Improving prediction of forest aboveground biomass maps: A combined approach of machine learning with spatial statistical model

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**Abstract：**Aboveground biomass (AGB) estimates in plot level is a bridge that connects single tree AGB measurements to AGB estimates at a regional scale. Accurate AGB mapping at the plot scale provides a basis for future upscaling to the regional scale. However, the uncertainty and error propagation inherent in different prediction models make this process challenging. Allometric models are most commonly used in building plot-level AGB models, but they cannot fully capture the complex and spatially heterogeneous landscapes where multiple environmental covariates (such as longitude, latitude, and forest structure) affect the spatial distribution of AGB. To address this challenge, we tested in this study, an approach that combines machine learning with spatial statistics for constructing a more accurate AGB plot-level model. The study was conducted in a *Eucalyptus* plantation in Nanjing, China. We develop, evaluate, and compare three different machine learning models (support vector machine (SVM), random forest (RF), and the radial basis function-artificial neural network (RBF-ANN)), one spatial statistics model (P-BSHADE), and three their combinations (SVM & P-BSHADE, RF & P-BSHADE, ANN & P-BSHADE), based on data from 30 sample plots and their corresponding environmental covariates. We found that the performance indices (RMSE, MAE, and MRE) of all combined models were substantially smaller than those of any individual models, with the RF & P-BSHADE combination method having the least values. Thus our results clearly demonstrate that combined models, especially the RF & P-BSHADE, can improve the accuracy of AGB plot-level models and reduce uncertainty in plot-level or even large forested landscape AGB estimates. The research results would be important by virtue of reducing the uncertainty in regional carbon balance estimates.

**Keywords:** Aboveground biomass, plot-level model, Machine learning, Spatial statistical model

# 1 Introduction

Accurate maps of aboveground biomass (AGB) provide a solid foundation for sound decision-making in sustainable forest management scenarios, such as reducing deforestation, forest degradation, and greenhouse-gas emissions (Bustamante et al., 2016; Houghton et al., 2009; Mendoza-Ponce and Galicia, 2010). However, AGB models have proven challenging to scale up, especially for sub-tropical forests. This is largely due to (1) inadequate sampling data used to construct prediction models and (2) model-dependent uncertainty, including unreasonable model parameter assumptions and improper model structure (Chen et al., 2015; Gao et al., 2016; McRoberts et al., 2016). For example, an estimated 18-103% of the uncertainty in AGB mapping can be attributed to model-dependent uncertainty, such as allometric model selection error (Djomo and Chimi, 2017; Malhi et al., 2004). The allometric model has produced fruitful results in terms of forest AGB modeling (Conti et al., 2019; Huang et al., 2019). However, the selection error in this model creates mapping uncertainties at the plot level. For example, different allometric equations were responsible for more than 40% of uncertainty (Djomo et al., 2016; Fayolle et al., 2013; Chave et al., 2014) and simple or complex forms of the allometric model accounted for 20-60% of uncertainty (Picard et al., 2015).

Many different prediction models have been applied to constructing accurate AGB maps, including linear models (Andersen et al., 2014; Morel et al., 2012), machine learning models (Chen, 2015; Gleason and Im, 2012), and spatial statistical models (Benitez et al., 2016; Propastin, 2012;Van der Laan et al., 2014). With the development of computer-science techniques and advances in nonlinear biomass modeling, machine learning methods have become prevalent. Traditional parametric methods, which summarize data with a fixed number of parameters based on sample size (e.g., logistic regression and perceptron) (Gao and Hailu, 2012), have difficulty characterizing nonlinear relationships between AGB and multiple environmental covariates. By comparison, nonparametric machine learning algorithms, in which the number of parameters is dependent of the number of training examples (e.g., K-nearest neighbour, support vector machine, and random forest), are advantageous because they are more elastic and they do not restrict variable types, the distributions of predictor variables, or the relationship between response and predictor variables (Lu et al., 2007). In addition, nonparametric machine learning algorithms may offer higher prediction accuracy (Frey et al., 2019;Gleason and Im, 2012).

Another frequently-used group of models used to estimate the relationships between forest AGB and multiple environmental covariates is based on spatial statistical approaches, including geographically weighted regression and Kriging (Du et al., 2010; Van der Laan et al., 2014; Viana et al., 2012). Spatial statistical methods are based on analyses of attribute information, such as spatial location (Schabenberger and Gotway, 2005). Compared with traditional statistical methods, spatial methods integrate spatial factors that affect model responses, thus removing the constraints of traditional statistical methods that assume sample independence (Rangel and Bini, 2010) and improving our understanding of spatial autocorrelation and heterogeneity (He et al., 2011; Rosenberg and Anderson, 2011).

Although many studies have integrated ground-based plot data, multi-source remote sensing data (e.g., LiDAR and Landsat), and machine learning or spatial statistical methods, the prediction accuracy of current AGB spatial mapping still suffers from uncertainty (McRoberts et al., 2018; Paul et al., 2016; Saatchi et al., 2011; Zheng et al., 2004; Jachowski et al., 2013; Zhang et al., 2014). First, existing studies that used machine learning methods have not considered the spatial heterogeneity of multiple environmental covariates (such as longitude, latitude, and forest structure), which affects the spatial distribution of AGB (Babcock et al., 2015; Fassnacht et al., 2014). Second, the assumptions of the spatial statistical method (e.g., spatial autocorrelation and spatial stratified heterogeneity) may not always apply to forest AGB.

AGB estimates in plot level is a bridge that connects single tree AGB measurements to AGB estimates at a regional scale. Accurate AGB mapping at the plot scale provides a basis for future upscaling to the regional scale. However, the uncertainty and error propagation inherent in different prediction models make this process challenging. Allometric models are most commonly used in construction of plot-level AGB models, but they cannot fully capture the complex and spatially heterogeneous landscapes where multiple environmental covariates (such as longitude, latitude, and forest structure) affect the spatial distribution of AGB. The objective of this study was to develop and evaluate a combined machine learning and spatial statistical method for improving the prediction accuracy of AGB spatial mapping at the plot level using ground-based samples. Our proposed method integrates the nonlinear mapping capabilities of machine learning algorithms (i.e., artificial neural network (ANN), support vector machine (SVM), and random forest (RF)) with the spatial autocorrelation and stratified heterogeneous advantages of a spatial statistical model (i.e., the point estimation model of biased sentinel hospitals-based area disease estimation, P-BSHADE) (Xu et al., 2013). Our aim is to answer two specific questions: (1) What are the differences in prediction accuracy of AGB maps based on different methods? (2) Can the integration of spatial statistical and machine learning methods improve the accuracy of AGB models at the plot-level? We explore these two questions using an empirical case for prediction of an AGB map at a *Eucalyptus* plantation in Nanjing County, China.

# 2 Materials and Methods

## 2.1 Site description

Nanjing County (117°00'–117°36'E, 24°26'–25°00'N, Figure 1b) is located in the upstream region of the Jiulong River in Fujian Province, China. Seventy-four percent (145,009 ha) of the county comprises forests and 79,346 ha are plantations. The region is affected by the South Asian tropical monsoon climate. In 2014, the average annual temperature in Nanjing County was 21.1°C, with an annual precipitation of 1,700 mm and 340 frost-free days. Red soil is the major soil type.

The study area has a complex topography with significantly varying elevation (0–1,566 m). Forest composition, structure, and biomass are spatiotemporally heterogeneous. The main tree species are *Eucalyptus grandis x urophylla*, *Pinus massoniana*, and *Cunninghamia lanceolata*. Recently, the area of *Eucalyptus* plantations has increased rapidly, reaching 13,338 ha and increasing by 10,862 ha in one decade.

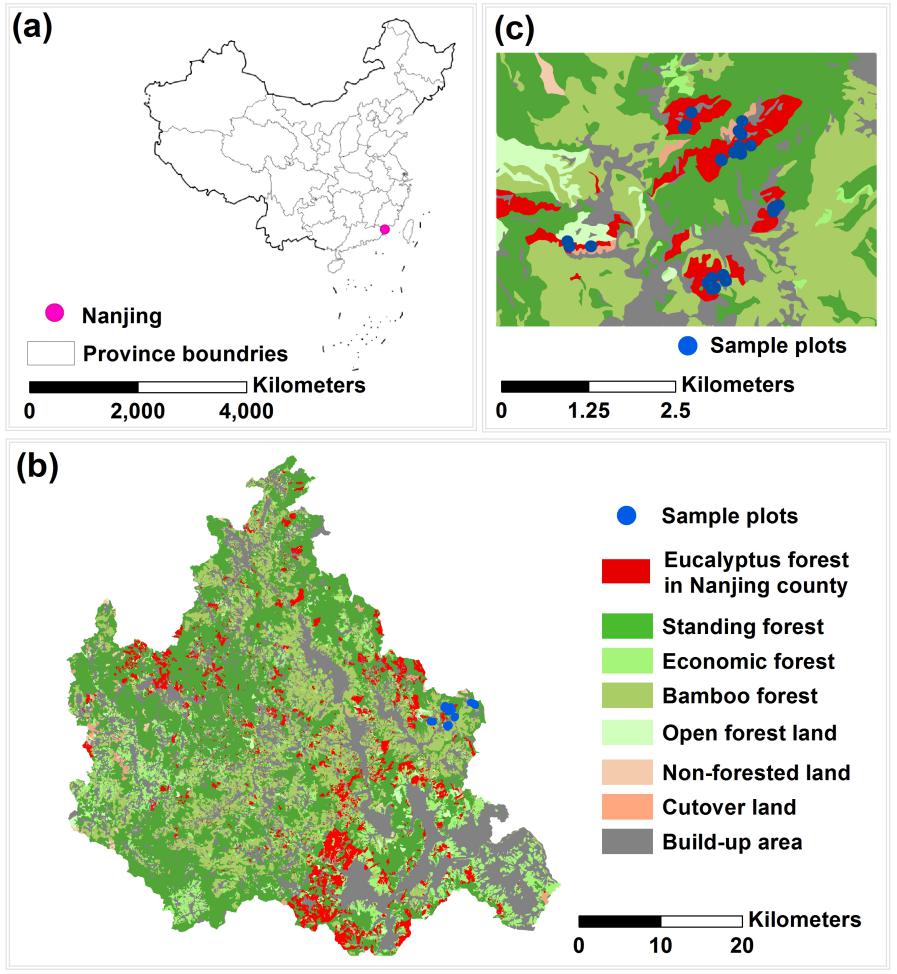


Figure 1. The study area is a typical example of a non-representative sample problem. (a) Geographical location of the study area. (b) Spatial distributions of *Eucalyptus* plantations (red) and other major forests. (c) Spatial distributions of the 30 sample plots used in this study (blue).

## 2.2 Data collection

### 2.2.1 Non-destructive sampling in sample plots

A total of 30 fixed sample plots were selected in the Yongfeng forest farm in 2012. The plots were located in the eastern section of the study area (Figure 1). The 30 sampling plots included ten *Eucalyptus* plantation age groups. In each plot (0.04 ha, 20 x 20 m), we measured the diameter at breast height (DBH) of all living stems ≥ 8 cm and tree height (H). In addition, we measured mean plot-level variables, including stand age, density, longitude, latitude, and altitude.

### 2.2.2 Destructive sampling in sample plots: tree harvest

Trees were harvested from standard wood in the 30 fixed sample plots. Three trees with a DBH close to that of the mean DBH of trees in each plot were cut down, for a total of 90 trees harvested from the 30 plots. We then weighed the H and DBH of each harvested tree, as well as the biomass of each organ (foliage, stems, and branches) to obtain the AGB of each harvested tree. Table B.2 in section S2 of the Supplementary Material presents the data for the 90 harvest trees. Details on selection of the standard wood and the cutting process are provided in section S1 of the Supplementary Material.

## 2.3 Construction of tree-level allometric models

All analyses were based on the underlying assumption that the relationship between the response and predictor variables in the sample data used to construct the models was the same as the relationship in the entire population. We divided the 90 harvested trees into three age groups (1-2 yr, 3-5 yr, 6-10 yr) for the tree-level allometric models. The allometric models were then applied to each tree in each sample plot according to their age, DBH, and H, thereby producing a true AGB for each sample plot.

## 2.4 Construction of plot-level models

Processing based on model screening was applied to alleviate uncertainty caused by model-dependence and consisted of the following four steps (Figure 2).

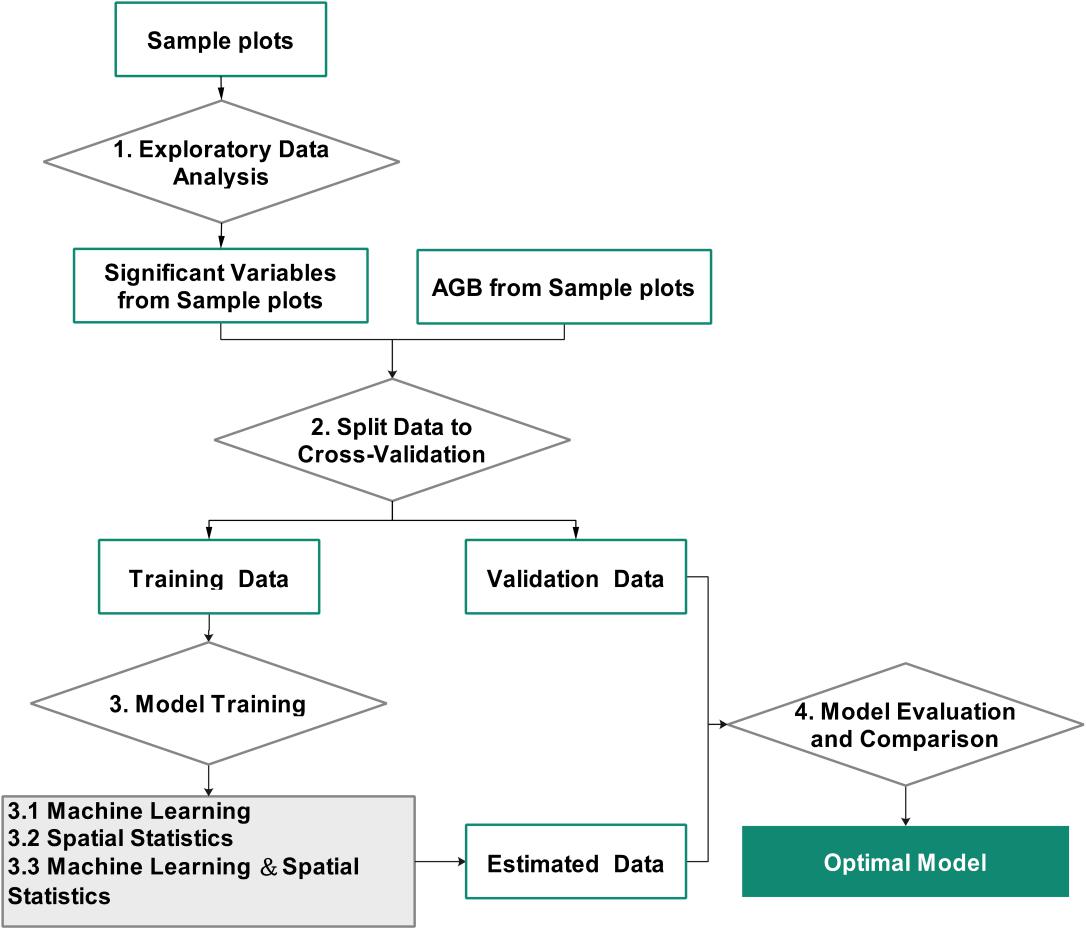


Figure 2. Workflow for screening an optimal model.

### 2.4.1 Exploratory data analysis

We first identified predictor variables to create the plot-level model. Based on our previous work (Ren et al., 2017), we selected plot-level environmental covariates including longitude and altitude, and forest attribute variables including forest distribution density, DBH, H, tree stem volume, and forest age. Pearson’s correlation coefficient was used to investigate the correlation between these variables and the true AGB of sample plots.

We then analyzed the spatial autocorrelation and spatial heterogeneity of AGB data from the selected sample plots. We used Moran’s *I* (Cliff and Ord, 1981), a commonly used global spatial autocorrelation index, to evaluate spatial autocorrelation among the true AGBs of sample plots. The spatial stratified heterogeneity (referring to the characteristic that the within-strata variance less than the between-strata variance, it is ubiquitous in ecological phenomena, such as AGB) of the true AGB of sample plots was evaluated using a q-statistic value by the GeogDetector model, which is a software tool based on spatial variation analysis of the geographical strata of variables, as proposed by Wang et al. (2016). First, we used the K-means algorithm to obtain the strata of true AGB for preprocessing of GeogDetector. Then, we regarded true AGB as Y, regarded the strata of true AGB as X and put them into the GeogDetector model to obtain the q-statistics value (Wang et al., 2010;Wang et al., 2016).

### 2.4.2 Split datasets

We used the leave-one-out cross-validation method to split the 30 sample plots into 30 sets with each set containing two groups of data: (1) validation data (the AGB of one plot) and (2) training data (the AGBs and predictor variables of the other 29 plots), see Table B.3. The leave-one-out cross-validation method assumes that in a dataset containing n samples, each sample is taken as a test sample and the other n-1 samples are taken as training samples. Thus, with n iterations we can obtain n training datasets and n validation datasets.

### 2.4.3 Model training

Seven models including three machine learning models (a, b, and c in Figure 3), one spatial statistical model (d in Figure 3), and three combined machine learning and spatial statistical models (a+d, b+d, and c+d in Figure 3) were developed and trained to predict the AGB of sample plots. The three machine learning models were SVM (a), radial basis function-ANN (RBF-ANN, b), and RF (c). The spatial statistical model (P-BSHADE) required AGB-related variables (reference series). In this case study, we designated the reference plot AGB data as the variables. The allometric model (Qiu et al., 2018) was applied at a local scale to obtain the AGB of each tree in each sample plot. Then, the reference plot AGB data was equal to the sum of AGB of each tree. By this method, P-BSHADE comprised “d” in Figure 3. For the combined machine learning and spatial statistical models, the reference plot AGB data in P-BSHADE was obtained from the results of “a,” “b,” or “c.” The three combined models are represented as RBF-ANN & P-BSHADE (a+d), RF & P-BSHADE (b+d), and SVM & P-BSHADE (c+d). Each model was trained based on 30 datasets, yielding a total of 30 predicted AGB datasets for 30 sample plots (see Table B.3, section S2 in the Supplementary Material).

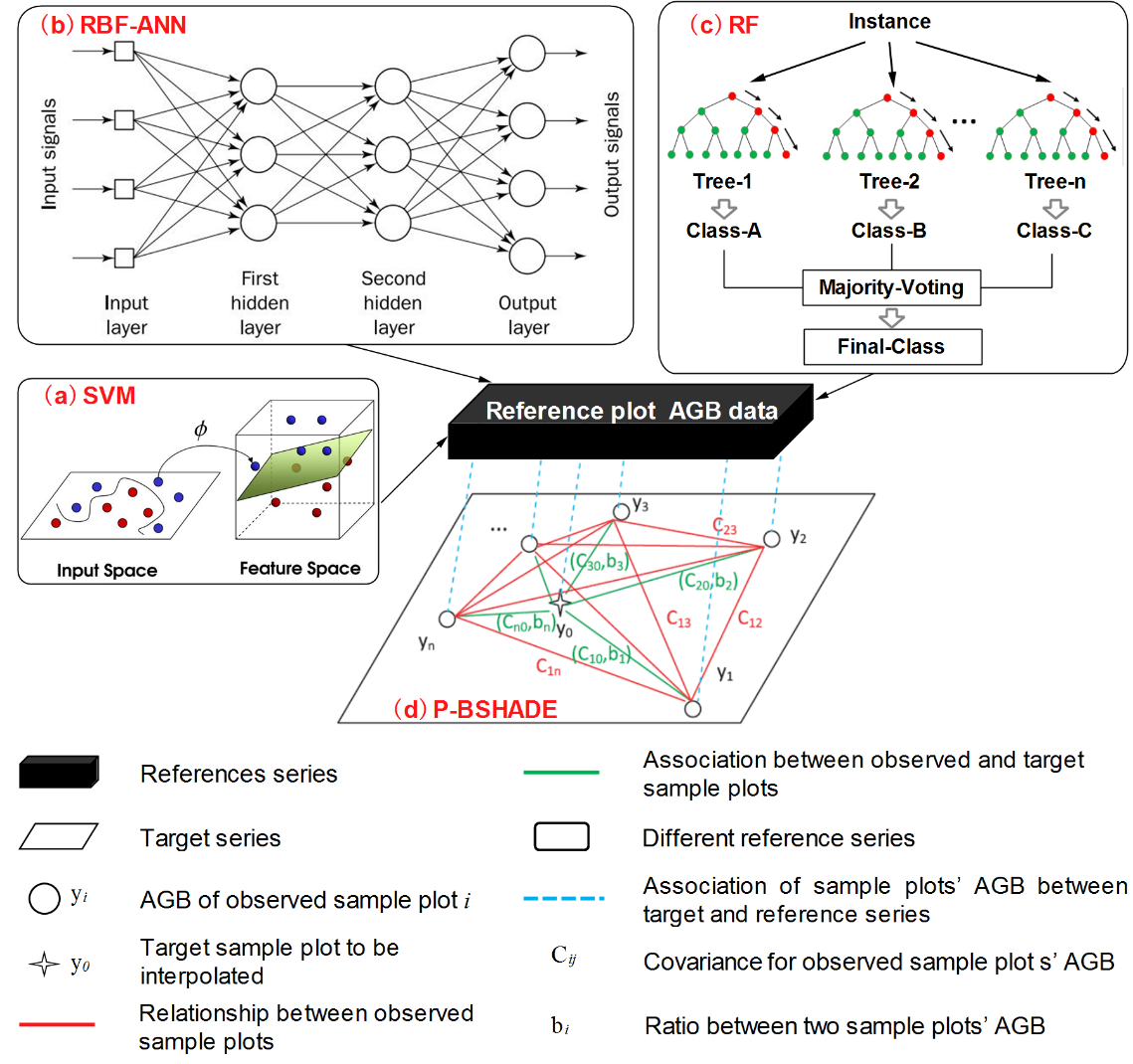


Figure 3. Estimation framework for the machine learning models (a, b, c), P-BSHADE (d), and three combined machine learning and P-BSHADE models (a+d, b+d, c+d).

(1) Machine learning

The SVM is a categorized algorithm that improves the generalized machine learning ability by minimizing structural risks in order to minimize the empirical risk and confidence intervals (Drucker et al., 1996). The RBF-ANN provides the best approximation for nonlinear functions and optimal global performance (Elanayar and Shin, 1994). The RF is a relatively new machine learning technique that combines self-learning technologies (Breiman, 2001).

The schematic function of machine learning is as follows:

(1)

where is the AGB of the -th sample plot predicted by a machine learning model; is a machine learning model represented by a function of ; and , , , and are the central longitude, the mean DBH, the mean H, and the forest age of the -th sample plot, respectively. A specific description of the three machine learning models is given in S1 of the Supplementary Material.

(2) Spatial statistical model: P-BSHADE

The P-BSHADE model is an interpolation approach based on the assumption of spatial autocorrelation and spatial heterogeneity. It is markedly different from the Kriging and Inverse Distance Weighting (IDW) algorithms, because the latter two algorithms only regard spatial autocorrelation as an assumption condition. Besides, P-BSHADE regards the strongly correlated sample plots as the neighboring plots. The core of the model is minimizing the variances of predicted error and unbiased estimation. The model is also a data fusion approach which could combine the observed samples with and reference series (related variable). In brief, the P-BSHADE includes two steps. First, obtain reference AGB of all sample plots according to the allometric model. Second, use the reference AGB of target sample plot and true of other sample plots to obtain the weights relationship between target sample plot and other sample plots, and put true AGB of other sample plots and weights into fomula (2) to obtain the predicted AGB of the sample plots. The specific mathematical formula for the P-BSHADE model is as follows (Hu et al., 2013; Xu et al., 2013):

(2)

where is the estimated AGB of the -th sample plot by the P-BSHADE model is the true AGB of the -th sample plot is the weight (contribution) of the true AGB of the -th sample plot to the AGB to be interpolated of -th sample plot (when ; when ); is calculated by the true AGB of the -th sample plot and the allometric model estimation of AGB in the -th sample plot. A detailed description of the P-BSHADE model and the corresponding algorithms are presented in S1 of the Supplementary Material.

(3) Combination of machine learning and spatial statistical models

P-BSHADE was separately integrated with the three machine learning methods (SVM, RBF-ANN, and RF) to form three combined models (SVM & P-BSHADE, RBF-ANN & P-BSHADE, and RF & P-BSHADE). The reference AGBs of the 30 sample plots were replaced by the estimates produced by the machine learning models. Each combined model was represented as follows:

(3)

where is the estimated AGB of the -th sample plot using the combined model is the true AGB of the -th sample plot ; is the weight (contribution) of the *i*th true AGB of the sample plot to -th sample plot AGB to be interpolated (when ; when ); is calculated using the true AGB of the -th sample plot and the machine learning estimation of the AGB of the -th sample plot. A detailed description of the combined models and the algorithm formulas are presented in S1 of the Supplementary Material.

### 2.4.4 Model evaluation and comparison

To evaluate the AGB prediction performance of the seven models (SVM, RBF-ANN, RF, P-BSHADE, SVM & P-BSHADE, RBF-ANN & P-BSHADE, and RF & P-BSHADE), the AGB results were compared to the reference AGBs of the sample plot groups (AGB group M in Table B.3). We calculated four performance indicators as shown in Eq. (4) – (7): mean absolute error (MAE), mean relative error (MRE), root mean square error (RMSE), and normalized root mean square error (nRMSE).

(4)

(5)

(6)

(7)

where is the predictive value of the different models, is the AGB of the th sample plot, and is the number of training datasets.

We then used the calculated MAE, MRE, RMSE, and nRMSE to identify the optimal model.

### 2.4.5 Robustness of combined models

To evaluate the robustness of the combined machine learning and spatial statistical models, we selected 22 independent sample plots (details in S1 and S3 of the Supplementary Material) and collected non-destructive measurements for each tree in July 2019. We repeated the workflow used for the plot-level model construction and evaluated the models. We then evaluated whether the combined models produced higher accuracy than the plot-level models using the accuracy assessment indexes (MAE, MRE, RMSE, and nRMSE).

## 2.5 Model application and upscaling

We treated the irregular polygon forest patches (2980 patches) of the Forest Management and Planning Inventory (FMPI) as a homogenous sample plot and used the optimal plot-level model to upscale forest AGB (see S1 of the Supplementary Material). We then compared the upscaled forest AGB with the AGB map obtained by the allometric model and calculated the MRE of AGB (see A.15 in S1 of the Supplementary Material) between the two methods.

# 3 Results

## 3.1 True AGB of sample plots

The true AGB for the 30 sample plots ranged from 1.02-135.79 Mg·ha−1, with an average value of 47.34 Mg·ha−1 and a standard deviation of 34.46 Mg·ha−1. The coefficients of variation of the AGB for all the sample plots and for the 10 age categories were 0.73 and 0.07-0.37, respectively.

## 3.2 Exploratory data analysis

### 3.2.1 Selection of variables

Figure 4 shows the correlation-coefficient matrix of variables. The following variables strongly correlated with AGB: longitude , DBH , H , trunk volume , and forest age . Timber volume and stem volume were both estimated based on H and DBH, so they were excluded as covariates for the AGB plot-level models. To summarize, four variables (longitude, DBH, H, and forest age) were selected as covariates for the AGB plot-level models of the *Eucalyptus* forest in the Nanjing region. Table B.4 in section S2 of the Supplementary Material lists the statistical descriptions of these covariates and the AGB statistics for the 30 sample plots.

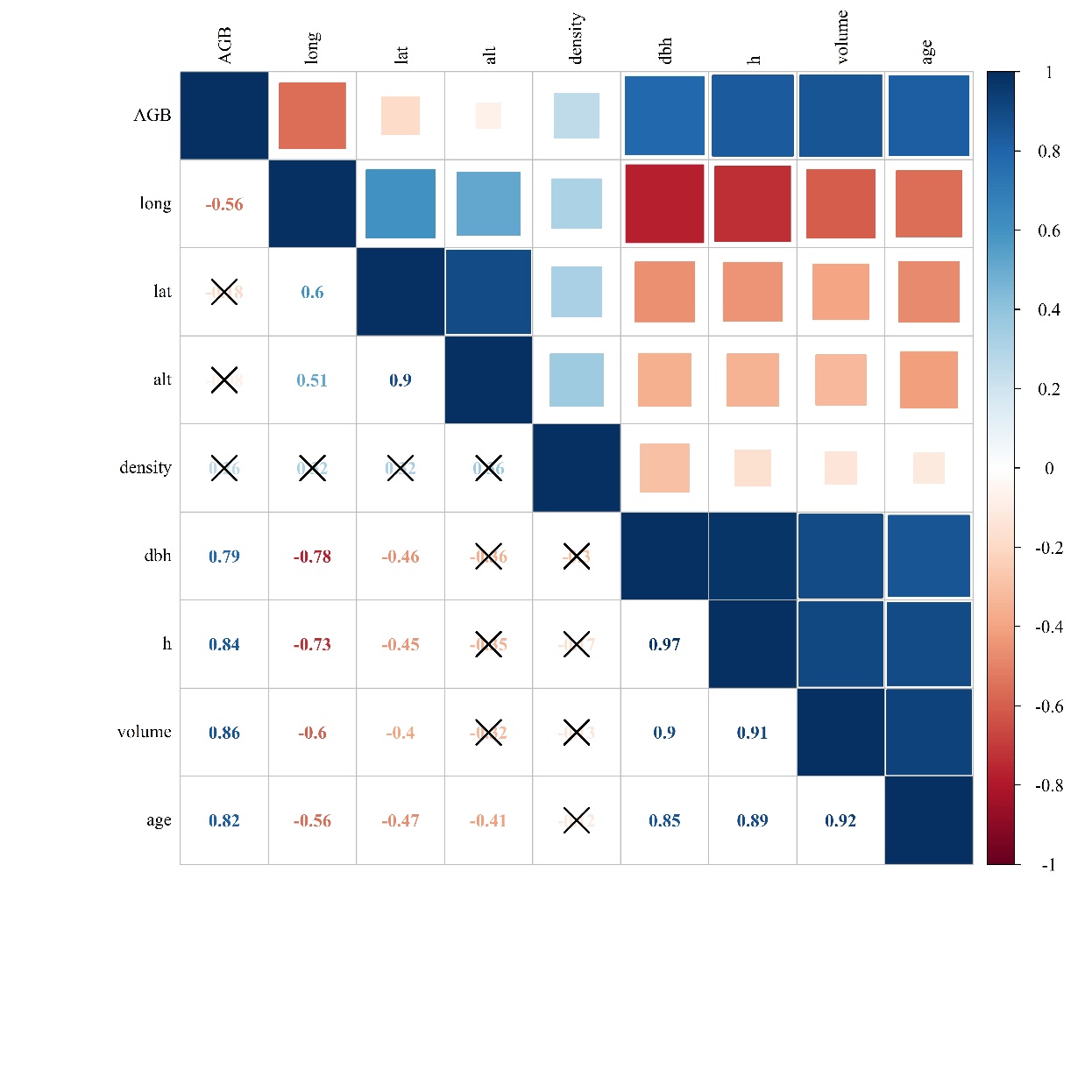


Figure 4. Pearson’s correlation coefficients between AGB and other variables represented by numbers and squares. Negative numbers represent that the corresponding variables are negatively correlated and are colored in red, while positive blue numbers represent positive correlations. Larger absolute numbers, darker colors, and larger squares all indicate stronger correlations, while “ indicates the correlation are insignificant.

### 3.2.2 Spatial autocorrelation test

The spatial distribution of the true AGBs of the 30 sample plots displayed a pattern of aggregation (see red regions in Figure C.1, S3 of the Supplementary Material and Table 1). In addition, because less than 1% of the AGB data was randomly distributed (see blue regions in Figure C.1, S3 of the Supplementary Material and Table 1), the possibility of an aggregated distribution was greater than that of random distribution. Furthermore, the null hypothesis was significantly rejected (*p* < 0.01). These results suggest that the spatial distribution of the AGB data displays aggregation and a pattern of strong spatial autocorrelation.

Table 1. Spatial autocorrelation and heterogeneity test.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Spatial autocorrelation** | |  | **Spatial heterogeneity** | | |
| **Items** | **Values** |  | **Factors** | **q-value** | ***p*-value** |
| Moran I | 0.36 |  | AGB | 0.87 | <0.01 |
|  | Longitude, long | 0.38 | <0.01 |
| z-score | 4.78 |  | Diameter at breast height, DBH | 0.54 | <0.01 |
| *p*-value | 0.00 |  | Tree height, H | 0.63 | <0.01 |
|  | Age | 0.92 | <0.01 |

### 3.2.3 Spatial heterogeneity test

As shown in Table 1, the true AGBs of the sample plots were divided into three strata using *k*-means clustering. Then we ran the Geogdetector model and obtained a value of 0.87 and a value less than 0.01. These results indicate that the within-layer variances were far less than the sum of variances among different strata. The results also suggest that the reference AGBs of the 30 sample plots were associated with obvious spatial stratified heterogeneity.

## 3.3 Performance of plot-level models

We developed seven models for AGB estimation: three machine learning models (SVM, RBF-ANN, and RF), one spatial statistical model (P-BSHADE), and three combined models that integrated each machine learning method with the spatial statistical method (SVM & P-BSHADE, RBF-ANN & P-BSHADE, and RF & P-BSHADE). Furthermore, we used the leave-one-out cross-validation method to split the datasets and evaluated the prediction performance of these seven methods in terms of the indicators of MAE (Figure 5a), MRE (Figure 5b), RMSE (Figure 5c), and nRMSE (Figure 5d).

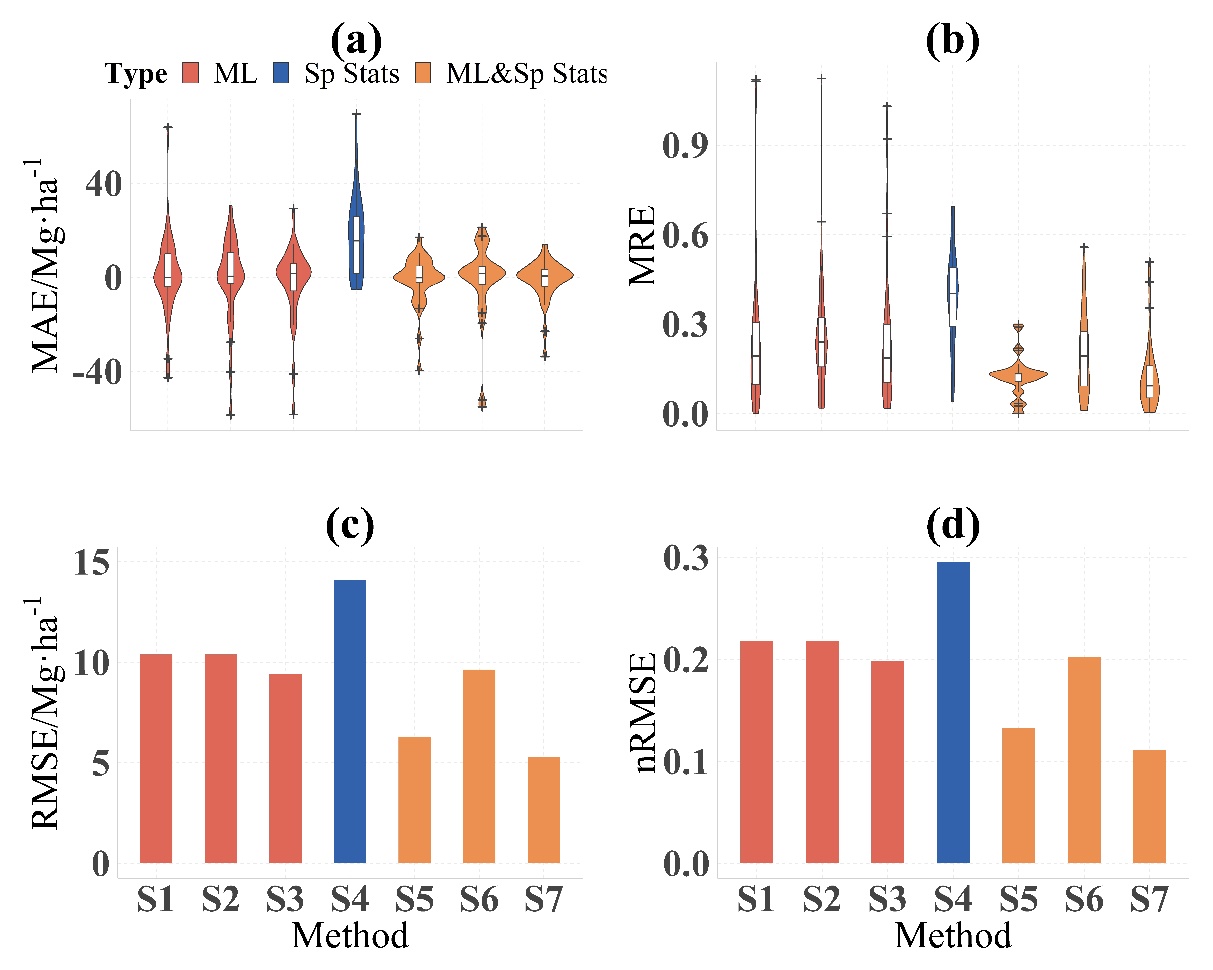


Figure 5. Prediction performance of the seven different models. MAE (a) and MRE (b) are presented as boxplots for each prediction method, with the median (black horizontal line in the box), inter-quartile range (25%-75% in the box), the range 5%-95% (whiskers), and outliers (asterisks) labeled. (S1=SVM, S2=RBF-ANN, S3=RF, S4=P-BSHDE, S5=SVM & P-BSHDE, S6=RBF-ANN & P-BSHDE, S7=RF & P-BSHDE, ML=machine learning, Sp Stats=Spatial statistics.) Histogram distributions of RMSE and nRMSE for each prediction method are presented in (c) and (d), respectively.

The forest AGB estimates obtained by the three machine learning methods were substantially more accurate than those obtained by the spatial statistical method. The performance indicators for P-BSHADE were MAE=18.37 Mg·ha−1, MRE=39.13%, RMSE=14.08 Mg·ha−1, and nRMSE=29.57%, whereas those of the machine learning methods covered the following ranges: MAE 10.16-12.15 Mg·ha−1, MRE 24.79-26.69%, RMSE 9.43-10.39 Mg·ha−1, and nRMSE 19.80-21.82%.

Among the three machine learning methods, the accuracy of RF was highest. The values of the four evaluation indexes (MAE=10.16 Mg·ha−1, MRE=25.93%, RMSE=9.43 Mg·ha−1, and nRMSE=19.80%) were substantially smaller than those of P-BSHADE and those of most of the other two machine learning methods (MAE=11.17-12.15 Mg·ha−1, MRE=24.79-26.69%, RMSE=10.39-10.39 Mg·ha−1, and nRMSE =21.82%). Finally, the combination of machine learning and spatial statistical models produced smaller MAE (5.68-10.14 Mg·ha−1), MRE (12.47-20.49%), RMSE (5.30-9.63 Mg·ha−1), and nRMSE (11.13-20.23%) than the single machine learning methods. Of the three combined methods, RF & P-BSHADE produced the highest accuracy with the smallest MAE (5.68 Mg·ha−1), modest MRE (12.97%), smallest RMSE (5.30 Mg·ha−1), and nRMSE (11.13%). In contrast, RBF-ANN & P-BSHADE had the highest MAE (10.14 Mg·ha−1), MRE (20.49%), RMSE (9.63 Mg·ha−1), and nRMSE (20.23%). Compared with the RF model, the RF&P-BSHADE model achieved a reduction of the cross-validated prediction error of 43.80~50.00% (44.08% for MAE, 50.00% for MRE, 43.80% for RMSE and nRMSE).

We also explored the relationships between the observed and predicted AGBs in terms of cross-validation results (Figure 6). R2 was calculated using the linear regression model between the observed and predicted AGBs. The R2 of every model was greater than 0.9. Although P-BSHADE had the highest R2, its distribution of dot was quite different from the 1:1 line. Of the seven models, the accuracy of RF & P-BSHADE was the highest and the distribution of dots was closest to the 1:1 line. Therefore, we determined that RF & P-BSHADE was the optimal model.

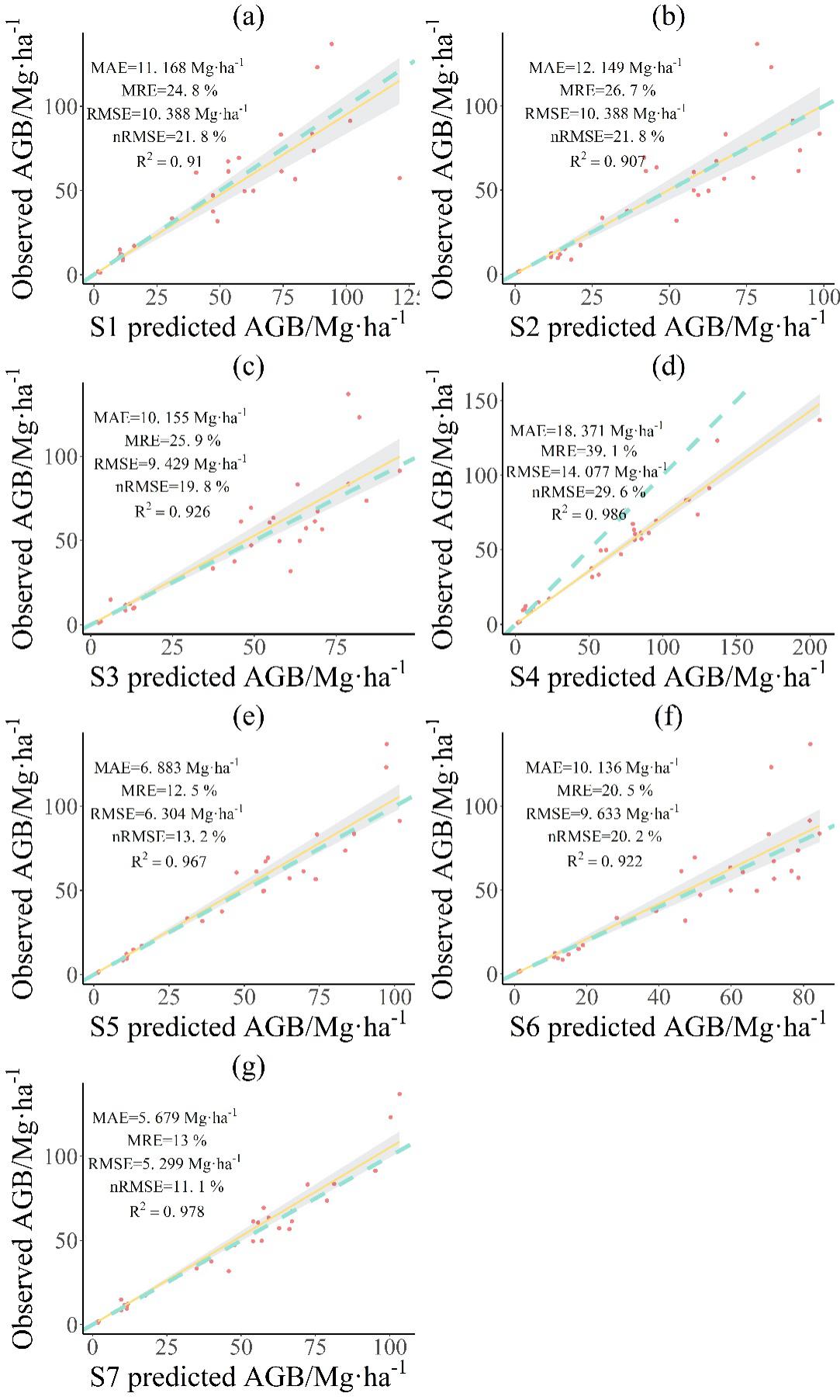


Figure 6. Comparisons of predicted and observed AGBs for accuracy assessment. (a), (b), (c), (d), (e), (f), (g) show SVM (S1), RBF-ANN (S2), RF (S3), P-BSHADE (S4), SVM & P-BSHADE (S5), RBF-ANN & P-BSHADE (S6), RF & P-BSHADE (S7), respectively. Green dashed lines represent a 1:1 relationship; dots represent individual sample plots; solid yellow lines indicate trend lines of dots.

We compared three machine learning methods with three corresponding combined machine learning and spatial statistical methods using differences in MAE, MRE, RMSE, and nRMSE during two periods, 2012 and 2019 (Figure 7). The results suggest that the combined models improved the accuracy of single machine learning models during both years. This suggests that the combined methods are robust.

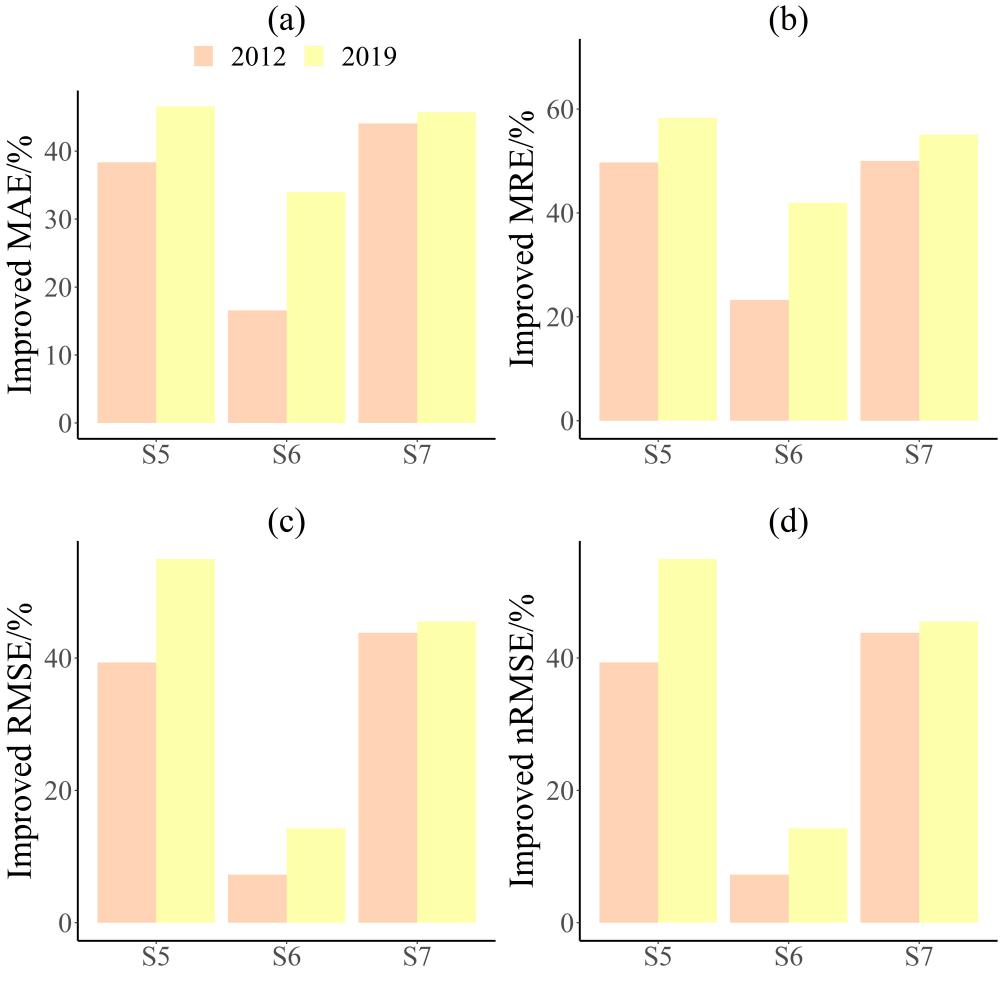


Figure 7. The improvement in accuracy assessment indexes of three combined machine learning and spatial statistical methods by comparison with three corresponding machine learning methods, (a), (b), (c), and (d) represent the MAE, MRE, RMSE, and nRMSE respectively; S1-S5 represents RMSE comparison of S5 with S1, S2-S6 represents RMSE comparison of S6 with S2, S3-S7 represents RMSE comparison of S7 with S3 (S1=SVM, S2=RBF-ANN , S3=RF, S4=P-BSHDE , S5=SVM & P-BSHDE, S6=RBF-ANN & P-BSHDE, S7=RF & P-BSHDE).

Figure C.3 in section S3 of the Supplementary Material shows the spatial distribution of AGBs predicted by the RF & P-BSHADE model. The predicted AGB values were 7.54-89.93 Mg·ha−1, with an average of 41.21 Mg·ha−1, a median of 43.53 Mg·ha−1, a standard deviation of 18.83 Mg·ha−1, and a coefficient of variation of 45.69%. The total AGB of the Nanjing region (2,980 forest patches) estimated by RF & P-BSHADE was 122,812.1 Mg, whereas that estimated by the allometric model was 123,021.5 Mg. The relative percent difference in total AGB between the two methods was 0.17%. Meanwhile, the MRE of AGB between the two methods ranged from 0.04% to 99.8%, with an average of 19.93%.

# 4 Discussion

## 4.1 Significance of the optimal AGB model at the plot-level

In the past, ecologists converted AGB estimates from forest sample plots into regional AGB estimates by scaling up from the tree-level to the regional scale (Malhi et al., 2004). Plot-level AGB models therefore link tree-level AGB models to regional scale AGB models. However, research by Chen et al. (2015) found that ignoring the uncertainty of plot-level models increased the total uncertainty of pixel-level estimates by 6%. In addition, Marvin et al. (2014) found that the distribution pattern of most AGB is either non-Gaussian, skewed, or multi-modal, especially in tropical and subtropical regions.

Here, we integrated the advantages of machine learning and spatial statistics at the plot-level (the key scale linking the tree-level scale to the landscape scale) to construct a plot-level AGB model for a subtropical region. The approach provides a high-precision plot-level AGB model whose estimates can be compared with those obtained from remote sensing, ground observations, and model simulations. It also provides a foundation for making informed forest management decisions (e.g., the method enables quantitative evaluation of carbon emissions from deforestation). Combining the advantages of machine learning-based quantification of AGB and the complex nonlinear relationships between multiple environmental covariates, in conjunction with the P-BSHADE model, enables incorporation of the spatial correlation and heterogeneity of multiple environmental covariates into the model. In addition, the sample points are subsequently rectified, thus leading to the best linear unbiased estimate (BLUE) of the target site. Given that current multi-source databases cannot provide high-precision mapping accuracy due to variations in AGB in subtropical areas, especially in regions with large variability, current studies mainly use fusion maps composed of different and independent datasets (Avitabile et al., 2015).

## 4.2 Model comparisons

Among the three machine learning methods, the AGB prediction accuracy of the RF model at the plot-level was highest (MAE=10.16 Mg·ha−1, MRE=25.93%, RMSE=9.43 Mg·ha−1, and nRMSE=19.80%). This is consistent with the results of Gleason and Im (2012) and Fassnacht et al. (2014). For example, Fassnacht et al. (2014) combined LiDAR with multiple sources of remote sensing data, including airborne hyperspectral data from Karlsruhe, Germany, to compare the AGB prediction accuracy of five machine learning methods: stepwise regression, SVM, RF, Gaussian processes, and K-nearest neighbor. The evaluation indexes for leave-one-out cross validation (i.e., R2 and RMSE) indicated that the RF method produced the highest prediction accuracy due to its self-learning capabilities. The RF method clearly differs from other machine learning methods in the flexibility of its conceptual design and method. Specifically, the following advantages of the RF method may underlie its AGB prediction accuracy (Breiman, 2001): (1) The RF method can generate highly accurate classifiers, detect interactions between variables, and also detect outliers and monitor data; (2) In the construction of a forest, the RF method can internally produce unbiased estimates for generalized deviations. In addition, RF is an ensemble learning method.

Regarding the AGB plot-level models, the machine learning methods outperformed the spatial statistical method (P-BSHADE) in terms of prediction accuracy. This may be because machine learning offers an array of supervised learning models capable of relating forest AGB to multi-variables, including forest variables and environmental variables, via complex, potentially nonlinear functional relationships. Machine learning models appear adept at tackling high-dimensional problems, particularly in areas where effective algorithms are lacking and where programs must dynamically adapt to changing conditions (Görgens et al., 2015; Latifi et al., 2010; Stojanova et al., 2010). In addition, the P-BSHADE model yielded negative weights between a small number of patches, which might introduce a slight degree of uncertainty into the results (Xu et al., 2013). Our results were consistent with those of Povak et al. (2014) and Li et al. (2011), who found that a machine learning method (RF) outperformed the spatial statistical method (e.g., Geographically Weighted Regression, Inverse Distance Weighting ) in terms of prediction accuracy.

The three combined machine learning and spatial statistical methods produced higher AGB prediction accuracy than any method individually. The accuracy of the RF & P-BSHADE and SVM & P-BSHADE methods were significantly higher than the individual methods, but the RBF-ANN & P-BSHADE method was only slightly higher. The accuracies of the combined methods depended on the accuracy of the reference series (machine learning predicted result) (Xu et al., 2013). In other words, the higher the accuracy of the predicted machine learning results, the higher the accuracy of the combined method. Therefore, the following probably reasons about different improvements of three combined methods maybe: (1) the RF and SVM models are easier to use and optimize than RBF-ANN (Raczko and Zagajewski, 2017). RBF-ANN is sensitive to hyper-parameters and usually requires optimized parameters to obtain better fitting results. However, in this study, we did not use any optimized algorithms, such as the genetic algorithm method, to obtain parameters in the machine learning model. Furthermore, the number of training samples determines the number of nodes in the hidden layer of the RBF-ANN model, and the number of nodes significantly affects the prediction accuracy. With only 30 training samples used in this study, the combined approach may have been unable to strongly improve prediction accuracy. (2) RBF-ANN is more suitable for nonlinear stochastic dynamic systems (Elanayar and Shin, 1994), whereas the relationship between AGB and environmental covariates in this study is likely a monotonically increasing function.

## 4.3 Why a combined model outperforms a single machine learning or spatial statistical model

As expected, the prediction accuracies of the combined methods were higher than those of any single method (either machine learning or spatial statistical). In the previous sections, we described how the advantages of the P-BSHADE model can compensate for the inherent defects of machine learning. However, the P-BSHADE model is also handicapped by the fact that the founding assumption does not conform to reality. The assumption is that estimated AGB is accurate in all sampling plots except the target sampling plot. In reality, each sampling plot has a varying degree of AGB uncertainty. In other words, the premise behind using only the P-BSHADE model is that the reference AGB data is accurate or strongly correlated with AGB. Since the P-BSHADE model combined with machine learning uses the results optimized by machine learning as the reference series, it further improves the accuracy of AGB mapping. Machine learning methods or the P-BSHADE model have been adopted to model the uncertainty of temperature observation obtained by weather stations (Fassnacht et al., 2014; Paul et al., 2016; Xu et al., 2013). However, methods in these studies were adopted independently. Conversely, the combination of machine learning and spatial statistics can improve the prediction accuracy of AGB maps, which in turn can be used as criteria for improving the accuracy of LiDAR remote sensing technology and the results of ecological process models. Eventually, these improvements can promote process-oriented projects that require dynamic AGB predictions for large-scale forests in different forest management scenarios.

In addition, we compared the prediction accuracy of AGB mapping obtained by the combined spatial statistical and machine learning models with that reported in recent local and international studies into AGB plot-level models. In the current literature on remote sensing estimation of forest AGB, nRMSE, RMSE, and R2 were commonly used as indexes for evaluating prediction performance of models affected by research sample size, data types, and forecasting methods (Fassnacht et al., 2014). In contrast, our study used four conventional indexes for evaluating prediction performance: nRMSE, RMSE, MAE, and MRE. The criterion for model selection is to choose indexes summarized from sample prediction (such as nRMSE), rather than choosing the goodness-of-fit R2 (Babcock et al., 2015). Based on calculated nRMSE indexes, the AGB prediction accuracy of the combined RF & P-BSHADE method (11.13%) was higher than that obtained by Babcock et al. (2015) (33.91%) in Colorado, USA. In that study, the authors used a combination of airborne LiDAR, a forest inventory database, and a Bayesian spatial hierarchical framework model and introduced spatial random effects to compensate for the residual spatial dependence and non-stationarity of model covariates. The AGB prediction accuracy of the method developed in the current work was also higher than that obtained by Ioki et al. (2014) (nRMSE=26%) in northern Borneo using a stepwise linear regression model with airborne LiDAR and a ground survey. Furthermore, it was higher than the accuracy obtained by Hansen et al. (2015) in the tropical submontane rain forest (34.4%) using fusion maps of multi-source databases combined with multiple regression analysis. Our prediction performance is close to that obtained by Kim et al. (2016) (9.2%) who studied the Intact Tropical Rain Forest using a voxel-based method based on airborne LiDAR in conjunction with field monitoring in Brunei. Our combined methods produce very small RMSE values for the prediction accuracy of AGB, which we attribute to the following reasons: (1) The true AGBs of the 30 sample plots were calculated from each tree using an allometric model constructed with 90 most accurate harvested trees. There were no differences in the range of true values. (2) Machine learning methods were used to quantify the complex nonlinear relationship between AGB and multiple environmental covariates. (3) We applied a spatial statistical method based on the hypothesis of spatial heterogeneity. Although the nRMSE index was calculated by different studies using different datasets and prediction methods in different locations, most studies agreed that nRMSE was the most commonly used indicator for measuring the AGB prediction errors of plot-level models and for calculating the true AGB of forest sample plots. In contrast to other studies, our work not only reflects an attention to subtropical forests, but also to the methodological differences in uncertainty mitigation, especially in terms of comprehensively addressing the sources of uncertainty caused by multiple spatial and environmental covariates.

## 4.4 Comparing upscaling of the RF&P-BSHADE with the allometric model

We used FMPI data to upscale the optimal plot-level AGB model from plot level to region scale. Because the allometric model offers a fast and simple calculation method, it has been used in many studies as the basis for determining the compared map. Nevertheless, spatial heterogeneity caused by multiple environmental covariates is not considered in the allometric model, because potential errors in the AGB estimate may be propagated and affect the accuracy of the regional AGB map. Although here we regarded the FMPI patches as homogeneous study units, the area of patches is quite from the sample plots. Upscaling results will have the large uncertainties (Figure C.4, S3 of Supplementary Material) (Chen et al., 2015). The current study found that the relative percent difference in total AGB between RF & P-BSHADE and the allometric method was 0.17%. Meanwhile, the relative error (RE) of AGB between the two methods ranged from 0.04% to 99.8% with an MRE of 19.93%. This suggests that the two methods are similar in terms of overall estimates of AGB, but that the local spatial distribution of AGB is different. Differences in AGB spatial distribution have been reported in many studies of AGB maps. Babcock et al. (2015) asserted that the main reasons for the differences in the spatial distribution of AGB maps between different methods include the following: (1) The structural framework of different research methods and schemes cannot truly reflect actual forest growth. (2) The model is usually a simplification of an ecological process and ignores spatial heterogeneity at the regional scale. (3) The model does not consider the influence of multiple environmental covariates (vegetation, topography, and others) on forest growth in the region.

# 5 Conclusions

Currently, extrapolations and predictions of AGB based on sparse and/or non-randomly distributed forest plots cannot address problems of regional carbon balance in tropical forests. With the continuous development of remote sensing, ground observations, and ecological process modeling, the number of global and regional AGB datasets is continuously increasing. As criteria to judge the differences between different estimates of biomass, AGB maps not only provide a basis for decision-making by forest managers to mitigate the negative impacts of climate change, they also help countries evaluate and implement policies and programs designed to reduce regional-scale deforestation and forest degradation, so as to avoid additional carbon emissions.

In this study, we proposed a method to integrate the advantages of machine learning and spatial statistics, different datasets, and multiple environmental covariates to improve the accuracy of plot-level AGB estimation models. Using the most accurate data for harvested trees and sample plots, we explored the prediction performance of different methods in AGB modeling. Although data from the sample plots and harvested trees were collected only from *Eucalyptus* forests located in the Nanjing region of China, the proposed method and the findings can provide references for AGB mapping in other countries and in different types of tropical forests.

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