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ESTIMATING CHANGES IN CARBON STOCKS OF FOREST VEGETATION IN HUNAN PROVINCE USING THE CELLULAR AUTOMATA-MARKOV MODEL

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The cellular automata (CA)-Markov model was used to examine variation in carbon reserves of Hunan forests. Landuse data from forestry statistical yearbooks of 2000, 2005, 2010 and 2015, and forest resource surveys were used to study the spatial distribution of carbon storage using the Kriging and CA-Markov models. Spatial distribution of forest vegetation in Hunan province was simulated and the application of the CA-Markov model in carbon storage quantification was verified. Kappa coefficients were used to examine changes in the area and distribution of different carbon stocks from 2000 to 2015. Carbon storage of montane and bamboo forests in 2015 was 152.5×10^6 and 61.8×10^6 t respectively—an increase of 96.8 and 87.3% respectively from 2000, while production forest and shrub wood carbon storage decreased by 53.4 and 27.9% to 10.9×10^6 and 10.1×10^6 t respectively. These carbon storage figures corresponded with changes in the forest coverage area. Carbon storage was high in western Hunan province due to better forest protection. Carbon storage was low in north and south Hunan. The Changsha–Zhuzhou–Xiangtan area cluster had the lowest carbon storage because of rapid economic and social development and lower levels of forest vegetation protection.

Keywords: Carbon storage, carbon sink, Returning Farmland to Forest Programme, spatial variation, spatial simulation

INTRODUCTION

Global climate change affects the survival and development of all species on earth. Reducing carbon emission and enhancing carbon sinks via biological approaches are the main ways to lower atmospheric CO_2 concentration (Kramer 1981, Waring & Schlesinger 1985). Forests are one of the most productive terrestrial ecosystems. Forests account for 90% of the annual exchange of carbon between terrestrial ecosystem and the atmosphere, through photosynthesis and respiration (Fang et al. 2001, 2006). Therefore, forest vegetation carbon sinks play a key role in the global carbon cycle. Global carbon storage of forest vegetation is estimated at 359 to 744 Pg C (Li et al. 2003). Forest vegetation in the northern hemisphere is an important carbon sink, especially in China (Fan et al. 1998). Forest carbon sink in China accounts for 44.4–63.2% of the total global forest carbon sink (Pan et al. 2011), while the forest carbon storage in China accounts for 77% of the global total carbon storage of terrestrial vegetation (Dixon et al. 1994).

Hunan is an important forestry province in China. Its forest carbon sinks have positive significant contribution in facing the challenge of global climate change (Li et al. 2015). Forest resources in Hunan play crucial role in maintaining the carbon and ecological balance, and conserving water resources in Dongting Lake and the watershed in Yangtze River (Meng 2014). With the implementation of phases I and II of the Returning Farmland to Forest Programme (hereafter RFFP), forest resources in Hunan have been considerably restored in recent years, and the composition of forest vegetation types has changed significantly. Research on carbon storage in forest vegetation could provide useful information about the current status of forest resources and also be an important reference for the future management of those resources.

Recent studies have used biomass methods to estimate and analyse forest vegetation and carbon storage. The carbon storage and carbon density in Hunan has been calculated and the spatial distribution analysed by Jiao et al. (2005) based on inventory data of national resources from 1990 till 1995. Forest vegetation and soil carbon storage in Hunan has been estimated using measured and inventory data of national resources from 1999 to 2003. The forest vegetation carbon storage in Hunan from 2000 to 2011 was calculated by Yin and Zhou (2013). While these studies have estimated carbon storage for Hunan forests, models simulating forest vegetation carbon storage in Hunan have not yet been developed.

Spatial changes of carbon storage in forest vegetation have been studied using several models including the system dynamics model (He et al. 2005), cellular automata (CA) (Xiong et al. 2005), CLUE-S model (Zheng et al. 2012), multi-agent model (Ralha et al. 2013), CA-Markov (Hou et al. 2004), artificial neural network (Tayyebi et al. 2010), ANN-CA model (Li & Yeh 2002) and LESP model (Zhang & Cui 2001). The CA model has advantage over spatial calculation in temporal evolution, whereas the Markov model is suitable for spatial calculation (Liu & Chen 2002). Unlike the CA and Markov models, the CA-Markov model works well for both spatial simulation and temporal evolution (Yang et al. 2007). Therefore, the CA-Markov model has been widely and effectively used for spatial dynamic simulation and prediction of landuse changes. Spatial dynamic simulation of carbon storage in Hunan using the CA-Markov model has not been studied.

The objectives of our study were to analyse the dynamics and spatial distribution of forest vegetation carbon storage in Hunan and to investigate spatial simulation of the forest carbon stocks.

MATERIALS AND METHODS

Study area

Hunan Province is located to the south of the Dongting Lake in central China, along the middle reaches of the Yangtze River. It has a total area of 211,800 km^2 and governs over 13 municipalities and one autonomous prefecture. The province is in the subtropical monsoon climate zone with four distinct seasons, namely, humid and rainy spring, hot, long and humid summer, drought fall, and short and humid winter. Mountains in an asymmetric horseshoe shape span the province in the east, south and west, with low terrain in the central and north-eastern regions. Mountains and hills account for 66.6% of the total area of the province. Complex terrain characteristics and a good climate enrich the diversity of forest vegetation (Liu et al. 2016).

Forest vegetation in Hunan Province is divided into four types: montane forest, production forest, bamboo forest, and shrubland (Anonymous 2013). Montane forest species include *Cunninghamia lanceolata*, *Pinus massoniana*, *Cupressus funebris*, *Pinus elliottii*, *Populus* spp., *Eucalyptus robusta* and mixed species of Taxodiaceae (*Metasequoia glyptostroboides*, *Taxodium ascendens*, *Taxodium distichum* and *Glyptostrobus pensilis*).

Data sources

Forest resource data for Hunan Province for the years 2000, 2005, 2010 and 2015 were obtained from the annual report on Hunan Forest Resources Statistics (Anonymous 2017). The inventory data of national resources, administrative division data, remote sensing satellite data, and the forest resources distribution data for Hunan Province for those years are available at the inventory database of Hunan Forest Resources. These data were used in this paper.

Estimation of carbon stock

In this study, we estimated carbon stocks in the four different forest vegetation types in Hunan Province, namely montane forest, production forest, bamboo forest and shrubland (Table 1). Carbon storage (t C) of forest vegetation was calculated as the product of forest vegetation biomass (t) and carbon content factor (g C g^{-1}), i.e. carbon content of each gram of material. Average carbon content of each forest type was cited from Fang et al. (2007), Piao et al. (2009), Hu et al. (2015) and Liu et al. (2016). Biomass of montane forest was calculated using the continuous function method of biomass conversion factor (Guo et al. 2013), which is commonly used in China. Biomass values from a previous simulation (Yin et al. 2010) were used for *C. lanceolata*, *P. elliottii*, *P. massoniana*

Table 1 Carbon storage calculations for the 11 forest types in Hunan Province

Forest type	Formula for biomass (B) (t)	Correlation coefficient	Unit biomass	Carbon coefficient (g C g^{-1})
Montane forest				
Cunninghamia lanceolata	$B = 0.3999 \times V + 22.5410$	0.97	-	0.508
Pinus massoniana	$B = 0.52 \times V$	-	-	0.520
Broad-leaved trees	$B = 1.0357 \times V + 8.0591$	0.91	-	0.500
Cupressus funebris	$B = 0.6129 \times V + 26.1451$	0.98	-	0.551
Pinus elliottii	$B = 0.5168 \times V + 33.2378$	0.97	-	0.515
Populus spp.	$B = 0.4754 \times V + 30.6034$	0.93	-	0.494
Eucalyptus robusta	$B = 0.7893 \times V + 6.9306$	1.00	-	0.494
Mixed Taxodiaceae	$B = 0.4158 \times V + 41.3318$	0.94	-	0.508
Production forest	$B = A \times S$	-	23.52 t ha^{-2}	0.484
Bamboo forest	$B = (A_B \times N_B) \times 1000^{-1}$	-	22.5 kg $plant^{-1}$	0.486
Shrubland	$B = A \times S$	-	19.76 t ha^{-2}	0.484

V = stand volume, carbon stock = biomass × carbon coefficient, A = biomass of the area under that forest type, S = area under that forest type, A_B = average biomass of a single bamboo plant, N_B = number of bamboo plants

and broad-leaved trees. Biomass of production forest was estimated using the average biomass of production forest (He et al. 1996). Total number of bamboo plantations and average biomass of per plant was used to estimate biomass of bamboo forest (Fang et al. 1996). Since there were few studies on the biomass of shrubland, shrub area and average biomass per unit shrub area were used to estimate the biomass of shrubland. In our study, we used the Kriging interpolation model to estimate forest vegetation carbon stocks, the CA-Markov model to simulate changes in these carbon stocks, and Kappa coefficients to verify the results.

The Kriging interpolation model

The Kriging spatial interpolation model assumes a complex geospatial relationship among the spatially continuous objects, and a stochastic model should fit them with mutual influence (Cheng et al. 2013). The model is based on the autocorrelation of spatial attributes. Thus, interpolation results are close to the natural distribution state, which can reflect mutual influence and relationship among objects. Building on variogram and structure analysis, we use the model to conduct unbiased and optimal estimation on spatial variables.

CA-Markov model simulation

The CA-Markov model is used to simulate and forecast landuse changes in the field of landscape ecology. The change forecasting model in the CA-Markov model defines the transfer rules of different spatial data using multi-criteria evaluation and a multi-objective decision support system. In this paper, the CA-Markov model (Hou et al. 2004, Liu 2005) was used to estimate carbon storage in the base period as the initial state. Based on the baseline, previous carbon storage transformation area and carbon storage distribution types of the suitable pixels, carbon storage spatial distribution types are recalculated until reaching the area of carbon storage type predicted by the Markov chain.

The CA model is a time-space computational dynamics model. Each variable is in a spatial discrete state, and the state change rule is expressed locally and temporally in time and space. The model is:

$$S(t + 1) = f(St, N)$$

where, S = cellular dispersion, the effective state set, N = cellular domain; t, t + 1 = time series and f = principle of local cellular state transformation.

The Markov model is a non-after-effect special stochastic process, which treats the object as an independent system. Therefore, the state of a motion system at T + 1 (t + 1) time is only related to the state at T(t) time, not to former state. The model formula is:

$$S\ (t+1) = P_{ij} \neq St$$

where, St and S(t + 1) are the state of the cellular in the time series and P_{ij} = transition probability matrix. The transition formula is:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nm} \end{bmatrix}$$

where, P_{ij} = the probability that the land type i is transferred to j and $0 \leq P_{ij} \leq 1$, and the sum of the probabilities of each row is 1, where $i \in (1, n)$, $j \in (1, n)$.

Kappa coefficient verification

In the present study, the accuracy of data processing was mainly verified using the validate module in IDRISI (He et al. 2011). Kappa coefficients were selected to check data precision, including the number Kappa coefficient (K_{no}), location Kappa coefficient (K_{loc}), and standard Kappa coefficient (K_{std}). Quantitative analysis of the changes (spatial distribution and quantity) in carbon storage for the four forest types was conducted to validate the objectivity, comprehensiveness and accuracy of the results (Bai et al. 2005).

The number Kappa coefficient (K_{no}) indicated the consistency of the spatial carbon storage distribution patterns at different levels without spatial location changes. The location Kappa coefficient (K_{loc}) indicated the consistency of carbon storage distribution in two periods under certain conditions. The standard Kappa coefficient (K_{std}) showed the consistency of ranked carbon storage distribution under an appropriate position.

RESULTS

Changes in forest vegetation carbon storage

From 2000 to 2015, implementation of the RFFP in Hunan resulted in significant changes in forest vegetation carbon storage in the province. Hunan forest carbon stocks were 147.9, 177.2, 181.1 and 235.3 Tg C in 2000, 2005, 2010 and 2015 respectively (Table 2). From 2000 to 2015, montane forest and bamboo forest carbon storage increased sharply from 77.5×10^6 to 152.5×10^6 t and 33×10^6 to 61.8×10^6 t respectively. During that same time period, carbon storage of production forest decreased from 23.4×10^6 to 10.9×10^6 t and shrubland carbon storage fell from 14.0×10^6 to 10.1×10^6 t. The carbon storage of montane forest increased nearly 40% from 2000 to 2005, 6.6% from 2005 to 2010, and 32.1% from 2010 to 2015. Bamboo forest carbon storage increased 29.3% from 2000 to 2005, fell by 3.7% from 2005 to 2010 and went up 50.4% from 2010 to 2015. These results corresponded to the changes in the areas under montane forest and bamboo forest in the province (Anonymous 2017). Production forest carbon storage had consecutive drops of 37.1, 19.1, and 8.4% every five years from 2000 till 2015. During those time periods, shrubland carbon storage fell by 17.9%, increased by 12.7%, but dropped again by 20.5% in the last five years of the study. The recorded decreases in shrubland carbon storage could be attributed to deforestation occurring because of lack of forest protection, while the increase in carbon storage could be due to less human disturbance (Li et al. 2015).

Table 2 Carbon storage (million t) of the four main forest vegetation types in Hunan Province from 2000 to 2015

Year	Montane forest	Production forest	Bamboo forest	Shrub wood	Total
2000	77.5	23.4	33.0	14.0	147.9
2005	108.3	14.7	42.7	11.5	177.2
2010	115.4	11.9	41.1	12.7	181.1
2015	152.5	10.9	61.8	10.1	235.3

The RFFP has resulted in the increase of total forest cover in Hunan Province (Yin et al. 2010), thus leading to significant change in the total amount of forest vegetation carbon storage. In the present study, total carbon storage went up by 59.1% from 2000 to 2015 (Table 2). The 2008 snowstorm that damaged significant areas of forest affected carbon stock increment from 2005 to 2010. During that time period, carbon stocks increased by only 2.2%, whereas increases of 19.8 and 29.9% were recorded for the five-year periods before and after respectively (Zhou et al. 2011).

Spatial variation in forest vegetation carbon storage

The spatial distribution map of forest carbon storage in Hunan from 2000 till 2015 showed that carbon storage was correlated to the distribution of forest vegetation (Figure 1). The highest carbon storage of forest vegetation was located in XiangxiTujia Nationality Autonomous Prefecture, and Huaihua and Shaoyang prefectures in western Hunan. Slow socio-economic development, less intensive human disturbances and better forest protections are likely to contribute to the high carbon storage in the three prefectures (Duan et al. 2016). Northern Hunan (Changde and Yueyang prefectures) and southern Hunan (Chenzhou, Hengyang and Yongzhou prefectures) also had large carbon storage. The implementation of the RFFP increased the area under forest cover, especially in Yongzhou and Chenzhou, thus increasing carbon storage in these two prefectures. Due to rapid urban and socio-economic development in the cities of Changsha, Zhuzhou and Xiangtan, forest vegetation carbon storage were lowest there.

Spatial simulation of forest vegetation carbon storage

Spatial distribution of carbon storage was closely related to the distribution of forest vegetation. The CA-Markov model was used to simulate spatial variability of carbon storage in forest vegetation. Using ArcGIS, the values of carbon stocks from 2000–2015 were reclassified into the following five classes by means of the natural breaks method (Hui et al. 2016): I (2.319, 10.0208), II (10.0208, 13.0331), III (13.0331, 16.7986), IV (16.7986, 20.8652), and V (20.8652, 29.117), in units of $\times 10^6$ t. Spatial intersections were conducted between 2000 and 2005, 2005 and 2010, and 2010 and 2015, and corresponding space transfer matrixes generated.

Large transformations occurred between different classes with the highest transformation of carbon storage distribution seen from class I to II (Table 3). Carbon storage distribution also

Table 3 Transition probability matrix of carbon storage space in Hunan Province for 2000–2005, 2005–2010 and 2010–2015

		2000				
		Class I	Class II	Class III	Class IV	Class V
	Class I	0.2121	0.0000	0.0000	0.0000	0.0000
	Class II	0.0849	0.0283	0.0000	0.0000	0.0000
2005	Class III	0.0000	0.0389	0.0201	0.0000	0.0000
	Class IV	0.0000	0.0000	0.0824	0.0164	0.0000
	Class V	0.0000	0.0000	0.0319	0.0679	0.0621
		2005				
		Class I	Class II	Class III	Class IV	Class V
	Class I	0.1066	0.0242	0.0000	0.0000	0.0000
	Class II	0.1056	0.0599	0.0134	0.0000	0.0000
2010	Class III	0.0000	0.0291	0.0363	0.0322	0.0000
	Class IV	0.0000	0.0000	0.0093	0.0642	0.0568
	Class V	0.0000	0.0000	0.0000	0.0024	0.1051
		2010				
		Class I	Class II	Class III	Class IV	Class V
	Class I	0.0132	0.0000	0.0000	0.0000	0.0000
	Class II	0.0440	0.0069	0.0000	0.0000	0.0000
2015	Class III	0.0735	0.1470	0.0129	0.0000	0.0000
	Class IV	0.0000	0.0000	0.0000	0.0000	0.0002
	Class V	0.0000	0.0000	0.0320	0.1213	0.1072

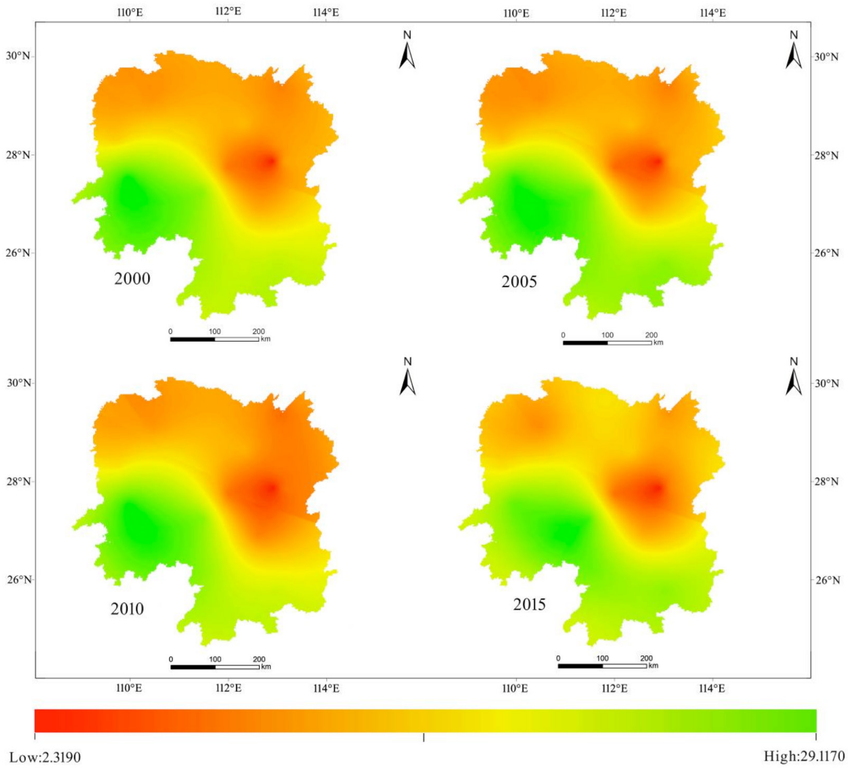


Figure 1 Spatial changes in carbon storage in Hunan Province from 2000 to 2015

transformed from class III to classes IV and V. The transformation of carbon storage distribution from class IV to V was the lowest. Forest vegetation distribution in Hunan changed dramatically from 2000 to 2005, leading to notable transformation in different carbon storage areas.

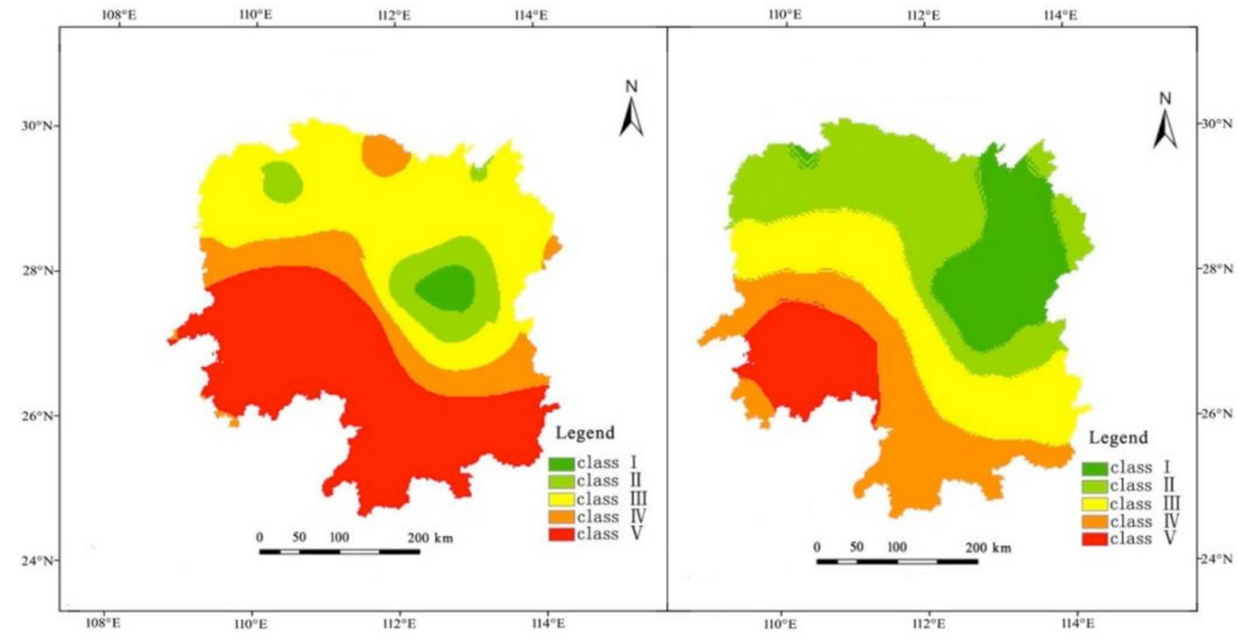
From 2005 to 2010, carbon storage distribution transferred from class I to class II and from class II to classes I and III (Table 3). The transformation of carbon storage distribution from class II to III was the highest. Transformation also occurred from class III to II and IV, from class IV to III and V as well as from class V to IV. There was a dramatic change in the distribution of different carbon storage in Hunan Province from 2005 to 2010. This might be caused by the 2008 snowstorm that extensively damaged the forested areas (Zhou et al. 2011).

From 2010 to 2015, there was obvious transformation between different carbon storage distribution areas (Table 3). Carbon storage distribution area of class I transferred to classes II and III, and the transformation from class I to III was the highest (Table 3). Transformation occurred from class II to III, from class IV to V as well as from class V to IV. These positive gains were the result of active protection measures that promoted restoration of forest vegetation in Hunan after the 2008 snowstorm. The resulting changes in forest vegetation led to marked transformation between different carbon storage distribution areas.

From 2000 to 2015, there was drastic transformation between different carbon storage classes. Based on the space transition matrices of 2000 and 2005, and 2005 and 2010, forest vegetation carbon storage in Hunan in 2015 was simulated using the CA-Markov model in IDRISI software. The distribution area of carbon storage in classes II, III and V fell drastically, while carbon storage distribution area in classes I and IV increased significantly (Figure 2). The implementation of the RFFP and active protection after the 2008 snowstorm impacted the distribution of forest vegetation in the province.

Kappa coefficients

K_{no} values of 0.6327, 0.6724, 0.4050 and 0.3839 for 2000–2005, 2005–2010, 2010–2015 and 2015–2015 respectively (Table 4), indicated changes in carbon storage (independent of location) of 36.7, 32.7, 59.5 and 61.6% respectively. K_{loc}



(a) (b)

Figure 2 Actual (a) and simulated (b) spatial distribution of carbon storage of Hunan Province in 2015

Table 4 Spatial check Kappa coefficients used to validate carbon stock simulations for periods between 2000 and 2015

	2000–2005	2005–2010	2010–2015	2015–2015
Number Kappa coefficient, K_{no}	0.6327	0.6724	0.4050	0.3839
Location Kappa coefficient, K_{loc}	0.7637	0.7902	0.5961	0.5416
Standard Kappa coefficient, K_{std}	0.6061	0.6544	0.3810	0.3565

values of 0.7637, 0.7902, 0.5961 and 0.5416 for 2000–2005, 2005–2010, 2010–2015 and 2015–2015 respectively indicated changes in carbon storage, regardless of the ranked distribution area, of 23.6, 21.0, 40.4 and 45.8% respectively. K_{std} values of 0.6061, 0.6544, 0.03801 and 0.0355 for the same years respectively suggested that 39.4, 34.6, 62.0 and 64.4% of ranked carbon storage distribution areas changed under the condition of maintaining a moderate ranked carbon storage distribution area. All Kappa parameters indicated that the RFFP, the 2008 snowstorm and active ecological protection had significant impacts on the spatial carbon storage distribution of forest vegetation.

DISCUSSION

Hunan forest carbon stocks were 147.9, 177.2, 181.1 and 235.3 Tg C in 2000, 2005, 2010 and 2015 respectively. Our results are close to the 173.974 Tg C reported by Jiao et al. (2005), but much lower than the 594.94 Tg C calculated by Yin and Zhou (2013). The variation can be attributed to differences in data sources, calculation methods, time scales, vegetation types and C coefficients. In the present study, forest vegetation was comprehensively divided into 11 types, with multiple C coefficients—unlike the use of a single C coefficient by Jiao et al. (2005). Therefore, we considered the present study results more accurate.

Carbon storage of the different vegetation types in decreasing order were: montane forest > bamboo forest > production forest > shrubland. Thus, montane forest are recommended as the best plantation tree species in Hunan Province, and that montane and bamboo forests must be better protected. Difference in spatial distribution of vegetation carbon storage in

Hunan was extremely varied, with the highest forest vegetation carbon storage in north-west Hunan, lower in north and south Hunan and lowest in the Changsha–Xiangtan–Zhuzhou cluster. More research in these separate regions are needed to formulate forestry policies on, e.g. imposing quotas on timber harvesting in north-west Hunan, encouraging forest planting in north and south Hunan, balancing urban expansion and urban green space protection, and implementing ecological green core quality improvement programmes in the Changsha–Xiangtan–Zhuzhou cluster.

Topographic factors such as forest age, meteorological data, more detailed vegetation classification and a smaller cellular scale in the CA-Markov model were not considered in the present study due to data limitations. With increasing data availability and improved data quality, relationships between vegetation carbon stock distribution and meteorological factors may be better elucidated in future. This information will, in turn, provide valuable information to guide forest management and landuse practices.

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