青藏高原森林碳储量定量化研究*

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摘要 森林碳储量估测可以为评估碳源 / 碳汇及其空间格局提供定量化信息。青藏高原由于其独特的地理、气候特征，了解其森林在陆地生态系统碳汇中的作用非常重要。文章提出了一种直观的、基于 GIS 数据来估测青藏高原地上森林碳储量的方法，这种方法结合了覆盖 3 个实验区（西藏、云南和四川）250 m 空间分辨率的 MODIS 数据、气候数据、1 km 的 DEM、1:2 500 000 林相图和 1 086 个森林资源清查小班数据（NFI）。采用相关分析和线性诊断方法对关键变量进行选择，线性回归模型和对数模型用于森林碳储量模型建立。结果表明，采用三个不同模型分别对地理特征不同的子区域内森林碳储量的测算结果，比使用一般模型对没有划分子区域的整个青藏高原森林碳储量的测算更准确。虚拟变量 (如层、从 DEM 提取的植被类型、NFI 和青藏高原森林地图) 的融合提高了碳估算模型的性能。同时，线性模型和对数模型可决系数（R^2）也分别随之增大。青藏高原地上森林碳储量不同子区域间变化较大，从 50 000 到 250 000 kg/hm^2，平均值 19 000 kg/hm^2，而灌木碳储量则不及 10 000 kg/hm^2。

关键词 森林碳储量；虚拟变量；对数模型；MODIS 数据；青藏高原

中图分类号：S714 **文献标志码**：A **文章编号**：2096-2053（2020）06-0009-11

Quantification of Forest Carbon Storage in Tibetan Plateau

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Abstract Estimating forest carbon storage can provide quantitative information to assess carbon source/ sink size and its spatial patterns. Tibetan Plateau is prone to climate change due to its unique geographic feature, and thus it is important to understand the role of Tibetan forests in China terrestrial ecosystem carbon sink. This paper presented a spatially explicit GIS based method, which incorporated MODIS data with 250 m spatial resolution, climate data, 1 km DEM, 1:2,500,000 forest map and 1 086 plot data of National Forest Inventory (NFI) covering the three test regions (Tibet, Yunnan and Sichuan), to estimate the above-ground forest carbon storage in Tibetan Plateau. Correlation analysis and linearity diagnosis were used to choose key variables, and linear regression model and logarithmic model were applied to develop the forest carbon storage models. The results showed that forest carbon storage estimation by using the three separated models for different respective sub-regions according to its physical geographic characteristics was more accurate than by using the general

*Fund Project: National Natural Science Foundation of China (31800529)

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model for the whole Plateau without dividing sub-regions. Incorporating dummy variables, such as aspect and vegetation types derived from DEM, NFI and forest map of Tibetan Plateau, improved the carbon estimation model performance. The determining coefficients (R^2) of the linear models and logarithmic models were also increased, respectively. The above-ground forest carbon storage in Tibetan Plateau varied greatly with the sub-regions, ranging spatially from 50 000 kg/hm^2 to 250 000 kg/hm^2, with the mean of 19 000 kg/hm^2, while the carbon storage of shrub was less than 10 000 kg/hm^2.

Key words forest carbon storage; dummy variable; logarithmic model; MODIS data; Tibetan Plateau

Forest carbon storage is an important component in the global Carbon cycle, and is extremely important in determining temporal and spatial patterns of the terrestrial carbon sources and sinks [1-2]. Many of the earlier studies on remote sensing approached estimation of forest carbon storage were manifested on forest biomass, covering boreal forests [3], temperate [4] and tropical forests [5-6]. Landsat TM was widely used to conduct forest biomass or carbon estimation [7-10]. In addition, WiFS data and MODIS data were also employed to estimate forest biomass in Sweden [11-12].

Recently, there is an increasing attempt in using remotely sensed data and ancillary variables (precipitation, temperature, elevation and etc.) to improve the estimation precision of terrestrial carbon storage and to examine the spatial variations across regions and continents based on [5,9,12].

Collection of field data to estimate carbon storage generally involves destructive sampling [13], and this is associated with time consuming and labor cost. Most commonly, forest carbon storage is estimated by using timber volume information derived from national forest inventories (NFI). NFI covers a range of conditions and disturbance regimes, with measurements of the basic components of carbon storage. Thus, inventory data is widely used for estimating carbon storage or biomass and productivity at various scales from regional [13-14] to continental [15-16]. Forest inventory data is one of the most reliable information sources for model development, testing, and validation. Such inventories are designed with statistical sampling using field plots, where forest parameters (i.e., tree species, tree height, DBH) are measured directly. For each plot, DBH of each individual tree was measured and stand volume was estimated. The volume is converted to biomass using biomass expansion factor (BEF) and then forest carbon storage is estimated by the use of the conversion coefficient [15]. Fang et al. [17-19] collected more than 700 sample data, built the volume-biomass models of all kinds of forest tree types by the method of BEF.

Known as “the Third Pole” of the earth, Tibetan Plateau has one of the most complex climates in the world and its unique physical geographic characters greatly influence the regional eco–environmental conditions in China and even in Asia as a whole. The above-ground forest carbon storage in Tibetan Plateau is highly concerned as one of the major components of China forest carbon pool and it is also prone to climate change.

In this study, forest inventory data, MODIS data, ancillary data such as climate data, DEM data and forest map in Tibetan Plateau were used to estimate the above-ground carbon storage and its spatial pattern. Due to complex topography in Tibetan Plateau, dummy variables, such as aspect and vegetation types, are very likely to affect the carbon storage estimation. Therefore, the dummy variables need to be quantified and incorporated into carbon storage models in order to increase the estimation precision of the above-ground forest carbon storage in the Tibetan Plateau. The objectives of this study were: (1)developing an effective method to map and quantify the above-ground forest carbon storage in Tibetan Plateau using MODIS data, climate data and dummy variables as alternatives to the National Forest Inventory (NFI), (2) exploring the spatial pattern of forest carbon storage in Tibetan Plateau.

Data and Methods

Study area

Tibetan plateau includes the whole Tibet, the most areas of Yunnan, Sichuan and Qinghai provinces, stretching from Pamir Plateau in the west to Hengduan Mountains in the east, covering 31 degrees of longitude and with a length of 2 945 km from west to east. It stretches from Himalayas Mountains in the south to the Kunlun Mountains-Qilian Mountains in the north, covering about 13 degrees of latitude and with a length of 1 532 km from south to north. The total area is greater than 2 500 × 10^3 km^2, accounting for 26.8% of the total land area of China [20]. Tibetan plateau is the highest plateau in the world with a mean altitude of 4 000 – 5 000 m. The annual mean temperature is less than 5°C in most regions.

Three regions of Tibet, Yunnan and Sichuan were used as the test sites, respectively (Fig.1).

Data

The data used in this study included the NFI, remotely sensed data, climate data and other auxiliary geographical data.

Forest Inventories/Forest Map of Tibetan plateau Forest inventories have typically been conducted about every 5 years in Tibetan Plateau. Plot carbon storage in Tibetan Plateau was based on the sixth NFI (2002) and the three regions were acquired (Tab. 1). The sampling space of acquired NFI data was 4 km by 8 km. The NFI data included sample plot number, geographic location, vegetation type, land-use pattern, dominant species, soil type, soil thickness and etc. In addition, stand type, tree species, and DBH parameters were recorded in NFI plots. The forest map of Tibetan plateau (2002) was obtained from the State Forestry Administration, China. Four forest types in the Plateau were identified, i.e., coniferous forest, broadleaved forest, mixed forest and shrubbery.

Note: the circles highlight the location of the test sites.

Fig. 1 Test sites

Tab. 1 Ground NFI and remote sensed data sets

Site	Field survey year	Remote sensed data	Number of plots total /used	Plot size/hm^2
Tibet	2001	MODIS 13Q1, July 2005	23/22	0.067
Yunnan	2002	MODIS 13Q1, July 2005	385/193	0.067
Sichuan	2002	MODIS 13Q1, July 2005	678/343	0.067

MODIS remotely sensed data

Moderate-resolution Imaging Spectroradiometer (MODIS) images were acquired (Tab.1) from the website of NASA1. Besides the NDVI, EVI vegetation indexes, the data sets also included NDVI quality band, EVI quality band, red band, nir-red band, blue band and other four bands. The file format of acquired data sets is the Hierarchical Data Format (HDF). For production purposes, MODIS bands are produced in tile units that are approximately 1200 km by 1200 km in the integerized sinusoidal grid projection. The Tibetan Plateau covers regions with MODIS data of 13 tiles. The type of MODIS data is MOD13Q1, with spatial resolution of 250 m and 16 days interval composite product.

Ancillary data

Topographic and climate variables including the hottest and coldest mean monthly temperature, the accumulated temperature ≥ 0℃ , the accumulated temperature ≥ 10 ℃ , annual precipitation, and the mean annual relative humidity were also incorporated in the analysis in order to supplement the MODIS data. The climatic data were interpolated to attain the grided data of the study area. Elevation and aspect could be derived from the DEM data. Vegetation types could be derived from the forest map. The resolutions of DEM and forest map were both of 1:100,000.

Methods

Pre-processing of MODIS data and ancillary data

The data sets' file format can be transferred, and files can be projected and be spatially mosaic by the MODIS Reprojection Tool (MRT) software provided by MODLAND. The HDF format was transferred to Geotiff format by the MRT, and projected the sinusoidal projection was transformed to Geographic projection and 13 tiles were mosaic. The further processes were dealt with ERDAS 8.5. To remove the effects of cloud cover and cover the whole Tibetan Plateau, the acquired date of remote sensing was 3 years prior to the field survey. The climate data were interpolated to attain the grided data of the study area. All the data sets (including MODIS data, climate data) were transferred to the uniform coordination and projection. The projection is Lambert, the longitude of central meridian is 90°0′0″E, and the two standard latitude parallels are 30°0′0″N and 35°0′0″N. The spheroid is Clarke1866. All the data were re-sampled to the grided data with 250 m spatial resolution.

Acquiring the remotely sensed data and other ancillary data of plot sites

The red band, nir-red band, blue band, mir-red band, NDVI, EVI and other indexes of the combination of different bands were extracted after pre-processing the MODIS images (Tab. 2), and then overlaid them with the sample sites data to extract the remotely sensed data of sample sites.

The respective distances from the Pacific and the Indian coastline to the plot sites were also considered as the two important variables. Based on the coastlines of the Asian Continent, "near" function in ArcGIS 9.1 was used to calculate the shortest distance of each plot site to the coastline of the Pacific Ocean and the Indian Ocean.

Meanwhile, the climate data were interpolated to get the grided climate data. Grided climate data were overlaid with the sample sites data to acquire the climate data of sample sites. The kriging method was employed for interpolation, and the semi-variance model was linear with quadratic drift, and the spatial resolution was 250 m.

Calculating carbon storage of plot sites from NFI

This study calculated the sample sites' above-ground carbon storage according to the models advocated by Fang et al [1].

Quantification of the dummy variables

Dummy variables represent information about group membership in quantitative terms without imposing unrealistic measurement assumptions on the categorical variables. Supposing we wish to introduce into a model the idea that there are three types (A, B, C) of vegetation that represent different types, Z1，Z2 could be set. Values can be assigned to Z1, Z2 as follows: if the type is A, Z1=1, Z2=0; if the type is B, Z1=0, Z2=1; if the type is C, Z1=0, Z2=0. The model included two extra variables Z1 and Z2. According to the principles above, the dummy variables of aspect

Tab. 2 Variables related to forest carbon storage

Variables	Variables descriptions
y_con	Distance to north Indian Ocean (m)
x_con	Distance to Pacific Ocean (m)
elv	Elevation (m)
blue	the blue band reflectance of the MODIS data
red	the red band reflectance of the MODIS data
nir	the nir-red band reflectance of the MODIS data
mir	the minimal red band reflectance of the MODIS data
NDVI	NDVI=(nir-red)/(nir+red)
EVI	EVI= 2.5*(nir-red)/(nir+6*red-7.5*blue+1)
RVI	RVI=nir/red
MIRVI	MIRVI=(nir-mir)/(nir+mir)
MRH	mean annual relative humidity(%)
hott	mean hottest monthly temperature (0.1℃)
coldt	mean coldest monthly temperature (0.1℃)
p	annual precipitation (0.1mm)
AT0	the accumulated temperature ≥ 0℃ (0.1℃)
AT10	the accumulated temperature ≥ 10℃ (0.1℃)
ST	annual sunlight time (0.1h)
slope	slope

Tab.3 Coefficients of dummy variables for aspect

Aspect	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
East	1	0	0	0	0	0	0	0
South	0	1	0	0	0	0	0	0
West	0	0	1	0	0	0	0	0
North	0	0	0	1	0	0	0	0
Northeast	0	0	0	0	1	0	0	0
Southeast	0	0	0	0	0	1	0	0
Northwest	0	0	0	0	0	0	1	0
Southwest	0	0	0	0	0	0	0	1
Flat	0	0	0	0	0	0	0	0

Tab.4 Coefficients of dummy variables for different vegetation types

Vegetation types	Y_1	Y_2	Y_3
Coniferous forest	1	0	0
Broadleaved forest	0	1	0
Shrub	0	0	1
Mixed forest	0	0	0

and vegetation types were shown in Tab. 3 and Tab. 4.

Aspect and vegetation types were acquired from the NFI data. Aspect was divided into nine types, and the forest vegetation was divided into four types: coniferous forest type, broadleaved forest type, coniferous and broadleaved mixed forest type, and shrub type.

Carbon storage modeling

To obtain good estimation precision of the forest above-ground carbon storage in Tibetan Plateau, the following two methods were used. The first one was taking the Tibetan Plateau as a whole unit. The second was that the Tibetan Plateau was divided into three sub-areas according to the forest map of Tibetan Plateau in the year of 2002 and the NFI data. Regression models were developed by using the two methods. Linear regression and log-arithmetic regression were employed to determine more accurate regression models for the forest carbon storage estimate in Tibetan Plateau.

Correlation test

In the premise of not seriously compromising the performance of the carbon storage model, the correlations between 35 variables (including 16 coefficients of dummy variables) and the forest above-ground carbon storage were tested, and then the variables that have weak relationships with the carbon storage were killed out. The kill-out criterion was: the significant linear relationship at the level of P=0.1.

Eliminating the general linearity between variables

If bad linearity exists between the variables, Least Square Theory (LST) of the regression could seriously affect the precision of the models and even distort the coefficients of the models. Variation Inflation Factor (VIF) could be used to test if the linearity existed between the variables and to kill out the variables for getting rid of linearity.

The biggest VIFi of all the variables usually be used as the index of weighing the linearity between different variables. If the VIF is bigger than 10, the corresponding variables may be considered as the linear combination of other variables.

Building carbon storage models The multiple regression models were developed with the selected variables. Linear regression models and logistic models were elaborated for both the three sub-areas and the whole Plateau. Best models were finally applied to the forest carbon storage estimation.

Validation test

About 10% plots were randomly selected from the respective three sites to test the precision of the three sub-area models and the general model. The test plot numbers were 2, 21 and 32, respectively, in Tibet, Yunnan, Sichuan, and the total test plot number was 55. Mean Error (ME), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated to test the precision of the models. The smaller ME, MAE, RMSE are, the higher precision of the models.

Forest carbon storage estimation on Tibetan Plateau

According to the results by the "Validation Test", the better carbon model was chosen to estimate the above-ground forest carbon storage on the Plateau with the pixel of 250 m. If the vegetation types or aspect have been imported to the carbon model, they should be spatially grided on the whole Plateau. Vegetation types of the Plateau were derived from the forest map. Aspect types were derived from DEM. Calculation and analysis of mapping were undertaken in ArcGIS 9.0. Correlation analysis and regression analysis were processed in Matlab 6.5.1.

Results

Correlation analysis

Key variables and the p-values strongly related to the forest carbon storage in Tibet, Yunnan, Sichuan and Tibetan Plateau were shown in Tab. 5.

Five key observations can be made from Tab. 5. EVI had a high correlation with carbon storage, either in one of the three sub-areas or in the whole Plateau. Red band reflectance was also a good indicator for the carbon storage estimation in Tibetan Plateau. The mean coldest monthly temperature had a significant negative linear relationship with the carbon storage. The correlation analysis showed that aspect and vegetation types had strong correlation with forest carbon storage, although the selected dummy variables of aspect and vegetation were not the same. Vegetation types were the most important variables in the forest carbon storage estimation, no matter which one of the established models was used. Elevation was an important factor influencing the carbon storage.

Diagnosis of linearity in variables

VIFs of key variables in Tibet, Yunnan, Sichuan and Tibetan Plateau are shown in Table 6. For the test sites of Tibet, Yunnan, Sichuan and the whole Tibetan Plateau, there were no serious linearity existing be-

Tab. 5 Correlation coefficients between carbon storage and variables in Tibet, Yunnan, Sichuan and Tibetan Plateau

Variables	Tibet (n=21)		Yunnan(n=174)		Sichuan (n=309)		Tibetan Plateau (n=504)	
	Correlation	*p*-Test	Correlation	*p*-Test	Correlation	*p*-Test	Correlation	*p*-Test
X_con							0.17	0
Y_con							0.14	0.006
elv	0.44	0.044	0.37	0	0.34	0	0.31	0
NDVI			–0.15	0.053	–0.13	0.018		
EVI	0.32	0.082	–0.15	0.049	–0.14	0.009	–0.08	0.072
MIRVI					–0.15	0.006		
mir					0.13	0.012		
blue			0.25	0.001				
red			0.19	0.007	0.14	0.008	0.12	0.006
coldt			–0.12	0.085	–0.1	0.071	–0.15	0.001
hott			–0.13	0.075	–0.11	0.045		
AT0			–0.14	0.059	–0.1	0.075		
AT10			0.25	0.044	–0.1	0.076		
ST					0.11	0.042		
p							–0.16	0
X_2							–0.08	0.089
X_5	0.45	0.041						
X_8					–0.12	0.032	–0.08	0.067
Y_1			0.227	0.001	–0.35	0	–0.2	0
Y_2	0.45	0.04			0.51	0	0.38	0
Y_3	–0.52	0.016	–0.36	0	–0.3	0	–0.31	0

Note: All the variables as identified in Tab. 2 - 4.

tween the variables since the VIFs of all the selected variables were no more than 10. For the test site of Sichuan, the VIFs of AT0 and AT10 are bigger than 10 and the VIF of AT0 is the biggest. According to the pre-determined criterion, AT0 variables should be killed out. After killing out the AT0, the multiple linearity between the 14 variables were diagnosed again and all the VIFs were no more than 10. There was no linearity existed among the selected 14 variables.

Regression model

Linear regression model and logarithmic regression models were used to build forest carbon storage models by the selected variables in the three sub-areas and the whole Tibetan Plateau.

Validation test

By using the selected variables, the determining coefficients (R^2) of different models were listed in Tab. 7. It showed that the inclusion of dummy variables significantly increasing the correlation. Meanwhile, the logarithmic models were much better than the linear models. The logarithmic models with dummy variables had higher correlation coefficients (R^2) than linear models no matter where they were in Tibet, Yunnan, Sichuan, or in the whole Tibetan Plateau.

To compare which had higher precision between the sub-area models of the three areas and the general model of the whole Tibetan Plateau, ME, MAE and RMSE were calculated of the sub-area logarithmic models and the general logarithmic model. Table 8 showed that the ME, MAE and RMSE of the sub-area models were all smaller than the general model. The sub-area models got higher precision.

Based on the above analysis, logarithmic models were more appropriate for the forest carbon storage estimation in the whole Tibetan Plateau.

Carbon storage pattern of the whole Tibetan Plateau

Based on the above regression analysis and precision test, the three sub-area models with logarithmic

Tab. 6 VIF of selected variables in the test site of Tibet, Yunnan, Sichuan and Tibetan Plateau

VIF	Tibet	Yunnan	Sichuan	Tibetan Plateau
X_con				0.03
Y_con				0.01
elv	0.05	0.01	0.04	0
NDVI		0.04	0.05	
EVI	0.08	0.05	0.01	0
MIRVI			0.03	0.03
mir			0.05	
blue		0.08		
red		0.08	0.06	0
coldt		1.22	1.04	0
hott		0.2	0.79	
AT0		5.83	38.03	
AT10		1.95	22.23	
ST			0.02	
p				0.02
X_2				
X_5	0.06			
X_8			0	0
Y_1	0.07		0.01	0
Y_2		0.01	0.02	0.01
Y_3	0.06	0.01	0.01	0

Note: All the variables as identified in Tab. 2 - 4.

Tab. 7 Correlation coefficients (R^2) for relationships between variables and carbon storage

Different model types	Tibet	Yunnan	Sichuan	Tibetan Plateau
Linear model without dummy variables	0.20	0.24	0.16	0.17
Linear model with dummy variables (1)	0.48	0.35	0.33	0.27
Logarithmic model without dummy variables	0.23	0.30	0.14	0.15
Logarithmic model with dummy variables (2)	0.60	0.65	0.59	0.55

models were used to estimate the forest carbon storage of the Tibetan Plateau (Fig. 2).

In Tibetan Plateau, the forest is mainly distributed on eastern and northeastern part with forest cover-of about 11.3% in 2002. The mean above-ground forest carbon storage was about 19 000 kg/hm^2. In Tibet, Yunnan and Sichuan, the mean carbon storages were 19 100 kg/hm^2, 18 600 kg/hm^2 and 19 900 kg/hm^2, respectively. The carbon storage of shrub was fairly low, less than 10 000 kg/hm^2, which was mainly located in Qaidam basin, partly in the west Sichuan Plateau and the southernmost part of Tibet. The forest carbon storages in the eastern-most and southeastern-most of Tibetan Plateau were mostly below 50 000 kg/hm^2. In the Minjiang River, the carbon storage was between 100 000 kg/hm^2 and 150 000 kg/hm^2. The carbon storage was high in the area of Linzhi of Tibet, with the value of more than 250 000 kg/hm^2. For the altitude being less than 3 500 m, the mean forest carbon storage in Plateau and the sum of the total carbon storage increased with the altitude.

Discussion and Conclusion

Separated models enhanced the precision of forest carbon storage estimation

Remote sensing approach has a great potential

Tab.8 Precision tests of the two kind models

	ME	MAE	RMSE
Sub-area models of three regions	28.71	60.48	86.15
The general model	33.81	66.13	94.52

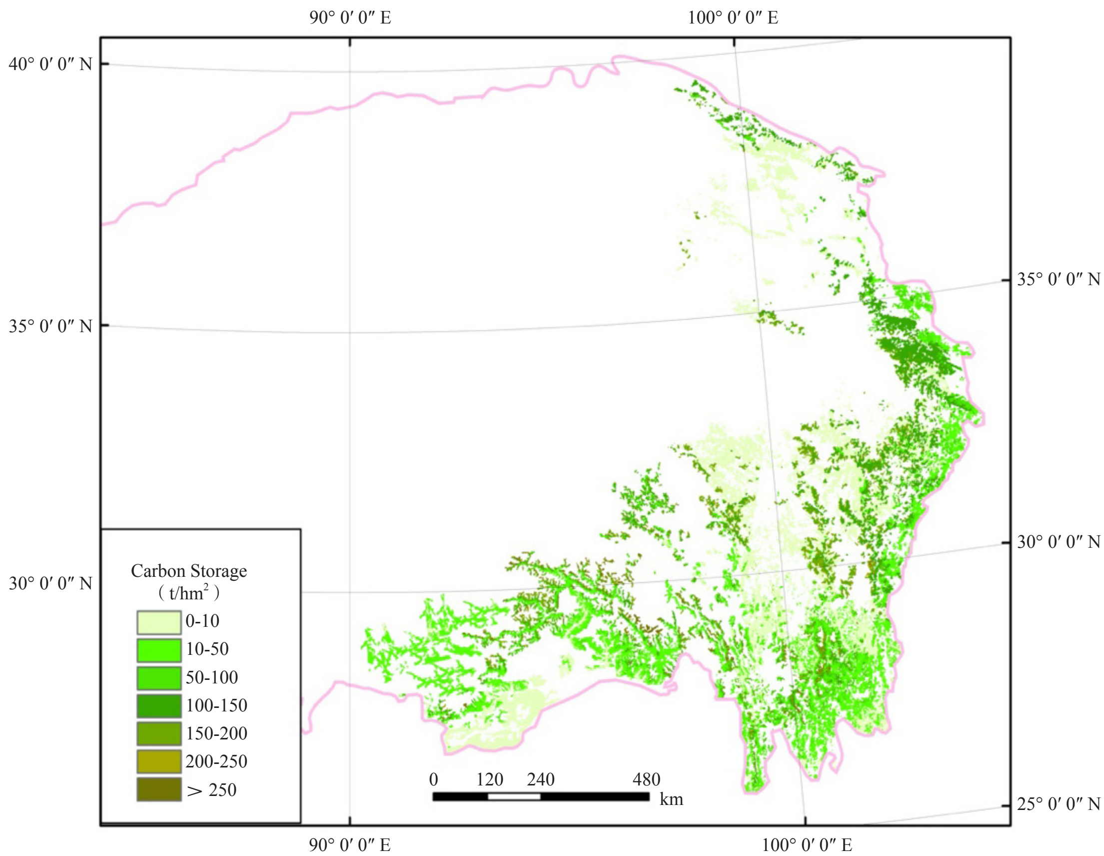

Fig. 2 Above–ground forest carbon storage map of the Tibetan Plateau

to provide dynamic information on the environmental changes at a range of spatial and temporal scales in a consistent manner. NDVI and EVI also show strong relationships with the carbon storage. While in many other studies, there was no significant relationship between carbon storage and NDVI. Weak relationship existed between the biomass and NDVI in northeastern Borneo [21-22]. NDVI was not a good indicator to the estimating of boreal forest biomass in the conifer-dominated boreal forest in Europe [4,22-24]. The design of EVI avoids the saturate of vegetation indexes based on the ration of different band reflectance, and EVI is a better indicator for the estimating of forest carbon storage. In this study, there was fairly high correlation between forest carbon storage and red band reflectance of MODIS data. EVI vegetation index showed strong correlation with forest carbon storage, while the NDVI vegetation index was not strongly correlated with the carbon storage observed from the analyses of the three sites and all the sites together. This suggested that the NDVI was unlikely to be a good indicator for forest carbon storage estimation, although it has remained one of the most widely used indexes. EVI index offered more information than NDVI on forest carbon storage in Tibetan Plateau. Therefore, the use of 250 m spatial resolution was a key challenge in this study because virtually all grid cells included multiple forest stands and mixtures of forest and shrubs. Mixed pixels in conjunction with the inherent variability of regression estimation equations can lead to over- and under-estimation of carbon storage [10,25-26].

Forest in Tibetan Plateau changed greatly along the elevation gradient and this was paralleled with the similar pattern of forest carbon storage along the elevation gradient. It was found in the study that forest carbon storage increased with increasing elevation when the elevation was lower than 3 500 m, while the opposite result occurred when the elevation was higher than 3 500 m. This result was consistent with other similar studies in the adjacent area of Minjiang River [27].

Dummy variables improved the precision of the forest carbon storage estimation

The determining coefficients (R^2) of the linear models were increased from 0.20, 0.24, 0.16 to 0.48, 0.35, 0.33 in Tibet, Yunnan and Sichuan respectively, after the inclusion of dummy variables in carbon models. If the linear regression models were replaced by logarithmic models, R^2 of Tibet, Yunnan and Sichuan were increased from 0.23, 0.30, 0.14 to 0.60, 0.65 and 0.59, respectively. Of the two dummy variables (aspect and vegetation), vegetation was proved to be more important. The accuracy of such a prediction would depend on how well the dummy variables could be set. A similar concept was also applicable in remote sensing for studying spectral response of biomass in vegetation types, which derived vegetation types from ETM+ data by the use of supervised classification [9,28]. Those variables should be carefully selected for different vegetation groups, which show a separate distinctive response between forest attributes and spectral information. In this work, dummy variables (aspect and vegetation types) were derived from the NFI data, while they extracted from the DEM data of 1:100,000 and vegetation map of 1:100,000 when mapping the forest carbon storage of the Tibetan Plateau. The different approaches of selecting dummy variables may reduce the accuracy of the models, but DEM and vegetation map with large scale should improve the precision. Meanwhile, increase in resolution in terms of the number of the vegetation types may also be attributable to increasing accuracy of the forest carbon storage estimation. Many studies [9,29-30] showed that the correlation increases in the exponential transformation of the variables in regression models. Rahman et al. [9] improved the precision of biomass estimation in Bangladesh by using the exponential transformation. It is similar with our study when the regression models were transformed to the logarithmic models, the coefficients have improved from 0.45, 0.35, 0.33 and 0.28 to 0.60, 0.63, 0.59 and 0.55 for Tibet, Yunnan, Sichuan and the whole Plateau, respectively.

Carbon storage of Tibetan Plateau was determined

The estimation results indicated that the mean above-ground forest carbon storage was about 19 000 kg/hm^2 in Tibetan Plateau, while the carbon storage of shrub was less than 10 000 kg/hm^2, which occurred in the Qaidam basin, the western Sichuan Plateau and the southernmost part of Tibet. The forest carbon storage in Tibetan Plateau varied with sub-areas. In the easternmost and southeasternmost of Tibetan Plateau, the carbon storage was mostly below 50 000 kg/hm^2. In the Minjiang Valley, the carbon storage was about between 100 000 kg/hm^2 and 150 000 kg/hm^2. In Tibet, the above-ground forest carbon storage was more than 250 000 kg/hm^2.

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