky desertification was expected to have caused changes in the vegetation carbon pattern. Impact factor analysis could be used to evaluate the treatment of rocky desertification.

Vegetation carbon in the karst area has been studied by many researchers (Liu et al., 2008; Wang et al., 2012; Ye et al., 2010; Luo et al., 2010; Tian, et al., 2011). However, most of the studies focused on the micro or local ecological system scale. Investigation of the spatial pattern of vegetation carbon is needed at regional scale. Furthermore, factors that affect the formation of vegetation carbon spatial patterns have been scarcely studied. Investigation of the changes in vegetation carbon patterns in a typical karst area, and further analysis of the main impact factors can provide a scientific reference for the evaluation of karst rocky desertification control and basic data for understanding the driving mechanisms of carbon characteristics in karst regions. This will permit an accurate estimation of the carbon storage in karst regions. We used forest resources inventory data collected in 2005 and 2010 to study vegetation carbon density in a typical karst area in northwestern Guangxi, China. In addition, a radial basis function network (RBFN) model was applied to test the influence of environmental factors on carbon spatial distribution.

2. Study area and methods

2.1. Study area

The study area was located in northwest Guangxi, China (104°29´–109°09´E, 23°41´–25°37´N) (Fig. 1), which includes 23 counties covering an area of 69,400 km^2 and sustaining a population of 7.97 million people. The region has a subtropical wet monsoon climate with an annual temperature 19.5°C and an annual precipitation of 1,000–1,600 mm. The elevation in this hilly region ranges from 100 m to 2,000 m above sea level and the dominant vegetation communities are mixed subtropical evergreen and deciduous forests. The landforms in this region are typical karst landforms, including poljes, cockpits, towers, and dolines. The region supports a mountainous agricultural region in which the cropland areas are generally not very fertile.

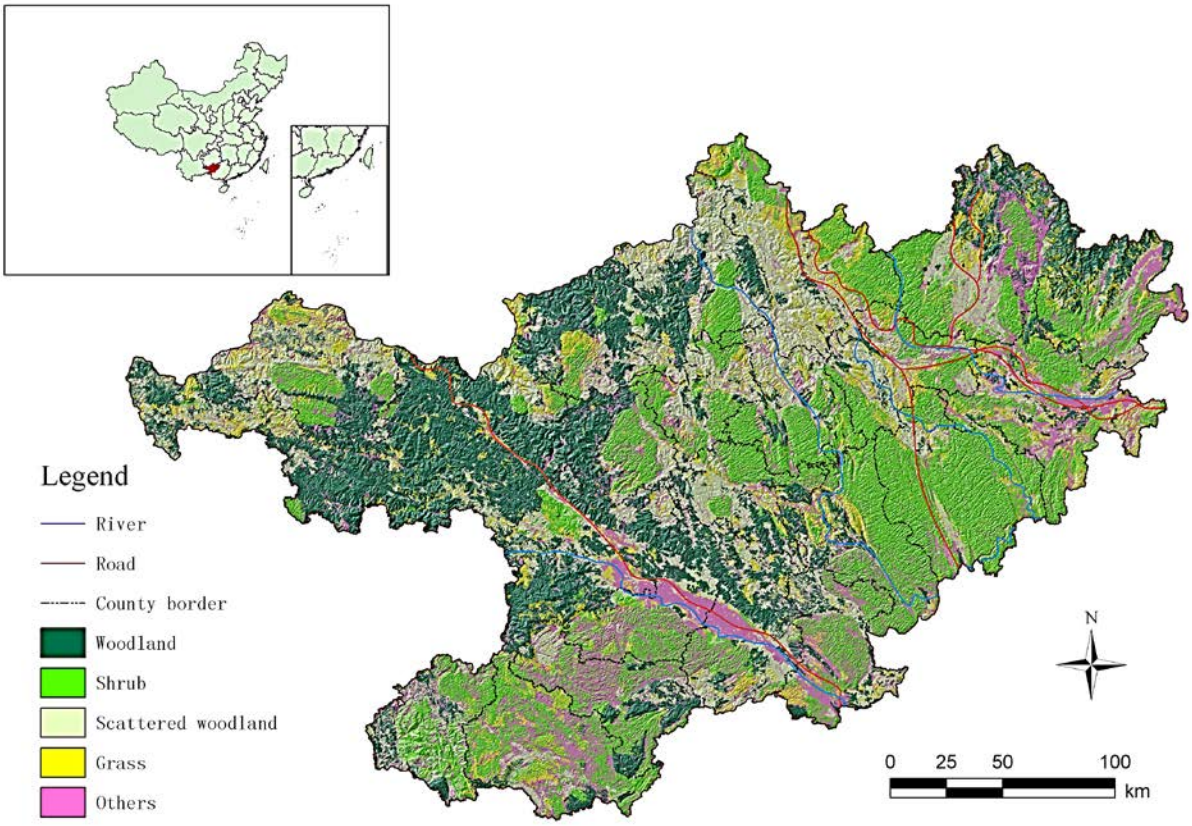


Fig. 1. Location and land cover of the study area

2.2. Data acquisition and preprocessing

2.2.1. Data sources and software

The main data used consisted of 2005 and 2010 forest inventory data from the Central South China Forestry Survey and Design Institute (a design qualification survey, planning, and design institute that is part of the State Forestry Administration, China). The data was obtained using systematic, fixed sampling of 25.82 × 25.82 m (0.0667 ha) sampling plots. More than 60 variables were measured at each sampling location, including altitude, slope position, slope, vegetation type, forest type, land type, vegetation coverage, soil thickness, humus, rocky desertification. ArcGIS 9.3 (Environment Systems Research Institute) was used to prepare data and for spatial analysis. Weather and radiation datasets were interpolated (i.e., Kriging) in ARCGIS 9.3. All data were projected or re-projected to an Albers Conical Equal Area, Krasovsky Spheroid projection and then re-sampled to a 100 × 100-m pixel spacing.

2.2.2. Biomass and vegetation carbon

We used biomass expansion factors (BEFs) to estimate the total biomass in the study area from the forest inventory data. BEFs are comprehensive reflections of habitat, climate, age, and other factors that influence vegetation (Jiao et al., 2005). BEFs are generally based on regression equations. We used the following equation to calculate BEF (f_{BEF}) (Jiao et al., 2005) (Eq. 1):

$$f_{BEF} = a + b / V \tag{1}$$

where a and b are conversion factors (constants) and V is forest volume.

The density of a biological stand (B, t hm^{-2}) can be estimated by multiplying V (m^3 hm^{-2}), i.e.(Jiao et al., 2005) (Eq. 2):

$$B = aV + b \tag{2}$$

Consequently, stand biomass (w) can be expressed by the following equation (Jiao et al., 2005) (Eq. 3):

$$w = \sum_{i=1}^{k} A_i \times F_{BEFi} \times V_i \tag{3}$$

where i is the dominant species, A_i is the tree stand area, V_i is the mean volume of the forest, and F_{BEFi} is the corresponding conversion factor.

Carbon storage can be estimated using a constant (Fang et al., 2002), derived from molecular formulas (Li et al., 1996), or measured directly (Mo et al., 2003). We used 0.05 as the constant for estimating carbon storage (Fang et al., 2002).

Vegetation carbon storage (C) was calculated by multiplying the carbon in vegetation biomass (W) by the carbon content (C_c), as follows (Fang et al., 2002) (Eq. 4):

$$C = W \times C_c \tag{4}$$

Vegetation carbon density was defined as the vegetation carbon of per unit area. The carbon in this paper only refers to the vegetation carbon and does not include carbon in the litter layer.

2.2.3. RBFN principle and training algorithm

RBFNs are artificial neural network models that are widely used in the fields of taxonomy and biodiversity (Schwenker et al., 2001; Huang et al., 2005). These models are composed of an input layer, a hidden layer, and an output layer that consists of three-layer feed-forward networks. Each layer has a plurality of neurons and a one-way connection between layers (Fig. 2), where Xk is the input layer (k = 1, 2, ..., N), Vj is the hidden layer input (j = 1, 2, … L), and Oi is the output layer (i = 1, 2, ..., M). Cjk = ($Cj1$, $Cj2$, ..., Cjn) is center and width of the hidden layer unit function. N, M, and K are the number of input, hidden, and output units, respectively. We used RBFN to analyze factors that affect the pattern of vegetation carbon in the karst area of northwest Guangxi, China by approximating the dataset distribution using a linear combination of Green's functions (Haykin, 1994; Moody and Darken, 1989; Park and Sandberg, 1991) (Eq. 5).

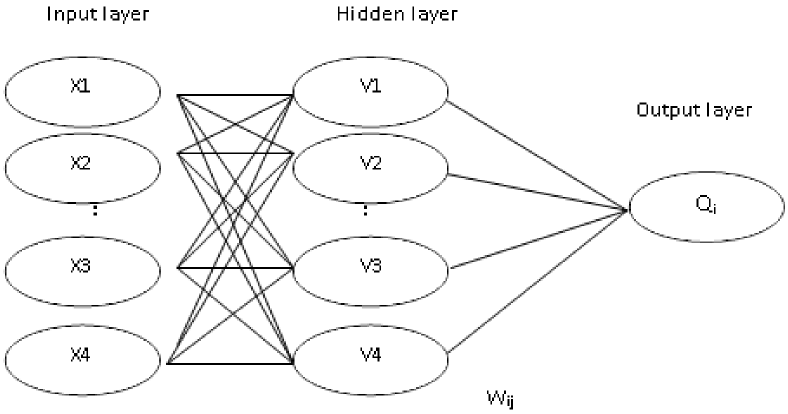


Fig. 2. The structure of a Radial Basis Function Network (RBFN)

$$F(x) = \sum_{i=1}^{N} w_i G(x - x_i) \tag{5}$$

where $G(x\text{-}x_i)$ is a Green's function and x is its center.

The Green's functions were characterized by a mean vector x_j and common variance σ^2, as (Eqs. 6-7):

$$G(x - x_i) = e^{-\frac{x - x_i}{2\delta_j^2}} \tag{6}$$

and

$$F(x) = \sum_{i=1}^{N} w_i e^{-\frac{x - x_i}{2\delta_j^2}} \tag{7}$$

where: each equation consists of a linear superposition of multivariate Gaussian basis functions (probability bells) with centers x_j, located at the data points and widths δ_j^2.

The initial number of nodes was set at two. The first node was assigned a Gaussian function centered on the center of data set, determined by Eq. (8):

$$x_{av} = \sum_{i=1}^{N} \frac{x_i}{N} \tag{8}$$

and the second node was assigned a Gaussian function centered on the point determined by the vector xp that maximized the function (Eqs. 9-10)

$$P(x) = \int_S Q(x) dS \tag{9}$$

where:

$$Q(x) = \begin{cases} 1, & \text{if } x \in D \\ 0, & \text{if } x \notin D \end{cases} \tag{10}$$

The variance of Gaussian functions is assumed to be constant and equal to (Eq. 11):

$$\delta = r \frac{\sum_{i=1}^{N} \prod_{j=1}^{m} (x_i^{(j)} - \overline{x}^{(j)})}{\prod_{j=1}^{m} \sqrt{\sum_{i=1}^{N} (x_i^{(j)} - \overline{x}^{(j)})^2}} \tag{11}$$

where m is the number of dimensions (number of nodes in the hidden layer), $x^{-(j)}$ is the mean value for dimension j and r is an arbitrary ratio defining the total number of Gaussian functions.

The second layer was carried out using a self-organizing algorithm with the following steps:

(1) Calculate the output of the Gaussian functions for all hidden nodes (Eq. 12)

$$y_i = e^{-\frac{x_j - c_i}{\delta^2}} \tag{12}$$

where $i < n$ (number of nodes).

(2) Identify the winner $y_w = \max (y_i)$, $i < n$.

(3) If $y_w > \alpha T$, then change the position of the center of the winner using (Eq. 13):

$$c_w^{(k+1)} = c_x^{(k)} + r(x_j - c_w^{(k)}) \tag{13}$$

where α is an arbitrary ratio (α = 2.0 in this case) and T is the threshold value ($T = 10^{-4}$).

(4) If $y_w < T/\alpha$, then construct a new hidden node with center at the point x_j and variance equal to δ and increase the number of total hidden nodes n by 1.

The algorithm stops when there are no new hidden nodes after testing all points of data set D.

2.2.4. Impact factors of vegetation carbon density

The following 13 factors were selected for analysis:

(1) Altitude: the range of altitude in the study area was 92–1876 m;

(2) Aspect: divided into 9 aspects; North (338–22°), the Northeast (23–67°), East (68–112°), Southeast (113–157°), South (158–202°), Southwest (203–247°), West (248–292°), Northwest (293–337°), and no slope (<5° slope). Aspects were coded 1, 2, 3, 4, 5, 6, 7, 8 and 9, respectively

(3) Slope position: 6 positions, ridge (mountain watersheds), above, middle, lower (the downhill), vale (collection waterline on both sides of the valley), flat (plain and tableland). Slope positions were coded 1, 2, 3, 4, 5, and 6, respectively;

(4) Slope angle: the slope of samples in the study area were between 0 and 80°;

(5) Soil thickness: sample thickness was 1–180 cm;

(6) Humic layer: the thickness of humus layer was 0–35 cm;

(7) Vegetation coverage: total vegetation coverage in the study area was 10–100%;

(8) Land type: according to the characteristics of land cover and utilization, including arbor, shrub, farmland, grass, and construction land;

(9) Vegetation type: including coniferous forest, evergreen broad-leaved forest, deciduous broadleaf forest, bamboo forest, deciduous shrubs, and evergreen shrub;

(10) Grade of rocky desertification: the degree of rocky desertification was defined as in the Forest Inventory Check Operating Rules of Guangxi. The study area included the following grades: no rocky desertification, potential, mild, moderate, and severe rocky desertification;

(11) Forest species: 23 sub forest species were categorized as in the forest inventory check operating rules of Guangxi. Species were categorized according to their potential for such uses as soil and water conservation, national protection, scenic value, timber, et al.;

(12) Forest type: the main two forest types were ecological forest and commercial forest. The ecological forest was subdivided into national ecological forest and local ecological forest.

Commercial forest was divided into timber forest, firewood forest, and economic forest;

(13) Area level: there were 7 categories, according to the contiguous area of each vegetation type. Categories were <1 hm^{-2}, 1–4.9 hm^{-2}, 5–9.9 hm^{-2}, 10–19 hm^{-2}, 20–49 hm^{-2}, 50–99 hm^{-2}, and >100 hm^{-2} and were coded 1, 2, 3, 4, 5, 6, and 7, respectively.

3. Results and discussion

3.1. Pattern characteristics of vegetation carbon

3.1.1. Temporal change in vegetation carbon

Vegetation carbon density in the study area increased from 29.04 t hm^{-2} in 2005 to 29.57 t hm^{-2} in 2010 (Table 1). Accordingly, the storage of vegetation carbon had increased from 4.19 × 10^4 t to 4.27 × 10^4 t with an increase of 1.84%. The vegetation carbon density in the study area was lower than the overall vegetation carbon density of China (38.05 t hm^{-2}), Fujian Province (32.85 t hm^{-2}) and Hainan Province (32.59 t hm^{-2}).

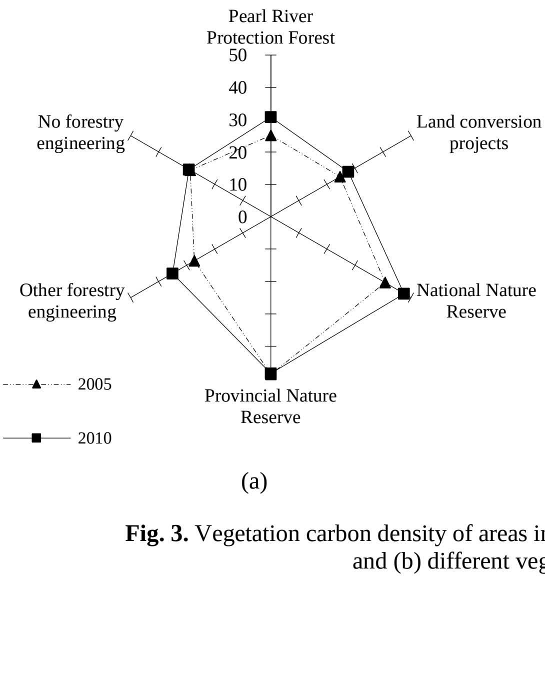
However, the vegetation carbon density in the study area was higher than in northern Hunan Province (18.53 t hm^{-2}) and Sichuan Province (18.47 t hm^{-2}) (Fang et al., 1996; Wang, 2004; Cao et al., 2002; Jiao et al., 2005; Huang et al., 2008). The vegetation carbon density at the study site was close to that of Jiangxi (25.38 t hm^{-2}) (Wang and Wei, 2007). The cover type with the highest vegetation carbon density was arbor (34.82 t hm^{-2} and 35.12 t hm^{-2} in 2005 and 2010, respectively), followed by bamboo, which accounted for about 50.82% and 54.62% of total vegetation carbon storage in 2005 and 2010, respectively.

Because the samples were fixed, changes in the number of samples in each land type classification may indicate regional vegetation changes to some degree. In the period from 2005 to 2010, the number of samples classified as arbor and shrub increased, whereas samples classified as no stumpage forest, unused land, and farmland decreased dramatically (Table 1). These changes indicate that the vegetation coverage in the study area has been improved by rocky desertification control policies, such as ecological migration program and the Green for Grain program.

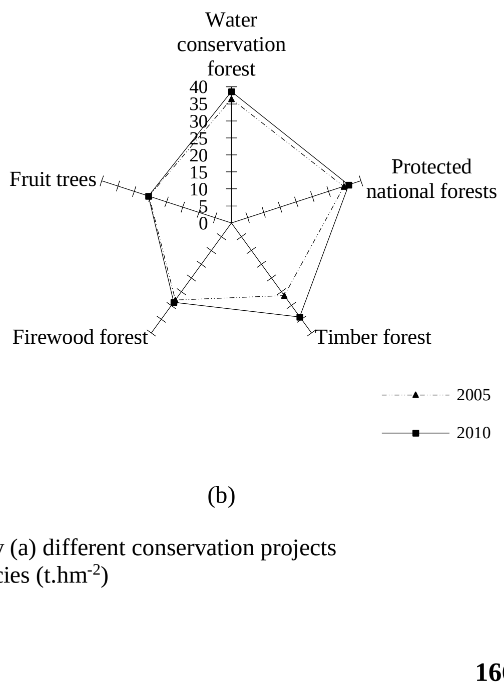
Although the greatest vegetation carbon density was in provincial and national nature protection areas, the other projects also resulted in dramatic increases in vegetation carbon (Fig. 3).

Table 1. Vegetation carbon density and their changes in Guangxi, China between 2005 and 2010

Land type	***Sample number***			***Vegetation carbon density (t.hm^{-2})***			***Vegetation carbon storage (* 10^4 t)***		
	2005	2010	05-10	2005	2010	05-10	2005	2010	05-10
Arbor	612	664	52	34.82	35.12	0.30	2.13	2.33	0.20
Bamboo	10	11	1	29.35	28.52	-0.83	0.03	0.03	0.00
Shrub	231	244	13	24.63	24.53	-0.11	0.57	0.60	0.03
No stumpage forest	134	108	-26	24.66	25.20	0.53	0.33	0.27	-0.06
Farmland	324	308	-16	24.86	24.80	-0.06	0.81	0.76	-0.04
Grassland	18	10	-8	24.90	25.31	0.40	0.04	0.03	-0.02
Water area	14	19	5	24.55	24.41	-0.15	0.03	0.05	0.01
Unused land	70	45	-25	24.41	24.55	0.14	0.17	0.11	-0.06
Construction land	31	35	4	25.11	25.61	0.50	0.08	0.09	0.01
Total	1444	1444	-	29.04	29.57	0.53	4.19	4.27	0.08



(a)



(b)

Fig. 3. Vegetation carbon density of areas influenced by (a) different conservation projects and (b) different vegetation species (t.hm^{-2})

The vegetation carbon density of water conservation forest and special use forest was relatively high (more than 30 t hm^{-2}) (Fig. 3). This could be attributed to the implementation of rocky desertification control measures.

3.1.2. Spatial distribution of vegetation carbon

Vegetation carbon density tended to be greater in the western part of the study area than in the eastern part of the study area (Fig. 4). Whereas vegetation carbon density was 28–35 t hm^{-2} in the western part, it was 25–30 t hm^{-2} in the eastern part of the study area. The distribution of vegetation carbon density was similar to that of vegetation net primary productivity (NPP) and vegetation coverage. The Previous research showed that mean vegetation coverage was more than 60% and mean NPP was more than 1000 g m^{-2} in the west, and vegetation coverage was less than 30% and NPP was 100 g m^{-2} in the east in 2005 (Zhang et al., 2011). The rocky desertification land in Guangxi China was the third largest region of rocky desertification in China and was mainly distributed in the counties of Pingguo, Dahua, Duan, Masan, Donglan, Bama, and Fengshan (Yang, 2003). These counties were mainly located in the eastern or middle part of the study area.

The spatial variation of vegetation carbon density differed from the spatial distribution of vegetation carbon density. The vegetation carbon density generally increased in the study area (Fig. 5). Between 2005 and 2010, the vegetation carbon density of 16 counties remained at the same level and that of 7 counties increased, including the counties of Napo, Pingguo, Longlin, Donglan, Leye, Huanjiang, and Tiane. According to results of rocky desertification monitoring in 2005, there was 83,366.67 hm^2 of rocky desertification in Pingguo county. In this county, the Green for Grain program was carried out in areas totaling 45,333.33 hm^2.

Vegetation carbon density had improved in this study region as the result of recent implementations of control measures for dealing with rocky desertification. Results of previous researches showed that the ecosystem service has improved since 2005 in typical karst regions (Zhang et al., 2011).

3.1.3. Distribution pattern of vegetation carbon

In order to evaluate the pattern of vegetation carbon distribution in the study area, we used hot spot analysis (spatial statistics, Getis-Ord General G). The resultant Z scores indicated whether features were tightly clustered or widely scattered. This method works by examining each feature within the context of neighboring features. A feature with high vegetation carbon density was interesting but may not be a statistically significant hot spot.

To be a statistically significant hot spot, a feature must have a high value and be surrounded by other features with high values as well. The local sum for vegetation carbon density and its neighbors is compared proportionally to the sum of all features; when the local sum is much different from the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score was generated. The G statistic returned in the dataset is a Z score.

Hot spot analysis of vegetation carbon density indicated a random pattern of distribution in 2005, but a highly clustered pattern in 2010 (Fig. 6). Large, positive Z scores indicate intense clustering of high values (hot spot). Small, negative Z scores indicate intense clustering of low values (cold spot). The Z score was -0.273287 in 2005, but was 2.780397 in 2010. This indicates that the distribution pattern of vegetation carbon density may have been impacted by rocky desertification control measures.

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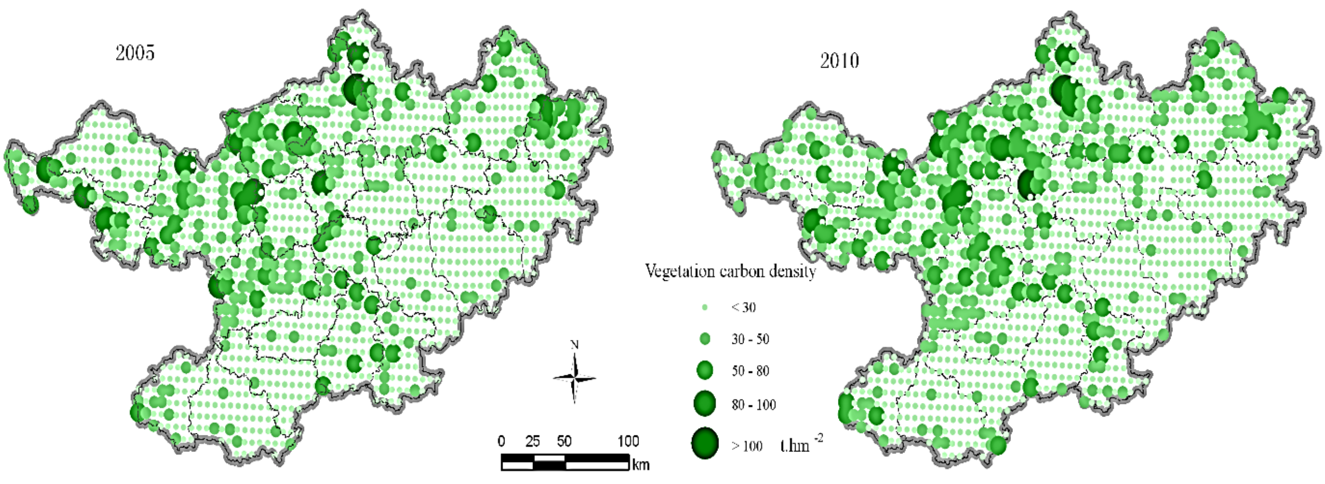


Fig. 4. Distribution of vegetation carbon density of samples in Guangxi, China in 2005 and 2010

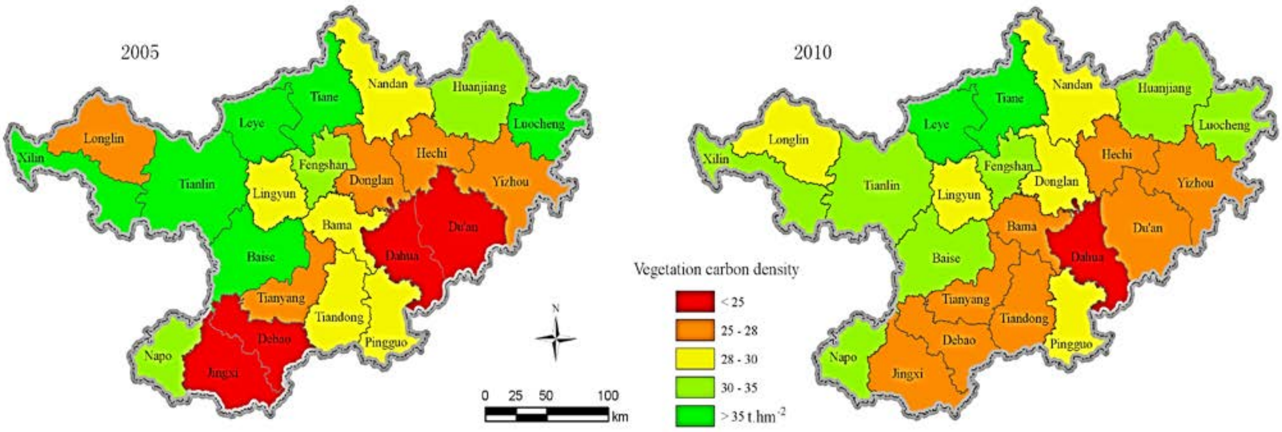
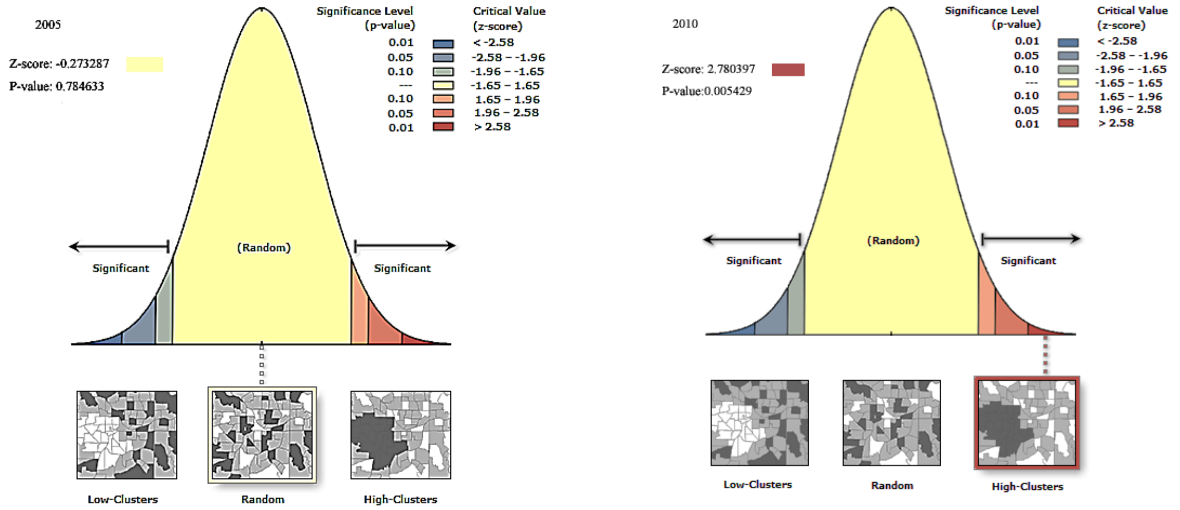


Fig. 5. Vegetation carbon density in each county in Guangxi, China



(a) (b)

Fig. 6. The general G for distribution of vegetation carbon in the study area in 2005 (a)and in 2010 (b)

3.2. Impact factor analysis of vegetation carbon pattern

3.2.1. The model

The total number of samples was 1377, excluding non-vegetated samples. The effective number of samples was 1297 (80 test samples were excluded from analysis automatically). We used 74.3% of the effective sample (964) for training and 25.7% of the effective sample (333) to test the model. There were 13 impact factors in the input layer of the FRBN model in this study. The output layers were vegetation carbon density, significance of impact factors, and an error function (Table 2). There were 516 hidden layer units in the trained model. The activation function was softmax and the error function was the sum of squares.

3.2.2. Results of impact factors on vegetation carbon

The rankings of the significance of the 13 factors that affect the spatial distribution of vegetation carbon density were (Fig. 7): land type > forest type > vegetation species > vegetation type > degree of rocky desertification > humus layer thickness > area level > vegetation coverage > soil thickness > slope position > slope > aspect > altitude. The top 4 impact factors were land type, forest type, vegetation species, and vegetation type, and their significances were all above 50%. The next 5 factors, rocky desertification degree, humus layer thickness, area level, vegetation coverage, and soil thickness, had standardization significances of 15–30%. The least significant impact factors for vegetation carbon density were the 4 topography factors, and their standardization significances were only 2–11%. This indicated that the impacts of topography factors on the distribution of vegetation carbon density were limited, and factors associated with human activities, such as land type, forest type, vegetation species, and vegetation type had relatively larger impacts on vegetation carbon density. Therefore, the ecological immigration program and the Green for Grain program had important impacts on the spatial distribution of vegetation carbon density.

Table 2. The network information of model processing

Levels	***Information***		
Input layer	Factors	1	Altitude
		2	Aspect
		3	Slope position
		4	Slope
		5	Soil thickness
		6	Humus layer
		7	Vegetation coverage
		8	Land type
		9	Vegetation type
		10	Degree of rocky desertification
		11	Vegetation species
		12	Forest type
		13	Area grade
	Units		516
Hidden layer	Units number		5[a]
	Activation function		Softmax
Output layer	Dependent variable	1	Total_c (Vegetation carbon density)
	Units number		1
	Scale dependent variable rescaling method		Standardization
	Activation function		Identical
	The error function		Quadratic sum

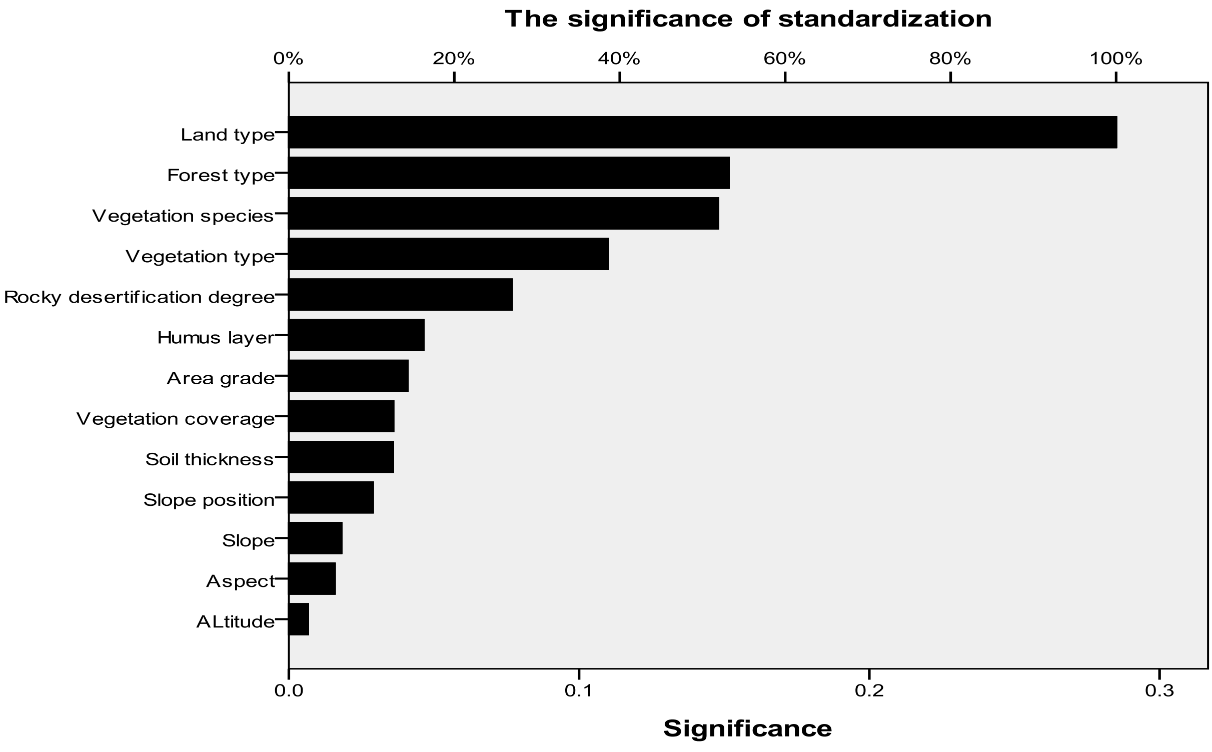


Fig. 7. The significance of impact factors for the distribution of vegetation carbon density

Table 3. The correlations between environmental factors and vegetation carbon density

	AL	AS	SP	SL	ST	HL	VC	LT	VT	DR	VS	FT	AG
VC	202**	-072**	-160**	065*	323**	348**	246**	.374**	-.089**	-205**	305**	236**	155**

*VC: Vegetation carbon density, AL: Altitude, AS: Aspect, SP: Slope position, SL: Slope, ST: Soil thickness, HL: Humus layer, VC: Vegetation coverage, LT: Land type, VT: Vegetation type, DR: Degree of rocky desertification, VS: Vegetation species, FT: Forest type, AG: Area grade. ** Significant at 0.01 level * Significant at 0.05 level*

Of the 13 impact factors investigated, 12 were significantly correlated with vegetation carbon density at the 0.01 level (Table 3). The remaining impact factor (slope) was significant at the 0.05 level. Soil thickness, humus layer, vegetation coverage, forest type, vegetation type, altitude, and area level were positively related to vegetation carbon density. The pattern of vegetation carbon density was positively affected by these environmental factors. Slope aspect, slope position, and rocky desertification were negatively correlated to vegetation carbon density. As the degree of rocky desertification increased, the vegetation carbon density decreased (Hu et al., 2008).

4. Conclusions

In this study, we used forest inventory data in 2005 and 2010 and geospatial technology to analyze the spatial pattern of vegetation carbon and factors that impact it in a typical karst area of northwest Guangxi, China. The results showed that vegetation carbon density increased from 29.04 t hm^2 to 29.57 t hm^2 between 2005 and 2010. The storage of vegetation carbon increased 1.84% during the same period. Spatial variation in vegetation carbon density generally increased in the study area between 2005 and 2010. Hot spot analysis indicated a random distribution in 2005, but a highly clustered distribution in 2010. The impacts of factors associated with human activities had relatively high impacts on the distribution of vegetation carbon density. The results indicated that the ecological immigration program and Green for Grain program had important impacts on the spatial distribution of vegetation carbon density.

The distribution trend of vegetation carbon density was similar to the distribution of vegetation. The spatial pattern of vegetation changes in the study region indicated that vegetation carbon density had increased as a result of recent rocky desertification control measures. For example, planting and protection of forest areas was the main measures for desertification control in Hechi City. Beginning in 2008, the counties of Duan, Dahua, Fengshan, and Huanjiang started to implement rocky desertification control projects, in which 9,000 hm^2 per county were comprehensively managed as part of a pilot program. In summary, the vegetation carbon density has increased in this study region due to rocky desertification control. The results of the present study showed that factors affected by humans have important effects on the pattern of vegetation carbon density in a typical karst region. Our study also showed that rocky desertification control measures had an important impact on the pattern of vegetation carbon density.

The conflict between economic development and environmental protection was a common issue worldwide and was also noted in rocky desertification in karst areas (Brown et al., 2011). Poor environmental quality was known to be an important restricted condition in karst areas. Therefore, conservation of karst areas should take priority over restricting the uncontrolled reclamation of these areas for economic purposes in future land use practices. Controlling karst rocky desertification requires the optimization of land use structure. Although discontinuing all reclamation activities in karst areas might not be possible, future land reclamation projects need to be controlled and should be implemented after rigorous environmental impact assessment. More detailed studies of the impacts of karst reclamation projects on ecosystem services provided in the southwest China were necessary.

The present study has some limitations that should be addressed in future studies. First, we did not consider the soil carbon pool, so the carbon capacity of the whole forest system was not estimated. Second, the degree of uncertainty associated with the BEF method of vegetation biomass estimation requires further research. Finally, although the main impact factors on the pattern of vegetation carbon density were investigated using RBFN, more comprehensive and accurate investigation into the driving mechanisms of the distribution of vegetation carbon density in karst regions are needed.

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