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Spatial heterogeneity and carbon contribution of aboveground biomass of moso bamboo by using geostatistical theory

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Abstract Moso bamboo extensively distributes in southeast and south Asia, and plays an important role in global carbon budget. However, its spatial distribution and heterogeneity are poorly understood. This research uses geostatistics theory to examine the spatial heterogeneity of aboveground biomass (AGB) of moso bamboo, and uses a point kriging interpolation method to estimate and map its spatial distribution. Results showed that (1) spatial heterogeneity and spatial pattern of moso bamboo's AGB can be revealed by an exponential semivariance model. The analysis of the model structure indicating that the AGB spatial heterogeneity is mainly composed of spatial autocorrelation components, and spatial autocorrelation range is from 360 to 41,220 m; (2) kriging standard deviation map showing the level of the model errors indicates that the AGB spatial distribution by point kriging interpolation method is reliable; (3) the average AGB of moso bamboo in Anji County is 44.228 Mg hm^{-2}, and carbon density is 20.297 Mg C hm^{-2}. The total AGB of moso bamboo accounts for 16.97% of the total forest-stand biomass in Zhejiang province. The total carbon storage of moso bamboo in China is 68.3993 Tg C, accounting for 1.6286% of the total forest carbon storage. This implies the important contribution of moso bamboo in regional or national carbon budget.

Keywords Geostatistics · Moso bamboo · Aboveground biomass · Spatial heterogeneity · Spatial distribution · Carbon contribution

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Introduction

Forests in the terrestrial ecosystem, accounting for 86% of total vegetation carbon pool, play an important role in carbon budget. Forest biomass has regarded as a key factor in carbon cycles of forest ecosystem, which affects carbon emission through forest harvest, burning, growth, and expansion. Research related to forest carbon and its function has obtained increasingly attention in the past decades (Woodwell et al. 1978; Liu et al. 2000; Fang and Chen 2001; Li et al. 2004; Zhou et al. 2006a). As a special forest type in subtropical regions of china, bamboo has huge biomass and carbon storage and its ecological function plays an important role in global carbon sink (Li et al. 2003; Li et al. 2004; Zhou and Jiang 2004). Among the bamboo species, moso bamboo forest accounts for the maximum proportion. For example, the total moso bamboo area in China is 3.37×10^6 hm^2, accounting for 70% of total bamboo forest in the world. In Zhejiang province of China, moso bamboo accounts for 9.8% of total forest area (Zhou et al. 2006b). It is imperative to understand the roles and impacts of forest biomass on carbon cycles from local to national and global levels (Lu 2006; Sun et al. 2006; Blackard et al. 2008) and to better understand the dynamic change of sources and sinks of atmospheric carbon.

Biomass, in general, includes the above ground biomass and below ground living mass. Because of the difficulty in collecting field data of belowground biomass, most previous researches relevant to biomass estimation focused on above ground biomass (AGB) (Lu 2006). Three major biomass estimation methods, including field measurement-based, GIS-based, and remote sensing-based techniques, were reviewed and some potential techniques to improve AGB estimation performance were discussed (Lu 2006). The advantages of remote sensing techniques over traditional methods make remote sensing-based methods become a major tool for AGB estimation at local and regional scales (Tiwari and Singh 1984; Tiwari 1994; Roy and Ravan 1996; Harrell et al. 1997; De Jong et al. 2003; Nelson et al. 2000; Lu 2005; Blackard et al. 2008). On the other hand, process-based ecosystem models or biogeochemical models are also used to estimate biomass, which remote sensing data provided important input parameters such as land use/cover distribution, leaf area index, and fraction absorbed photosynthetic active radiation (Qin et al. 2002).

An alternative for AGB estimation is to use geostatistics. It provides an effective way to facilitate quantification of the spatial variation and spatial interpolation (Wang 1999) and widely applies to analyze spatial heterogeneity of forest and soil distributions and to assess landscape pattern (Wang et al. 1998; Li et al. 2000; Wu 2000; Han and Wang 2002; David et al. 2004). Spatial heterogeneity is defined as the complexity and/or variability in spatial distribution of species and their properties (Wang 1999; Chen et al. 2000; Chen et al. 2002). Spatial heterogeneity is ubiquitous in nature across all scales (Wu et al. 2000), from basically ecological processes to environmental processes with continuous variation in the spatiotemporal scale. From this point of view, biomass should have spatial autocorrelation and spatial heterogeneity, too. However, quantitative retrieval of biomass based on the relationship of pixel values with field data in its spatial features has not obtained sufficient attention. The estimation methods of bamboo biomass are still based on traditional statistic analysis (Nie 1994; Isagi et al. 1997; Chen et al. 1998; Hong et al. 1998; Lin 2002; Zhou and Jiang 2004; Chen et al. 2008), and these methods cannot timely and accurately update its spatial distribution, and cannot effectively examine spatial autocorrelation and heterogeneity. It is an urgent task to map bamboo biomass distribution and to understand its spatial pattern and heterogeneity. Therefore, the object of this research is to examine moso bamboo's AGB and examine its spatial pattern and heterogeneity by using the geostatistical theory.

Method

Study area

Anji County, locating in the northwest of Zhejiang Province, China (119°14′–119°53′E and 30°23′–30°53′N) is selected as the study area (Fig. 1). There is approximately 6.7×10^4 hm^2 moso bamboo forest, accounting for 38% of total forestry are in this county. Because of its wide distribution and its importance in local economy, Anji County is called bamboo town of China. This county has an undulating topography, with elevation ranging from 500 to 1,000 m. It has a subtropical oceanic climate with yearly precipitation of 1,400 mm and mean temperature of 15.6°C.

Field data collection and biomass calculation

Field surveys were conducted during August 19 and September 2, 2008 for collection of moso bamboo biophysical properties. During the field work, moso bamboo's diameter at breast height (DBH) and age (i.e., du, 1 year bamboo or new birth bamboo is referred as 1 du, 2–3 years as 2 du, and 4–5 years as 3 du, and so on) were measured. A total of 55 sample plots were collected, and its spatial distribution was illustrated in Fig. 1. The size of each plot is 30 m by 30 m. Based on the field measurement, AGB (Kg) of

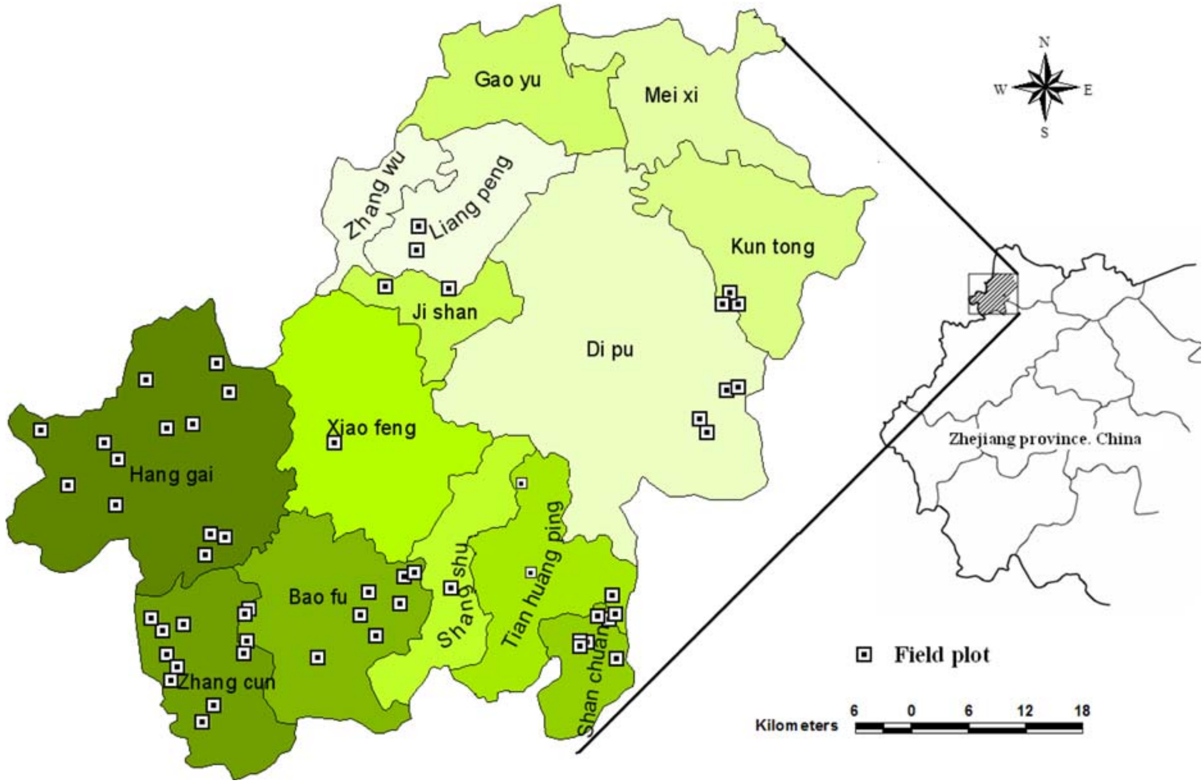

Fig. 1 Study area—Anji county, Zhejiang province, China, and spatial distribution of measured sample plots

individual moso bamboo is calculated using Eq. 1 (Zhou 2006):

$$M(D,A) = 747.787D^{2.771}\left(\frac{0.148A}{0.028+A}\right)^{5.555} + 3.772 \quad (1)$$

where M, D, and A represent AGB (dry weight in Kg), DBH (cm), and age (du). For each plot, the AGB is a sum of all individual moso bamboo AGB within the plot. Table 1 summarizes the statistical characteristics of the 55 plots.

Table 1 Statistical characteristics of selected plots

	Minimum	Maximum	Mean
Number of moso bamboo	153	500	292
DBH (cm)	2.5	16.2	9.3
du	1	5[a]	–
AGB (Kg)	1767.236	6889.767	3712.692

[a] The number of 4–5 du moso bamboo is very limited, with 1 for 5 du and 39 for 4 du

Geostatistical analysis

Geostatistics is based on the theory of a regionalized variable, distributing in space and showing spatial autocorrelation so that samples close together in space are more alike than those are apart far. Its central tool is the semivariance function (semivariogram), a measure of spatial variability of a regionalized variable, and provides the input parameters for the spatial interpolation of kriging (David et al. 2004; Zawadzki et al. 2005). The following formula is the most frequently used in the semivariance calculations:

$$\gamma(\hat{h}) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[Z(x_i+h) - Z(x_i)]^2 \quad (2)$$

where $\gamma(\hat{h})$ is an unbiased estimate value of $\gamma(h)$ (i.e., semivariance for interval distance class h); h is a lag vector; $N(h)$ is the number of pairs of sample points separated by the lag distance h; x_i is a data location; $Z(x_i)$ and $Z(x_i+h)$ represent the data value at location x_i and x_i+h, respectively.

A semivariogram is obtained by plotting $\gamma(h)$ against h (Ge et al. 1995; Villard and Maurer 1996). It may present many shapes and can be fitted by theoretic models such as spherical, exponential, linear, linear to sill, and Gaussian model. These models are also examined in this research. The model's parameters, including sill, range and nugget, are usually used to analyze the spatial structure of variable (Zawadzki et al. 2005). Sill is the sum of total variation explained by the spatial structure and nugget effect. Range is the distance at which the semivariogram reaches the sill, or at which two data points are uncorrelated. Nugget effect is the vertical discontinuity at the origin. The nugget effect is a combination of sampling error and short-scale variation that occurs at a scale smaller than the closest sample spacing.

The spatial distribution of the moso bamboo's AGB can be estimated through spatial interpolation based on the fitted model. Kriging is regarded as the best linear unbiased estimator, including point kriging, block kriging, and others. Its process, in general, includes four steps (Wang 1999; David et al. 2004):

(1) Semivariogram and its theoretical fitted model of research area;
(2) Covariances C_{ij} and C_{i0} in a moving window, where C_{ij} is the covariance among the known sampling points x_i and C_{i0} is the covariance between x_i and the unknown sampling point x_0, $i,\ j = 1,\ 2,\ \ldots,\ n$, the number n is selected according to the size of moving window and user definition;
(3) Weight coefficients λ_i of each sampling point within the moving window by kriging equation groups, and $\sum_{i=1}^{n} \lambda_i = 1$;
(4) For the unknown sampling point x_0, its value can be estimated by $\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i)$.

After the AGB distribution is mapped with kriging method, average AGB is calculated for the study area. Assuming this study area has good representative in moso bamboo in Zhejiang province and the other provinces in China, the average AGB value is used to calculate total AGB in Zhejiang and in China, in order to examine the moso bamboo's contribution in regional and national AGB and carbon stock.

Normality test

Application of semivariogram requires meet the intrinsic hypothesis for a regionalized variable (Zawadzki et al. 2005), and normal distribution of the raw data (David et al. 2004; Sun et al. 2006). The Kolmogorov–Smirnov method has been used to analyze the normality of biomass. Semivariance and point kriging interpolation with 16 neighbors are conducted with GS+, and spatial distribution maps of moso bamboo's AGB and kriging standard deviation (KSD) are produced with GIS software.

Results

The normality test indicated that the raw data has normal distribution, thus, the geostatistic method can be used to analyze spatial heterogeneity and point kriging interpolation method can be used to map spatial distribution of moso bamboo's AGB. Figure 2 illustrates the AGB histogram and its cumulative frequency distribution. The histogram of AGB shows a light positive skewness (skewness is 0.6) (Fig. 2a),

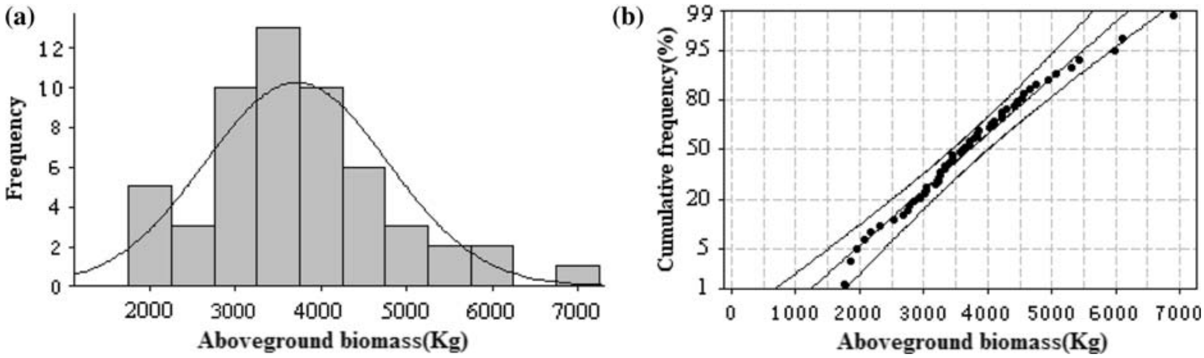

Fig. 2 Histogram of aboveground biomass and its cumulative frequency distribution

but normality test based on Kolmogorov–Smirnov method shows normal distribution in 95% confidence interval (K_S value > 0.05) (Fig. 2b).

A comparative analysis of selected models shows that the exponential model has the best performance, followed by the linear model. Other three models are significantly poor comparing with exponential model (see Table 2). The exponential mode can be expressed as Eq. 3 (Wang 1999)

$$\gamma(h) = \begin{cases} 0 & h = 0 \\ C_0 + C\left(1 - e^{-\frac{h}{a}}\right) & 0 < h < 3a \end{cases} \quad (3)$$

where $h = 3a$, then $e^{-\frac{h}{a}} = 0.95 \approx 1$, thus, the total variance becomes $\gamma(h) \approx C_0 + C$ the range of exponential model becomes $3a$. Since the exponential model has the best performance, it is used in this research to fit the semivariogram. Figure 3 illustrates the fitted result.

Spatial heterogeneity is composed of nugget variance C_0 (random components) and structure variance C (autocorrelation components). The $C/(C + C_0)$ value of 0.587 (Table 2) shows that spatial heterogeneity of moso bamboo's AGB is mainly composed of autocorrelation component with moderate level. The range of 41,220 m implies that the length of the spatial autocorrelation of moso bamboo's AGB is increased from the minimum sampling space of 360 to 41,220 m. Outside of this distance range, the spatial autocorrelation is disappeared.

The ratio of nugget variance to total variance is 0.413, implying that 41.3% of spatial heterogeneity comes from random factors. In comparison with the proportion of structure variance, nugget variance is not small and thus can not be neglected, implying that

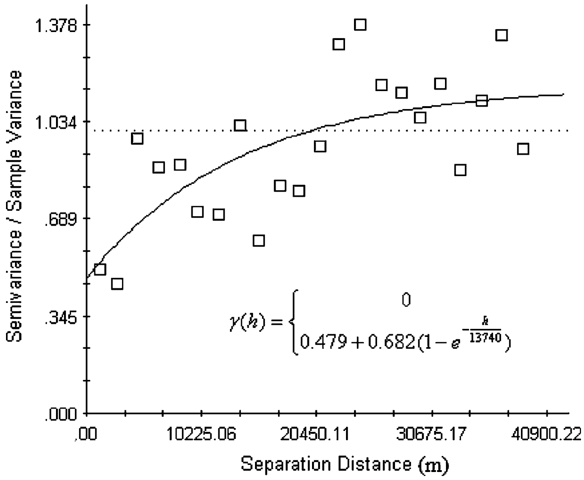

Fig. 3 Isotropic variogram model

random factors such as management and fertilization may affect moso bamboo's AGB and its spatial distribution.

The range of spatial autocorrelation of moso bamboo's AGB is greater than the closest sampling interval implying that the sampling density is appropriation for this study and it is expected that a good spatial structure will be shown on the kriging interpolation map (David et al. 2004).

Cross validation was used to evaluate the effectiveness of the exponential semivariance model (Fig. 4). The result shows that the actual AGB had a linear relationship with estimated AGB values despite larger errors in some sampling sites. Therefore, parameters of the exponential model can be used as input to estimate the spatial distribution of moso bamboo AGB by kriging interpolation. Figure 5 illustrates spatial distribution pattern of moso bamboo's AGB with the cell

Table 2 Isotropic semivariogram models and corresponding parameters

Model	Nugget C_0	Sill $C_0 + C$	Range (m) a or 3a[a]	Proportion of spatial $C/(C_0 + C)$	R^2	RSS
Spherical	0.002	0.990	6000.00	0.998	0.289	0.983
Exponential	*0.479*	*1.161*	*41220.00*	*0.587*	*0.468**	*0.723*
Linear	0.646	1.221	38805.92	0.471	0.432	0.773
Linear to sill	0.022	0.990	4680.00	0.978	0.299	0.976
Gaussian	0.291	0.995	19260.00	0.708	0.307	0.948

C_0 and C represent nugget variance and structure variance, respectively. R^2 is coefficient of determination. RSS is reduced sums of squares, $\mathrm{RSS} = \sum_{i=1}^{N(h)} (s_i - \hat{s}_i)^2$, where s_i is actual semivariance, $\hat{s}_i$ is theoretical semivariance

[a] The range of exponential model is 3a

*Significant correlativity in 0.01 level

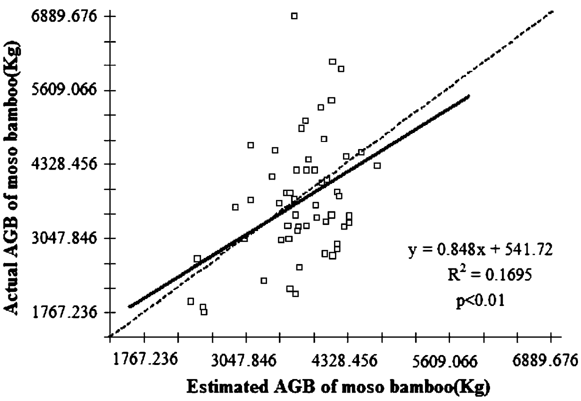

Fig. 4 Result of cross validation using the exponential variogram model

size of 30 m × 30 m, the same as the plot size. As shown in Fig. 5, moso bamboo's AGB value is highest in the southwest, followed in southeast and east parts of Anji county such as Shanchuan, Dipu, Tianhuangping, and lowest in the west of Anji County.

The average AGB of moso bamboo in Anji County is 44.228 Mg hm^{-2} based on the statistical analysis of the estimation as shown in Fig. 5. Assuming that the average AGB developed from Anji county be good representative in Zhejiang province, we can approximately infer that the total AGB of moso bamoo in Zhejiang province is 2.565×10^7 Mg according to the total moso bamboo's area of 5.8×10^4 hm^2. This accounts for 16.97% of forest AGB (1.511×10^8 Mg) in Zhejiang province (Zhang and Wang 2008), indicating its important role and large contribution in carbon budget in the regional ecosystem.

Previous research has indicated that the conversion rate from biomass to carbon for moso bamboo is 0.504 (Zhou and Jiang 2004), thus, based on this conversion rate, the carbon density of moso bamboo in Anji county is 20.297 Mg C hm^{-2}. If this carbon

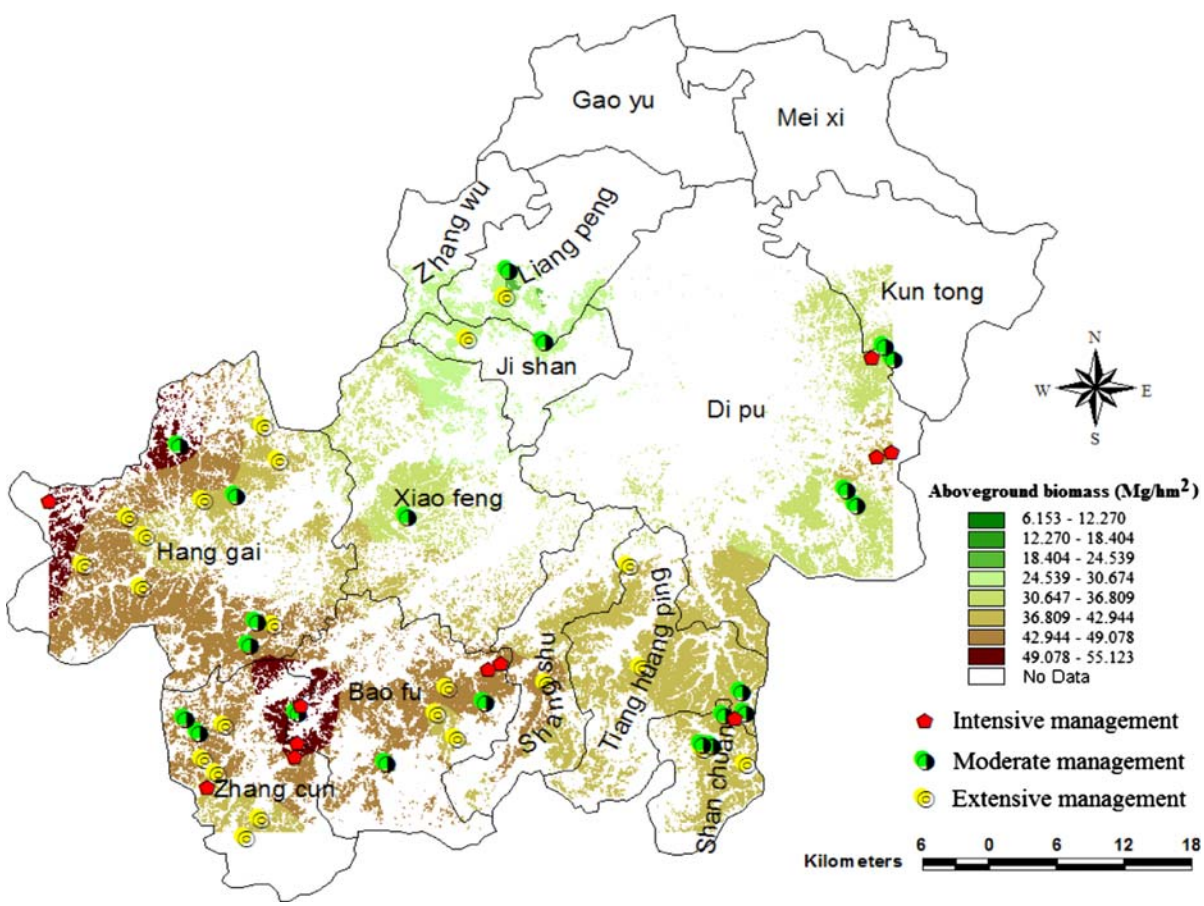

Fig. 5 Spatial distribution of aboveground biomass of moso bamboo by point kriging interpolation

density in Anji county is used to extrapolate to the whole country, the total carbon storage of moso bamboo in China is 68.399 Tg C, accounting for 1.627% of the total carbon of Chinese forest (total forest carbon in China is 4.2 Pg C) (Liu et al. 2000). Moso bamboo's area accounts for 1.926% of the total forest area in China, the average carbon contribution rate is proximately 0.85 (i.e., the ratio of 1.629 to 1.926). Therefore, moso bamboo is also a huge carbon contribution at national level, although moso bamboo is mainly distributed in south and southeast China such as Zhejiang, Jiangxi, and Fujian provinces.

Discussion

Spatial autocorrelation has a determinative influence on the spatial heterogeneity and spatial distribution pattern of moso bamboo's AGB. However, random factors cannot be neglected because the nugget effect accounts for 41.3% of total variance. Taking management levels as example, in the measured 55 plots, 11 plots are in intensive management level, 21 plots in moderate management, and 23 in extensive management level. The average AGB is 4422.290 Kg for intensive management, 3708.057 Kg for moderate management, and 3377.548 Kg for extensive management. One-way analysis of variance showed that *P* value is 0.026, less than 0.05. The small *P* value indicates that differences between the management levels are highly significant in 95% confidence level. However, as shown in Fig. 5, the AGB variation for some plots is not consistent with the management level. This implies that in addition to the management levels, some factors such as soil, topography and climate, may influence the AGB growth, thus affect AGB estimation performance.

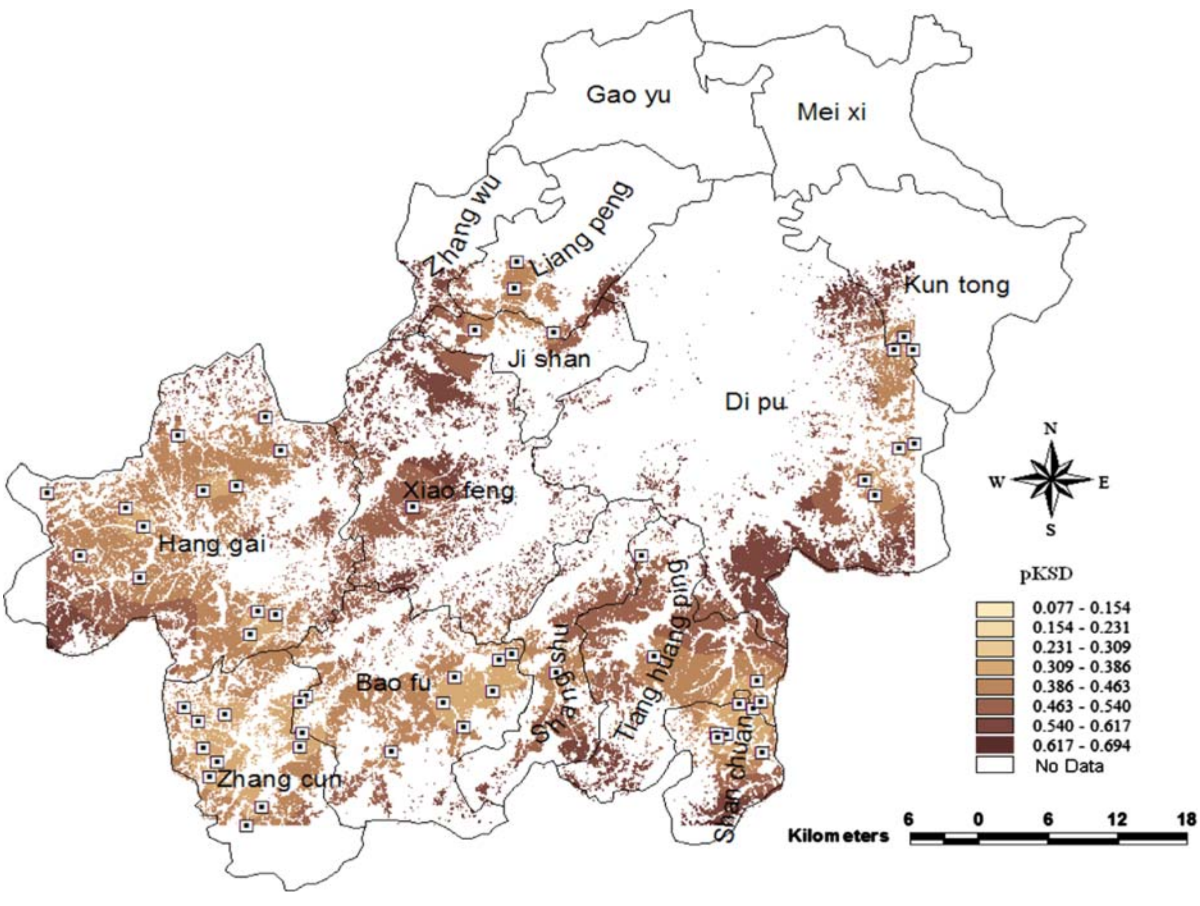

Fig. 6 Point kriging standard deviation of aboveground biomass of moso bamboo

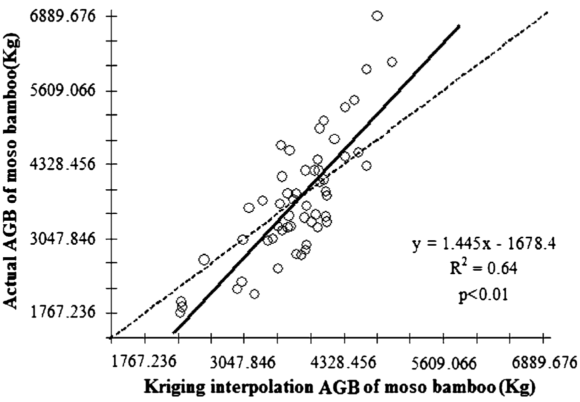

Fig. 7 Relationship between the actual AGB of moso bamboo and predicted by point kriging interpolation

Kriging standard deviation is the square root of kriging variance, reflecting the authenticity of spatial distribution for regionalized variable. The KSD map for moso bamboo's AGB is shown in Fig. 6. The KSD values ranging from 0.077 to 0.649 imply that the total error of spatial estimation is small. The maximum KSD value is 0.649 and minimum is 0.077 for the 55 sampling sites. Smaller KSD values may be reflected higher accuracy in the kriging interpolation method. The KSD values around the sampling sites are generally smaller than those far away from the sampling sites, and are high for missing samples. Relative high KSD values in the missing sample sites result in overestimation or underestimation of moso bamboo's AGB. The relationship between actual AGB of moso bamboo and predicted AGB by point kriging interpolation (Fig. 7), shows a good linear correlation, indicating that the results predicted by kriging interpolations are reliable. The kriging interpolation method provides an alternative for the estimation of moso bamboo's AGB. In the future, more research should focus on the combination of geostatistics and remote sensing to improve AGB estimation performance.

Conclusions

This research employed geostatistical theory to examine the spatial patterns and heterogeneity of moso bamboo's AGB estimate. A comparable analysis of different models, such as spherical, exponential, linear, linear to sill, and Gaussian model, indicates that the exponential semivariance model has the best performance for AGB estimation and for examining its spatial heterogeneity. Kriging interpolation based on geostatistical theory provides a promising method for estimating AGB. This research indicates that moso bamboo has an important contribution in regional and national carbon budget in China.

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