Anonymous Referee #1

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The study presented in this manuscript compares the suitability of machine learning as well as geostatistical modelling approaches to retrieve maps of tree AGB on a regional scale based on plot-based surveys. The paper is reasonably written, however it is lacking a lot of important details that will be outlined in the more specific comments below.

Response:

Thank you for your affirmation and criticism of our manuscript. You have some misunderstanding about the manuscript, which shows that our article is not well written. The goal of the study was not to predict the forest AGB on a regional scale, but rather to improve the accuracy of the plot-scale AGB prediction model. We provide technical support for the mapping accuracy at the regional scale in the future. Plot scale is a bridge connecting single trees and regional scale. The rest of the specific questions are answered below.

GENERAL COMMENTS

1) Important information on the methodology are not given. In the method section it's not even mentioned which predictors were used for the machine learning model training. But this essential as the success of the models is only marginally depending on the choice of the algorithm but in the first place on the ability of the variables being used to serve as predictors for AGB! Only in the result section we get an idea on the variables (longitude, DBH, H, and forest age). I'm surprised about these variables as remote sensing information (especially NDVI) would present much more obvious predictors for AGB when the aim is to model AGB on a regional scale. With the selected variables, how could you upscale the results to a regional scale? I guess neither DBH nor H are not available in a spatial continuous way. So your model cannot be used for regional mapping! However, your motivation is to use it for regional modelling so my question is a) can you really do it with your approach and b) if yes, why are you not doing so and also show the results in the manuscript?

Response:

1. Answers to question regarding important information on the methodology.

We totally agree that the success of the model depends not only on the choice of the algorithm but also on the predictors of the model. Therefore, in the Materials and Methods section (2.4, Construction of the plot-level models), there are five subsections. In the first subsection (2.4.1, Selection of variables and analysis of resulting spatial distribution), the selection method for the prediction variables for the model is introduced in detail. Based on the previous results of our research group (doi:10.1007/s11676-016-0237-y), a series of environmental variables (including soil and topography variables) and forest attribute variables were selected, and Pearson's correlation analysis was used to test the correlation between them and our research objective (forest AGB) in order to select significant correlation variables as the prediction variables of the model. We have included the results of the variable selection in the Results section (3.2, Spatial distribution test and the selection of variables).

2. Answers to other questions related to the misunderstanding of the research purpose.

We are sorry that our manuscript was not written clearly enough to allow you to understand the goal of the study. We will revise the manuscript accordingly.

The purpose of our study was to improve the accuracy of the plot-level prediction model. Sample plots not only provide validation data for large-scale prediction but also provide multi-source environmental variable information to calibrate models. The AGB estimation at the plot level is a bridge connecting the accurate AGB measurement of single trees to the estimation of regional-scale AGB. Therefore, accurate AGB estimation at the plot level provides a basis for up-scaling to the regional level in the future. However, the uncertainty and error propagation inherent in different plot-level models make reliable up-scaling challenging. At present, allometric models are the most commonly used method to build AGB models at the plot level, however they cannot fully capture the impact of the complex spatial heterogeneity of multiple environmental covariates on the spatial distribution of AGB, nor can they adapt to the spatial dependence of model residual or the instability of model variables. The purpose of this study was to develop and evaluate a method that is superior to allometric models, that is, one involving a combination of machine learning and spatial statistics, in order to improve the accuracy of plot-level AGB prediction models.

Remote sensing information such as NDVI and other indicators are used in the next step of out of this manuscript, namely, the application of the optimal plot-level model. That includes (1) the results of the optimal plot-level model provide more plot data (compared to only observed plot data) and more accurate plot data (compared to data from the allometric model) as input data and validation data for the prediction of a regional AGB map based on the wall-to-wall remote sensing data. This was performed to improve the accuracy of the plot-level model, which is the first step of your concern. Additionally, remote sensing data are not the only way to predict the AGB map over a large region. Forest inventory data at the national scale can provide the tree height, DBH, longitude. and other information needed for our model.

2) The cross-validation strategy that you used is not suitable if you have spatially clustered data (as you obviously have looking at the map). This is shown by several studies (see references below, to mention just a few). What would be appropriate is a spatial cross-validation that is testing the ability of your model to make predictions for spatially new samples. At least you should take care that you never use data points from the same forest patch for both training and testing. Otherwise, it is not possible to evaluate the ability of your models for regional mapping. Including coordinates as predictors when the data are spatially clustered is very dangerous (see Meyer et al 2019) and can lead to high overfitting which can only be revealed with spatial cross-validation. So I recommend that in addition to spatial cross-validation, to perform a spatial variable selection (i.e. can the predictors be used to make predictions for new locations?)

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2. Pohjankukka, J., Pahikkala, T., Nevalainen, P., Heikkonen, J., 2017. Estimating the prediction performance of spatial models via spatial k-fold cross validation. Int. J. Geogr. Inform. Sci. 31, 2001–2019. https://doi.org/10.1080/13658816.2017. 1346255.

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4. Valavi, R., Elith, J., Lahoz-Monfort, J.J., Guillera-Arroita, G., 2018. blockcv: an r package for

generating spatially or environmentally separated folds for k-fold cross validation of species distribution models. BioRxiv.

Response:

1. Thank you very much for your suggestions. After studying the four references you recommended and considering carefully, we tested a spatial cross-validation method (blockCV) to evaluate our model's ability with and without the "longitude" variable. The new evaluation results were compared with the old ones, as shown in figures 1–3 below.

   From the perspective of machine learning, each performance indicator value of blockCV is higher than that of the leave-one-out cross-validation (see figures 1–3 below: Figure 1 compared to Figure 2 and Figure 3 compared to Figure 2), which confirms your point of view. The cross-validation strategy we previously used may not be suitable as we have spatially clustered data. However, when we combined machine learning with spatial statistics, we found that there was no significant difference between the results of the two cross-validation strategies (see figures 1–3). This hints that the combination of spatial statistics and machine learning may alleviate the possible overfitting phenomenon to some extent. However, in our manuscript, we chose blockCV instead of leave-one-out cross-validation. The results and discussion will be revised one-by-one.

2. Furthermore, we investigated 22 additional plots, using the same predictors to test the seven models (see Section 2.4.5). We found that the observed results of model performance of these 22 plots was still stable (see Section 3.3 and Figure 7) when compares to the results of previous 30 plots. This proved the feasibility of the model to some extent.

Figure 1. blockCV (exclude longitude)

	model	MAE	MRE	MAEsd	MREsd	RMSE	nRMSE	method	Type
1	SVM	18.259926	2.2600814	18.724252	6.38939812	25.929442	0.5477280	S1	ML
2	ANN-RBF	14.224423	0.3230649	15.124339	0.26072165	20.578022	0.4346857	S2	ML
3	RF	16.401448	1.2910516	22.223087	3.23974756	27.320522	0.5771128	S3	ML
4	PBSHADE	12.069387	0.2509008	15.564449	0.22142772	19.489667	0.4116955	S4	Sp Stats
5	SVM & PBSHADE	5.074986	0.1084286	4.122087	0.04103023	6.494666	0.1371919	S5	ML&Sp Stats
6	ANN-RBF & PBSHADE	11.601607	0.2548966	13.447962	0.18986444	17.590245	0.3715726	S6	ML&Sp Stats
7	RF & PBSHADE	6.154559	0.1521969	10.085011	0.18624791	11.670295	0.2465208	S7	ML&Sp Stats
8	Allometric Model	16.412314	0.5766961	19.288690	0.61802362	25.080188	0.5297885	S8	Allome

Figure 2. Leave-one-outCV (include longitude)

	Method	MAE	MRE	RMSE	maesd	mresd	Type	nRMSE
1	SVM	11.167837	0.2478704	10.387622	18.26950	0.26814000	ML	0.2181603
2	ANN-RBF	12.148633	0.2669469	10.387868	18.28645	0.21892925	ML	0.2181654
3	RF	10.155275	0.2593000	9.429181	16.46633	0.25093935	ML	0.1980312
4	P-BSHADE	18.371450	0.3912975	14.077459	17.31066	0.16984299	Sp Stats	0.2956540
5	SVM&P-BSHADE	6.882970	0.1246758	6.303799	11.00541	0.06971198	ML&Sp Stats	0.1323920
6	ANN-RBF&P-BSHADE	10.135638	0.2049183	9.633279	16.89584	0.14301587	ML&Sp Stats	0.2023176
7	RF&P-BSHADE	5.678865	0.1296616	5.299004	9.23540	0.12137309	ML&Sp Stats	0.1112894

Figure 3. blockCV (include longitude)

> modeleval

	model	MAE	MRE	MAEsd	MREsd	RMSE	nRMSE	method	Type
1	SVM	18.259926	2.2600814	18.724252	6.38939812	25.929442	0.5477280	S1	ML
2	ANN-RBF	14.664950	0.3244150	15.892523	0.23924533	21.429278	0.4526675	S2	ML
3	RF	16.434818	1.2918308	22.322241	3.25310871	27.418539	0.5791833	S3	ML
4	PBSHADE	12.069387	0.2509008	15.564449	0.22142772	19.489667	0.4116955	S4	Sp Stats
5	SVM & PBSHADE	5.074986	0.1084286	4.122087	0.04103023	6.494666	0.1371919	S5	ML&Sp Stats
6	ANN-RBF & PBSHADE	12.163764	0.2438393	12.861101	0.17556948	17.545697	0.3706315	S6	ML&Sp Stats
7	RF & PBSHADE	6.344222	0.1530373	10.692854	0.19070479	12.279048	0.2593800	S7	ML&Sp Stats
8	Allometric Model	16.412314	0.5766961	19.288690	0.61802362	25.080188	0.5297885	S8	Allome

3) The concerns outlined above can be improved, however, I have also doubts about the general value of the paper. Relying on 30 plots only is very very limited for machine learning application (the spatial CV will probably reveal this). So I doubt that the results will produce results that allow for general conclusions on the value of combining machine learning with geostatistical modelling.

Response:

We concede that our reports have to be interpreted cautiously, as they are limited to 30 plots. In our opinion, it is very valuable to investigate 30 plots with 90 constructive trees with different tree ages from the full lifecycle of *Eucalyptus*. Additionally, we investigated another 22 plots, and the observed trend of comparison among the models is still stable when compares to the results of previous 30 plots. We welcome other researchers to repeat our analysis on new datasets using our models. Expanding our research to more diverse datasets (possibly remote sensing data such as Lidar data or possibly more environmental data such as terrain, soil, and climate data) and also to a larger sample size.

We agree that the articles published in *Biogeosciences* should be universal and representative, and the research results can help to solve the hot issues in ecology and geosciences. Therefore, we understand your concern about the influence of our manuscript. We are sorry that we did not clearly explain the innovation and influences of our manuscript. We believe that our contribution has the following values:

1. The innovation of our manuscript is to integrate machine learning and a spatial statistical model. The integration of these two can help to complement each other's advantages and improve the accuracy of AGB estimation models. Machine learning has the advantage of being able to handle complex and potentially nonlinear relationships between forest AGB and other variables. However, the initial samples of machine learning are randomly selected, which may lead to differences in the results of each operation of the model. Additionally, specific machine learning algorithms have their own disadvantages, such as RF uses the average value of all regression trees in the calculation, which may result in the overestimation of the lower value and the underestimation of the higher value. As opposed to machine learning, the P-BSHADE model (a spatial statistical model) takes into account the spatial autocorrelation and spatial heterogeneity of forest AGB and of environmental covariates, and remedies the bias of the observed values of the sampling plots in theory, which corresponds more to actual situations. A combined model takes the result of machine learning as the reference data (input data) of P-BSHADE, so that the fitting process of the combined model accounts more for spatial relationships than is the case for the single machine learning model. In addition to the theoretical advantages of these methods, case studies presented in this study also demonstrate the empirical superiority of the combined model.
2. Allometric model is a simple, fast, and universal equation that has been used in many studies. However, selection error in plot-level allometric modeling still leads to over 40% uncertainty (Djomo et al., 2016; Fayolle et al., 2013; Chave et al., 2014), and simple or complex forms of the allometric model account for 20% – 60% of the uncertainty (Picard et al., 2015). In our manuscript, we propose an improved method of AGB estimation which involves a combination of machine learning which is good at prediction and a spatial statistical model which is good at reflecting spatial relationships in order to improve the estimation accuracy of the AGB model at the plot level.

3. Over the past 20 years, with the growing area of *Eucalyptus* plantations around the world, Brazil, India, China, Chile, Spain, DR Congo, Australia, South Africa, and other countries have established contiguous *Eucalyptus* planting areas. There have been many studies and reports on

the biomass estimation of *Eucalyptus* plantations using ecological process models at different temporal and spatial scales. China is the country with the largest area of planted forest in the world. However, China's planted forest suffers from the three practical problems of low productivity, unsustainability, and incongruous production function and ecological function, which urgently need to be solved by appropriate management measures. On the one hand, with the rapid growth of the global population, the timber demand is also increasing rapidly. On the other hand, there is the severe reality that total global forest resources have declined sharply in recent years. Thus, many countries and regions are vigorously developing fast-growing non-native trees to alleviate the contradiction between the supply and demand of timber and forest products in order to maintain economic and social development. *Eucalyptus* is one of the fastest-growing trees, and is controversial in the development of planted forest. A special study on Eucalyptus is of great significance.

4. Although *Eucalyptus* is taken as a case study in our manuscript, the model we proposed can also be applied to other tree species or mixtures of tree species. There is no particular relationship between our model settings and tree species. No unique characteristics of *Eucalyptus* is added to the model, and other forest types also can provide the input data such as tree height, DBH, longitude, and other variables. Therefore, the model we proposed can be expanded and its influence is not limited to *Eucalyptus* forests. In fact, this idea of improving the accuracy of the model also has the potential to solve other ecological problems.

In view of the influence of the four aspects of the manuscript we described above, we believe it can attract attention

SPECIFIC COMMENTS

Line 25: I disagree that longitutde and latitude on this scale affect AGB. Even on a large scale they don't but are just proxies for e.g. climate but they are certainly not underlying factors for AGB on your small study area.

Response:

Perhaps you have mainly considered the direct influence of direct factors. However, in ecology, the influence of indirect factors is also very important and should not be ignored. Forest ecosystems are complex systems. The relationship between forest biomass and the surrounding environment also deserves attention on a small scale. How forest biological factors and abiotic environmental factors affect the distribution and estimation of forest biomass has not been studied thoroughly. In the field of forest biomass estimation, many other scholars have emphasized and attached importance to the potential of topographic factors for improving model estimation (e.g., Fassnacht et al., 2014). It is necessary to consider the interaction and the nonlinear and indirect effects of these environmental factors to improve the accuracy of forest biomass estimation. We referred in particular to the fact that latitude and longitude are not suitable in here, and therefore we changed them for topographic, soil, and climatic information. Additionally, as the comparison with or without the longitude factor as the predictor yielded similar model performance (see Figures 1 and Figures 3 above: Figure 1 compared to Figure 3), we removed the longitude from the predictors.

Line 49-51: One important thing is missing: The model might also fail because the predictor variables are not sufficient to estimate AGB.

Response:

Thank you for your reminder. We have included it as one of the sources of model-dependent uncertainty. The modifications are as follows:

"The uncertainty of such regional maps can be attributed to three primary sources: (1) the use of inadequate sampling data to construct the plot level prediction models, (2) model-dependent uncertainty, including unreasonable model-parameter assumptions, improper model structure (Chen et al., 2015; Gao et al., 2016; McRoberts et al., 2016), ***and the predictor variables are not sufficient to estimate AGB (Meyer et al., 2019).*** *The present study mainly focuses on reducing the second source of uncertainty."*

Line 54: "An estimated 18%–103% of the uncertainty in AGB mapping can be attributed to model-dependent uncertainty". In fact between nearly nothing (~18) and everything (>100). That sounds unreasonable, consider taking that sentence out.

Response:

Thank you for your suggestion. We have modified the expression as follows:

"Up to 103% of the uncertainty in AGB mapping can be attributed to model-dependent uncertainty".

Line 60-62: This differentiation between allometric models and statistical models does not seem to make sense. E.g. Allometric models can be based on linear relationships as well. Please improve the logical structure here.

Response:

We were referring to the spatial statistical model, generally the geostatistical techniques, such as geographically weighted regression (GWR), ordinary least-squares regression (OLS), and so on. They are different from allometric models. However, there are logical problems. As you said, allometric models can be based on linear relationships as well. Therefore, we revised the expression as follows:

"Many different plot-level prediction models other than allometric models have been applied to constructing accurate AGB maps, including ***other*** *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)."*

Line 67-71: Be careful with the logical structure here as well: The major advantage is that machine learning is able to fit complex relationships which e.g. linear models don't. And THEREFORE they might be advantageous in predictions (not "in addition" as you write in Line 72).

Response:

Thank you for your suggestion. We have modified the expression as follows:

"By comparison, nonparametric machine learning algorithms, in which the number of parameters depends on the number of training examples (e.g., K-nearest neighbor, support vector machine, and random forest), are advantageous because they are more elastic and do not restrict variable types, the distribution of predictor variables, or the relationship between response and predictor variables (Lu et al., 2007). ***Therefore,*** *nonparametric machine learning algorithms may offer higher prediction accuracy (Frey et al., 2019; Gleason and Im, 2012)."*

Line 74-81: The fundamental difference between the approaches is not getting clear here but this is important because combining the two approaches is the objective of the paper. In contrast to the statistical (including machine learning) approaches explained above, the spatial statistical approaches have the major assumption that "near things are more related that distant things". I think the general idea should be made clear and it should be explained why you expect that a combination might be the way forward.

Response:

Your question does not correspond to the number of lines shown. In lines 74–81, we briefly introduced some research and applications of spatial statistical models to the study of the relationship between forest AGB and multi-source environmental factors and compared the advantages of the spatial statistical model and the traditional statistical model. The two methods which were combined in our study were machine learning and spatial statistics. Lines 99–104 show why we hope the combined method might be the way forward.

Lines 74-81 read as follows: *"Another group of models frequently used to estimate the relationship 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)."*

Lines 99-104 read as follows: *"The proposed method integrates the nonlinear mapping capabilities of machine learning algorithms [i.e., radial basis function artificial neural network (RBF-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 hospital-based area disease estimation, P-BSHADE) (Xu et al., 2013)."*

Line 85-88 "studies that used machine learning methods have not considered the spatial heterogeneity of multiple environmental covariates (such as longitude, latitude, and forest structure)". I disagree. Most approaches use environmental covariates which of course have been heterogeneous as well. No information on model tuning is given. Also please state which software implementations and settings of the algorithms you used.

Response:

1. Thank you for your suggestion. We have revised the inappropriate expression as follows:

*"**some existing** studies that used machine learning methods have not considered the spatial heterogeneity of multiple environmental covariates (such as longitude, latitude, and forest structure)".*

2. The information on model tuning includes: (1) SVM: (type="eps-regression",kernel="radial",cost=10,gamma=0.2); (2) RF: (size=3,maxit=2500). The rest are default parameter settings. We will list the model code in the supplementary material.
3. Using R 3.5.3 (https://www.r-project.org) to implement the algorithms.

Line 157-158: please explain why you tested for spatial autocorrelation etc. Why is this information relevant for the modelling?

Response:

1. Testing spatial autocorrelation and spatial heterogeneity are the premises of applying the P-BSHADE spatial statistical model. It assumes that the research object has spatial autocorrelation and spatial heterogeneity, so we must detect the spatial autocorrelation and spatial heterogeneity of the research object (forest AGB in our manuscript) before using the P-BSHADE model.
2. P-BSHADE is a spatial statistical inference model. P-BSHADE is an optimal linear unbiased estimation interpolation method based on the assumption of the simultaneous existence of the spatial autocorrelation and heterogeneity of the target object.

Line 205:"Because of the Law of Large Numbers, RF does not overfit." That's wrong! Maybe random forest is robust to overfitting in terms of hyperparameter selection but it is not the case if you have data that are not independent. See e.g. the references mentioned above.

Response:

Thank you for your professional guidance in machine learning. The incorrect description has been deleted.

Line 206-207: Accurate predictions of random forest do NOT in the first place originate from injecting randomness. E.g. If the predictors are not sufficient to estimate a response variable, random forest will fail (and so will other algorithms)!

Fig. 6 : Is this based on the cross-validation?

Response:

1. Thank you for your professional guidance in machine learning. The incorrect description has been deleted. We agree with you that predictors are important to the model. This manuscript focused on the comparison and screening of different models. The same predictors are used in all the machine learning models used in our study. The determination of predictors was based on the results of Pearson correlation analysis. However, since this manuscript did not compare different predictors of the accuracy of the model, we may consider this in future work.
2. Yes, based on the cross-validation.

Line 502-503: "The assumption is that estimated AGB is accurate in all sampling plots except the target sampling plot. 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. " I don't understand that. The same reference data were used for all modeling approaches and for sure we assume that the reference data are accurate for both types of models.

Response:

P-BSHADE needs the reference value of the target object (which is forest AGB in our manuscript) as input data. Although we assumed that the reference value is accurate, there are many ways to obtain the reference value. On one hand, how to obtain the reference value is the key to combining other methods with the P-BSHADE model, and therefore this leads to differences among the different combined models in our manuscript. On the other hand, we used an allometric model to obtain the reference data of the single P-BSHADE, which leads to differences between the single P-BSHADE model and combined models. The specific steps included: (1) we first used the machine learning method or allometric method to estimate AGB and then (2) used the estimated AGB as a reference value in the P-BSHADE model to estimate AGB again.

Therefore, when comparing combination models with the single P-BSHADE model in the discussion, it is logical to compare and illustrate their reference values.

Line 578: <u>"We used FMPI data to upscale the optimal plot-level AGB model from plot level to region scale." Did you? We don't get to see the results for the regional upscaling. I wonder: Is your model really better than simply using the average measured AGB from each forest site as estimate for AGB for the entire patch?</u>

Response to the first question: Yes, we did this work, but as it is not the main objective of our manuscript, we put this result in Section 6 of the supplementary material (Figures C.3 and C.4).

Response to the second question: We do not quite understand the method you want to compare with our optimal model. Do you mean simply using the average value of AGB measured at all forest sites as the estimated AGB of the whole forest class? This method may be relatively simple, and may have advantages in specific circumstances, such as when the accuracy requirements are not high. However, we insist that our approach is better for the following reasons:

1. The purpose of our study is to improve the accuracy of the plot-level AGB estimation model. This goal is an important prerequisite to improving the accuracy of regional AGB estimation because regional AGB estimation often needs to use the verification data and training data provided by sample plots.
2. The way to achieve this goal is to combine machine learning with spatial statistics and make use of their complementary advantages to establish an optimal model with high accuracy for the estimation of AGB in sample plots.

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