Dear editor,

Thanks for processing out paper. Now we have finished revising our manuscripts according to the reviewers' comments. It is noted that there are no new comments and suggestions from Reviewers #1 and #2 in this round of revision. We have carefully addressed the comments and suggestions from Reviewers #3 and #4 in the revision.

Best wishes,
Nannan An

Responses to #Reviewer 3

Thanks for your constructive suggestions and comments for our manuscript to improve the quality of our manuscript. We have carefully addressed the comments and suggestions in the revision, and detailed revisions and responses are listed below. In addition, it should be noted that some comments you raised have been revised in the last round of revision according to comments of the other reviewers. Thus, the corresponding revisions may be not tracked in this version of manuscript and the corresponding revision can be found via line number in the revised manuscript.

1. The introduction is long and repetitive, with plenty of room for making tighter. Just state once that climate change is affecting the number of species, the size of their populations, they distribution and also many NCP, and use fires as example.

[Response]: This comment is not related to our manuscript. We did not mention the related content of NCP in the Introduction section in the manuscript.

More minor comments:

2. The choice of periods (1970-2000 and then 2041-2060) with a crucial 40-year gap in between, is not justified.

[Response]: "The choice of periods (1970-2000 and then 2041-2060) with a crucial 40-year gap" was not mentioned in our manuscript. It is not our study period at all. In our study, the prediction of key plant functional traits did not include the time period. We cannot revise it in the revised manuscript.

3. L 200: "attitude" is not the right word in this context.

[Response]: Sorry. We cannot find "attitude" in L 200. And we have checked this word throughout the manuscript and not find it in this manuscript.

4. The random forest model is described in minute detail, but how the life history traits are used, and why each of the traits is important to the main question is not mentioned.

[Response]: In description of random forest model, we did not use the term "life history traits", so we are not sure if you meant the life history traits are plant growth form, leaf type and leaf phenology because we did not use the term "life history traits" to represent

this information in the manuscript. If you meant the life history traits are plant growth form, leaf type and leaf phenology, we explained it as follows. We used plant growth form (tree, shrub and grass), leaf type (broadleaf and needleleaf) and leaf phenology (deciduous and evergreen) as the basic information to match species to plant functional type (PFT). First, we predicted the trait values for six PFTs separately by building the machine learning models using the field measurement data and environmental variables and vegetation indices at a 1 km spatial resolution. Then, we obtained six prediction layers for single plant functional trait. Second, the classification of natural PFT types includes evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous needleleaf forest (DNF), deciduous broadleaf forest (DBF), shrubland (SHL) and grassland (GRL). We calculated the abundance of individual PFT within 1 km grid cell using a land cover map with a spatial high-resolution of 100 m. Finally, the final community weighted mean trait values were calculated according to the predicted trait values (the second step) and corresponding abundance of each PFT (the third step) refer to the equation of CWM calculation in the community as Eq. (1) (Garnier et al., 2004).

$$\mathrm{CWM} = \sum_{i=1}^{n} W_i \, X_i \tag{1}$$

where n is the total number of PFT in a given grid, W_i is the relative abundance of the ith natural PFT, and X_i is the predicted trait value of the ith natural PFT.

We have added this information in the sections 2.2, 2.3 and 2.5 in Materials and methods in the revised manuscript (see Lines 167–171, 231–239, 289–298).

5. Results in L 267-270 are fully confirmatory, as the authors admit.

[Response]: L 267-270 in our manuscript is the Materials and methods section instead of Results section.

6. The change in threat risk (L 294-296) appear very low (between 0.02 and > 0.04). If this is not the case, it deserves discussion.

[Response]: This comment is not related to our manuscript. We did not mention the term "threat risk" in the manuscript.

7. DATA ID 149 and 150 one leaf area is around 9 cm2 and the other 0.4.

Leaf area for Acer burgerianum several between 2 and 9 and one around 150.

Acer pictum: all LA are between 20 and 28 cm2 but there is one of around 2400

[Response]: We cannot grasp the meaning of this comment because it did not clearly

mention what the question is. We wonder if the question is about the large variation of each trait is large. Our explanations are below.

We have considered the large variation of the LA values when we performed the data processing. First, we have checked the sources of leaf area data that are collected from the China Plant Trait database (Wang et al., 2018) and we ensured the correctness of these data. In the China Plant Trait database, authors have identified outliers or discrepancies, and those doubtful measurements have been removed from the database, which can ensure the data quality and correctness. Second, we know that leaf area is a trait indicator that has larger intraspecific variability relative other leaf traits. In our dataset, for those same species that not only has the leaf area data, but also has other trait indicators such as specific leaf area, leaf N concentration and leaf P concentration, we found that other traits have no obvious abnormal values, so we kept the leaf area data of this species. Two possible reasons are related to large variability in leaf area within the same species in the dataset. One is that sample collectors have inconsistent understandings of leaf collecting on relatively young but fully expanded and hardened leaves from adult plants. The other is the plant adaptation to different environmental conditions. Third, during the periods of model training, we calibrated the models 10 times using randomly selected 80% of the data for training the models and validating against the remaining 20% based on cross-validation. To some extent, this procedure can reduce the effects of large values on the final predictive results. Therefore, we can ensure the correctness and quality of our dataset.

References

Wang, H., Harrison, S. P., Prentice, I. C., Yang, Y. Z., Bai, F., Togashi, H. F., Wang, M., Zhou, S. X., Ni, J. The China Plant Trait Database toward a comprehensive regional compilation of functional traits for land plants. Ecology, 99, 500-500, https://doi.org/10.1002/ecy.2091, 2018.

8. Plant functional traits must be sampled and measured according to standardized measurement 134 procedures (Perez-Harguindeguy et al., 2013) to reduce the variation and uncertainty among 135 different data sources. In this study, we included SLA measurements on both sun-leaves and shade136 leaves, WD measurements on both heartwood and sapwood of tree species, SM measurements on 137 both seeds and fruits, and plant height measurements on both vegetative and generative organs.

[Response]: According to the comment from Reviewer #1 in the last round of revision,

we have deleted the results of plant height and SM in new version of manuscript due to the sparse sampling sites of these two traits across China. We have checked the literature that those literature of SLA data that introduced the sampling and measurement methods all sampled the sun leaves, which require sampling sun leaves during field sampling for trait studies (Perez-Harguindeguy et al., 2013). And WD is the oven-dry mass of a section of the main stem of a plant divided by the volume of the same section (g cm^{-3}). We also checked the WD literature that introduced the sampling and measurement methods conformed to the sampling methods of WD. We have corrected this sentence as "*we included SLA measurements on sun-leaves, and WD measurements on main stem of woody species*" in the section 2.2 in Materials and Methods in the revised manuscript (see Lines 155–156).

9. Enough new data?

Second, illogical values, 143 repeated values and outliers were removed, which were defined by observations exceeding 1.5 144 standard deviations of the mean trait value for a given species (Kattge et al., 2011).

[Response]: After the data collection, we have processed the outliers in the dataset according to the suggested methods from the TRY database (Kattge et al., 2011) and this method was also used in the global mapping of leaf traits (Moreno-Martínez et al., 2018). This method is carried out at the species level to identify the outliers.

References

Kattge, J., Diaz, S., Lavorel, S., Prentice, C., Leadley, P., Bonisch, G., Garnier, E., Westoby, M., Reich, P. B., Wright, I. J., Cornelissen, J. H. C., Violle, C., Harrison, S. P., van Bodegom, P. M., Reichstein, M., Enquist, B. J., Soudzilovskaia, N. A., Ackerly, D. D., Anand, M., Atkin, O., et al.: TRY - a global database of plant traits. Glob. Change Biol., 17, 2905–2935, 1098, https://doi.org/10.1111/j.1365-2486.2011.02451.x, 2011.

10. The use of continuous functional trait data are proposed as a step forward with respect to PFTs. However, PFTs still seem to play an important and unclear role in the modelling: "To calculate community weighted mean trait values, the abundance of individual PFT within 1 km 260 grid cell was estimated using a land cover map with a spatial resolution of 100 m. The final 261 community weighted mean trait values were calculated according to the predicted trait values and 262 corresponding abundance of

each PFT."

[Response]: Thanks for your comment. We have added more detailed description on how PFTs were used in the machine learning models. We generated the plant functional trait maps in four steps as follows. First, we associated each species with a corresponding PFT based on plant growth form (tree, shrub and grass), leaf type (broadleaf and needleleaf) and leaf phenology (deciduous and evergreen). For example, the information on *Salix matsudana* is: tree, deciduous and broadleaf, thus, we were able to associate the PFT of deciduous broadleaf forest (DBF) to this species. The species that did not correspond to any PFT were discarded. Second, we predicted the trait values for six PFTs separately by building the machine learning models using the field measurement data and environmental variables and vegetation indices at a 1 km spatial resolution. Then, we obtained six prediction layers for single plant functional trait. Third, the classification of natural PFT types includes evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous needleleaf forest (DNF), deciduous broadleaf forest (DBF), shrubland (SHL) and grassland (GRL). We calculated the abundance of individual PFT within 1 km grid cell using a land cover map with a spatial high-resolution of 100 m. Forth, the final community weighted mean trait values were calculated according to the predicted trait values (the second step) and corresponding abundance of each PFT (the third step) refer to the equation of CWM calculation in the community as Eq. (1) (Garnier et al., 2004).

$$CWM = \sum_{i=1}^{n} W_i X_i \tag{1}$$

where n is the total number of PFT in a given grid, W_i is the relative abundance of the *i*th natural PFT, and X_i is the predicted trait value of the *i*th natural PFT.

Because this comment has been mentioned by other reviewers, and We have added this information in the sections 2.2, 2.3 and 2.5 in Materials and methods in the revised manuscript (see Lines 167–171, 231–239, 289–298).

11. Cross-validation showed that the performance of the predictive models differed greatly among the plant traits and in no case were higher than .68, and were variable and often quite low. This casts doubts on the applicability and confidence to be put in all the results.

[Response]: Indeed, the performance of the predictive models differed greatly among the plant functional traits. Results showed that WD, SLA and LPC had relatively higher

performance with R^2 values higher than 0.45. However, LDMC and LNC showed relatively poor performance with R^2 values less than 0.35. On the one hand, we have considered environmental variables and vegetation indices as the predictors as many as possible to improve the predictive ability of plant functional traits in our study. On the other hand, we have added the relevant explanations of the poor predictive performance in plant functional traits in the Discussion section in the revised manuscript (see Lines 419–422, 527–532). It is noted that the results of plant height and SM were deleted in the revised manuscript due to the sparse sampling sites according to the comments of the other Reviewers in the last round of revision. In addition, the great variability of performance among plant traits is common in the global and regional studies (Table 1). To analyze the differences between our study and previous studies, we have added quantitative comparisons between our results with the regional and global studies from the predictive accuracy and spatial differences in sections 4.1 and 4.2 in Discussion section in the revised manuscript.

Table 1 Comparisons in predictive performance between our study and previous studies.

References	Traits	Spatial scale	Predictive performance (determinate coefficient, R^2)
Dong et al., 2022	SLA, LNC	Global	SLA: 0.73, LNC: 0.39
Vallicrosa et al., 2022	LNC, LPC	Global	LNC: 0.63, LPC: 0.32
Schiller et al., 2021	SLA, LNC, LA, WD	Global	SLA: 0.30, LNC: 0.16, LA: 0.45, WD: 0.20
Boonman et al., 2020	SLA, LNC, WD	Global	SLA: 0.36, LNC: 0.24, WD: 0.38
Madani et al., 2018	SLA	Global	SLA: 0.68
Bodegom et al., 2014	LMA, WD	Global	LMA: 0.35, WD: 0.52
Loozen et al., 2020	LNC	Regional: Europe forests	Overall performance: 0.63. Performance is relatively low in Deciduous Broadleaf Forest: 0.09-0.39
Yang et al., 2015	LMA, LNC	Regional: China	LNC: 0.16, LMA: 0.13

SLA, specific leaf area; LNC, leaf N concentration; WD, wood density; LPC, leaf P concentration; LA, leaf area; LMA, leaf mass area, SLA=1/LMA.

References:

Boonman, C. C. F., Benitez-Lopez, A., Schipper, A. M., Thuiller, W., Anand, M., Cerabolini, B. E. L., Cornelissen, J. H. C., Gonzalez-Melo, A., Hattingh, W. N., Higuchi, P., Laughlin, D. C., Onipchenko, V. G., Penuelas, J., Poorter, L., Soudzilovskaia, N. A., Huijbregts, M. A. J., and Santini, L.: Assessing the reliability of predicted plant trait distributions at the global scale. Glob. Ecol. Biogeogr., 29, 1034–1051, https://doi.org/10.1111/geb.13086, 2020.

Dong, N., Dechant, B., Wang, H., Wright, I. J., and Prentice, I. C.: Global leaf-trait mapping based on optimality theory. Glob. Ecol. Biogeogr., https://doi.org/10.1111/geb.13680, 2023.

Madani, N., Kimball, J. S., Ballantyne, A. P., Affleck, D. L. R., van Bodegom, P. M., Reich, P. B., Kattge, J., Sala, A., Nazeri, M., Jones, M. O., Zhao, M. S., and Running, S.W.: Future global productivity will be affected by plant trait response to climate. Sci. Rep., 8, 1–10, https://doi.org/10.1038/s41598-018-21172-9, 2018.

Schiller, C., Schmidtlein, S., Boonman, C., Moreno-Martinez, A., and Kattenborn, T.: Deep learning and citizen science enable automated plant trait predictions from photographs. Sci. Rep., 11, https://doi.org/10.1038/s41598-021-95616-0, 2022.

Vallicrosa, H., Sardans, J., Maspons, J., Zuccarini, P., Fernández-Martínez, M., Bauters, M., Goll, D. S., Ciais, P., Obersteiner, M., Janssens, I. A., and Peñuelas, J.: Global maps and factors driving forest foliar elemental composition: the importance of evolutionary history. New Phytol., 233, 169–181, https://doi.org/10.1111/nph.17771, 2022.

van Bodegom, P. M., Douma, J. C., and Verheijen, L. M. A fully traits-based approach to modeling global vegetation distribution. P. Nat. Acad. Sci. USA, 111, 13733–13738, https://doi.org/10.1073/pnas.1304551110, 2014.

Yang, Y. Z., Zhu, Q. A., Peng, C. H., Wang, H., Xue, W., Lin, G. H., Wen, Z. M., Chang, J., Wang, M., Liu, G. B., Li, S. Q. A novel approach for modelling vegetation distributions and analysing vegetation sensitivity through trait-climate relationships in China, Sci. Rep., 6, 24110, https://doi.org/10.1038/srep24110, 2016.

12. Not sure about the usefulness of the spatially continuous at a 1-km spatial resolution using machine 503 learning methods in combination with field measurements, environmental variables and vegetation 504 indices Ver clear. First, the predictive ability of machine learning methods was relatively worse for certain 459 traits,

[Response]: Thanks. First, the account of the trait data used to predict the spatial distribution is large and the sampling sites are relatively even across China, which is an important advantage in subsequent model training. Second, we considered the different aspects of predictors including climate, soil, topography and vegetation indices (enhance vegetation index, MERIS terrestrial chlorophyll index and bands) as many as possible in the models. Third, we used two machine learning methods via parameter

selection and cross validation, and an ensemble model was used to applied to merge the predictions of random forest and boosted regression trees to reduce the variability of different single-models and to construct a more stable and accurate model. Our results showed that WD, SLA and LPC had relatively higher performance with R^2 values higher than 0.45, while LDMC and LNC showed relatively poor performance with R^2 values less than 0.35. The great variability of predictive performance among plant functional traits is common due to the differences in responses to environment and vegetation predictors. In addition, we have added the quantitative comparisons of our study and previous studies from the perspectives of predictive performance and spatial correlation and the differences in spatial distribution in the Discussion 4.1 and 4.2 section in the revised manuscript. We have also explained the possible reasons of low predictive performance of LDMC and LNC in the Discussion 4.1 and 4.4 section (see Lines 419–422, 527–532). Therefore, our work is an effort in predicting the spatial distribution of key plant functional traits using machine learning methods in combination with in combination with a large dataset of field measurements, environmental variables and vegetation indices in China.

13. In addition, due to the challenges of measurements for small shrubs 468 and low vegetation, WD data is mainly confined to eastern forests (Perez-Harguindeguy et al., 2013),???

[Response]: we guessed this comment is that this expression of "challenges of measurements for small shrubs and low vegetation" may be misleading. Therefore, this sentence should be corrected as "*Due to the few measurements for shrubs and the lack of herbs, WD data is mainly confined to eastern forests*" and we have revised it in the revised manuscript (see Lines 533–536). Wood density is closely related to mechanical support, water transport and storage capacity of woody tissues, which is common functional trait measured in trees (Chave et al., 2009). The spatial distribution of sampling sites of WD was relatively even across China and the predictive performance used by machine learning methods was high (best R^2=0.68), which is higher than the global WD prediction (Boonman et al., 2020). This improvement in precision may be attributed to the large number and dense occurrence of sample sites as well as the inclusion of vegetation indices in our study. In addition, we quantitatively compared the spatial distribution of predictive values in WD in our study with previous studies at the global scale (Schiller et al., 2022; Boonman et al., 2020). Specifically, for the global

studies, we extracted the maps of China to compare with our study. We found that WD did not show the lower and higher predictive values across China in our study (Fig. 1), however, the WD values in the studies of Boonman et al. (2020) and Schiller et al. (2021) had more predictions at higher values and no lower values (< 0.3 g cm^{-3}). This result also suggested the predictive ability of our study is more robust than that of previous studies.
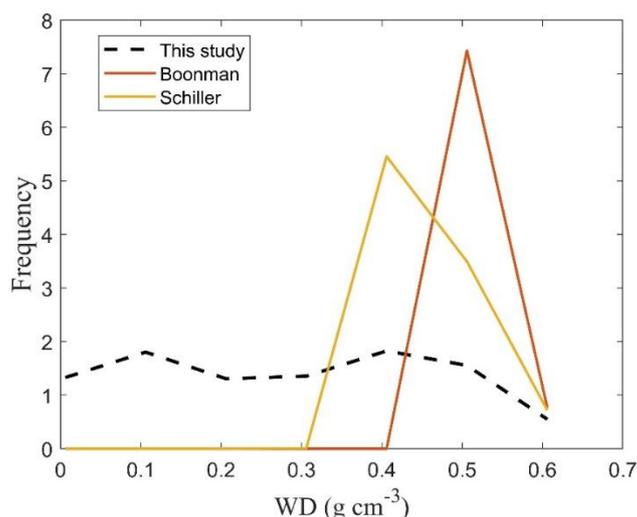
Figure 1. Frequency distributions of WD in our study ("This study", dashed black lines) and other trait maps, identified by the first author of the corresponding publication.

References

Boonman, C. C. F., Benitez-Lopez, A., Schipper, A. M., Thuiller, W., Anand, M., Cerabolini, B. E. L., Cornelissen, J. H. C., Gonzalez-Melo, A., Hattingh, W. N., Higuchi, P., Laughlin, D. C., Onipchenko, V. G., Penuelas, J., Poorter, L., Soudzilovskaia, N. A., Huijbregts, M. A. J., and Santini, L.: Assessing the reliability of predicted plant trait distributions at the global scale. Glob. Ecol. Biogeogr., 29, 1034–1051, https://doi.org/10.1111/geb.13086, 2020.

Chave, J., Coomes, D., Jansen, S., Lewis, S. L., Swenson, N. G., Zanne, A. E. Towards a worldwide wood economics spectrum, Ecol. Let., 12, 351-366, https://doi.org/10.1111/j.1461-0248.2009.01285.x, 2009.

Schiller, C., Schmidtlein, S., Boonman, C., Moreno-Martinez, A., and Kattenborn, T.: Deep learning and citizen science enable automated plant trait predictions from photographs. Sci. Rep., 11, https://doi.org/10.1038/s41598-021-95616-0, 2022.

14. Not really the global spectrum: in abstract "two-dimensional spectrum of plant form and function,"

[Response]: Thanks for your suggestion. We have corrected it as "they can reflect plant

resource acquisition strategies and ecosystem functions" in Abstract section in the revised manuscript (see Lines 20–22).

15. Global biodiversity data (e.g., sPlot and 474 Global Biodiversity Information Agency databases) that contains information on species occurrence 475 or the proportion of species in a community has the potential for enabling the calculation of 476 community-weighted trait values and the re-evaluation of our results in future work (Telenius, 2011; 477 Bruelheide et al., 2019).

[Response]: Thanks for your suggestion. The dataset (e.g., sPlot and Global Biodiversity Information Agency databases) can be considered as a potential direction and way to perform the spatial prediction of plant functional traits in the future work. The Global biodiversity data is mentioned in our manuscript because it is a potential dataset and tool to be used for calculation of community-weighted trait values and obtain the spatial maps of plant functional traits, because it includes species occurrence or the proportion of species in a community. However, there are some limitations and uncertainties that must be considered by users, such as biases towards certain regions and communities (few plots in China), taxonomic uncertainty and incomplete records. We did not use this dataset in our study.

16. Sction 4 on applications is unconvincing. However this is not crucial for the paper.

[Response]: Thanks for your suggestion. We are not sure if you meant the Section 4 on applications refers to the section 4.5 "Potential applications" in our manuscript. If yes, we have modified this section to clarify the significance of application of this dataset. The two potential applications mentioned in the manuscript have been preliminarily attempted in the current studies. Firstly, the maps of plant functional traits can be used in the vegetation models (e.g., dynamic global vegetation models (DGVMs)). Because conventional DGVMs are still insufficient realistic, largely due to their dependence on the plant functional types (PFTs) assumption (Sitch et al., 2008; Yurova and Volodin, 2011; Scheiter et al., 2013). PFTs in conventional DGVMs commonly have fixed attributes (mostly trait values) (Van Bodegom et al., 2012; Wullschleger et al., 2014) that do not reflect plant adaptation to environments, limiting the quantification of carbon-water-nutrient feedbacks between terrestrial ecosystems and the atmosphere (Zaehle and Friend, 2010; Liu and Yin, 2013). An increasing number of researchers proposed that the merits of a traits-based vegetation model are important directions to deal with current shortcomings. For example, van Bedegom et al. (2014) suggested that

the combination of selected traits (seed mass, leaf mass per area and wood density) is sufficiently to distinguish among vegetation types at the global scale. Yang et al. (2016) showed that leaf mass per area-leaf N concentration-leaf area index combination had an accuracy of 72.82% in simulating vegetation distribution in China. These studies shed new light on the development of next-generation trait-based DGVMs. Second, incorporating maps of plant functional traits with maps of ecosystem carbon budgets will allow to assess the importance of plant functional traits in driving ecosystem processes at a large spatial scale to be assessed (van Bedegom et al., 2012). Currently, some studies have emphasized the effects of plant functional traits on ecosystem carbon progresses at individual, species and community scales. However, how such effects scale up to regional or global scales remains unclear. Therefore, a way forward is to combine maps of functional traits of species assemblages with maps of ecosystem carbon sink estimates. For example, Šímová et al. (2019) have used the maps of plant height and leaf nutrients to analyzed their effects in improving prediction of forest productivity across the Americas. In addition, the assessments of China's terrestrial ecosystem carbon sink have large uncertainties so far (Piao et al., 2022), but the spatial continuous trait maps will provide an effective way to link ecosystem characteristics to ecosystem carbon sink estimates in China (Madani et al., 2018; Šímová et al., 2019). For example, Yang (2015) has combined the maps of leaf mass per area, leaf N concentration and leaf area index to replace plant functional types in Integrated Biosphere Simulator (IBIS) model (one type of DGVMs) to predict the carbon budget (gross primary productivity, net primary productivity and net ecosystem exchange) from 1984 to 2013. They found that results based on plant functional traits were highly consistent with those based on plant functional types, suggesting the feasibility of using plant functional traits in vegetation models. Therefore, the maps of plant functional traits derived by our study will provide potential applications and important directions in future work.

We have revised the relevant content in the Section 4.5 in the Discussion section in the revised manuscript (see Lines 554–570).

References:

Šímová, I., Sandel, B., Enquist, B. J., Michaletz, S. T., Kattge, J., Violle, C., McGill, B. J., Blonder, B., Engemann, K., Peet, R. K., Wiser, S. K., Morueta-Holme, N., Boyle, B., Kraft, N. J. B., Svenning, J. C., and Hector, A.: The relationship of woody plant size and leaf nutrient content

to large-scale productivity for forests across the Americas. J. Ecol., 107, 2278–2290, https://doi.org/10.1111/1365-2745.13163, 2019.

van Bodegom, P. M., Douma, J. C., Witte, J. P. M., Ordoñez, J. C., Bartholomeus, R. P., and Aerts, R.: Going beyond limitations of plant functional types when predicting global ecosystem- 1257 atmosphere fluxes: exploring the merits of traits-based approaches. Glob. Ecol. Biogeogr., 21, 625–636, https://doi.org/10.1111/j.1466-8238.2011.00717.x, 2012.

van Bodegom, P. M., Douma, J. C., and Verheijen, L. M. A fully traits-based approach to modeling 1260 global vegetation distribution. P. Nat. Acad. Sci. USA, 111, 13733–13738, 1261 https://doi.org/10.1073/pnas.1304551110, 2014.

Yang Y. Z. Construction and application of new generation of dynamic global vegetation models (DGVMs) based on plant functional traits, 2015, Doctoral dissertation.

Responses to #Reviewer 4

The revised manuscript has improved substantially, especially concerning the description of the upscaling method. To my mind, the manuscript is now much beyond a data description paper only.

[Response]: Thanks for your positive comments and constructive suggestions for our manuscript to improve the quality of our manuscript. We have carefully addressed the comments and suggestions in the revision, and detailed revisions and responses are listed below. In addition, we have used tracks to highlight the revisions in the revised manuscript.

1. However, I think I identified one major problem in Equation 4 for upscaling: How did you calculate the relative abundance W? W must be relative to the vegetated area for which meaningful trait values exist (excluding e.g. bare soil and vegetation without trait values, crops?), for WD W must be relative to the area of woody PFTs only which have meaningful values for WD (excluding crops, bare soil, herbaceous vegetation (and shrubs?)). I think, at least for WD, there is a problem here because in Figure 5f, the predicted values have a density >0 at unrealistically small WD values, and they have a peak at (almost) zero, which makes no sense. However, there may be this problem for the other traits as well because all trait prediction means are lower than the mean of the observations. The predicted mean may indeed vary from the observed, but it seems unlikely that the mean of predictions is lower than the mean of observations for all traits. If you check for this problem, the correlations to environmental predictors will also change.

[Response]: Thanks for your constructive comments. The calculation of the relative abundance W in Equation 4 is used a land cover map with a spatial resolution of 100 m to estimate the relative proportion of each land cover type within 1 km grid cell. In this step, we considered all land cover types including natural vegetation areas and artificial and crop areas. When we calculated the relative abundance during the step of data processing, we also considered whether the relative abundance is based on the natural vegetation areas for meaningful trait values, i.e., excluding the artificial and crop areas. However, we did not adopt this method. But we thought that we should use the true abundance of natural vegetation types to all land cover types within 1 km grid cell, otherwise the relative abundance of natural vegetation types may be overestimated if only natural vegetation types were considered. When there are both natural vegetation

types and artificial areas within 1 km grid cell, the proportion of natural vegetation relative to all land cover types should be meaningful. In addition, we also referred to the study of Moreno-Martínez et al. (2018), in which the spatial abundance of PFTs at 500 m resolution was calculated using Landsat data (30 m) and the mean values for each grid cell was calculated from leaf trait values corresponding with that PFT. In our manuscript, we calculated the final trait value in a given 1 km grid cell based on the abundance of each natural PFT and corresponding predicted trait values. In addition, for grid cells with the total abundance of artificial areas is 100%, these grid cells were not displayed in the maps (e.g., the sparse areas in Figs. 3, 4 and 6). So, in our opinion, we used the abundance of natural PFT relative to all land cover types within 1 km grid cell. We have added the detailed description of relative abundance in section 2.5 in Materials and Methods in the revised manuscript (see Lines 289–298).

WD observations in our dataset were from woody plants including trees and shrubs, and no data was from herbaceous plants. Therefore, we used the term "wood density" instead of "stem-specific density" in the manuscript. We calculated the relative abundance for estimation of WD as the relative abundance of each natural PFT to all land cover types within 1 km grid cell. The peak at (almost) zero of WD may be related to the lower values of shrubs in northwestern China (Fig. D8 in Appendix D). In addition, we performed quantitative comparisons between our study and previous WD maps. We found that WD did not show the lower and higher predictive values across China in our study (Fig. 1), however, the WD values in the studies of Boonman et al. (2020) and Schiller et al. (2021) had more predictions at higher values and no lower values (< 0.3 g cm^{-3}). This discrepancy may be related to that the shrubs were not considered in the previous studies.
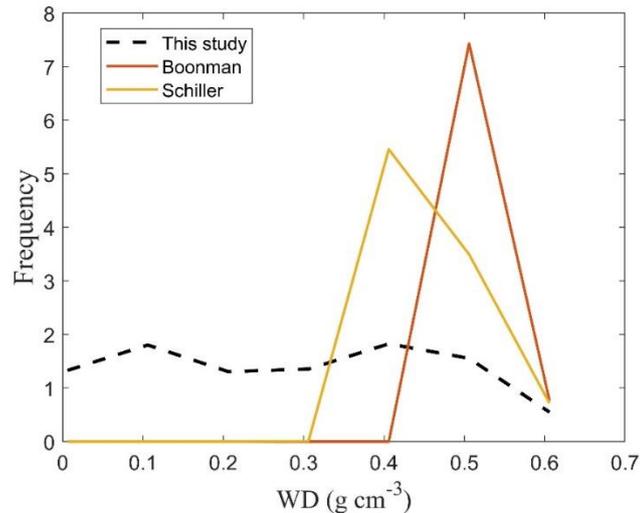
Figure 1. Frequency distributions of WD in our study ("This study", dashed black lines) and other trait maps, identified by the first author of the corresponding publication.

For mean of predictions is lower than the mean of observations for all traits, we have checked the predicted maps of all plant functional traits. The possible reason is that the mean values of trait observations were from the individual level, while the mean values of predicted values were based on the relative abundance of PFTs and corresponding predicted values within 1 km grid cell, which may cause the mean of predictions lower than the mean of observations.

References:

Moreno-Martínez, Á., Camps-Valls, G., Kattge, J., Robinson, N., Reichstein, M., van Bodegom, P., Kramer, K., Cornelissen, J. H. C., Reich, P., Bahn, M., Niinemets, Ü., Peñuelas, J., Craine, J. M., Cerabolini, B. E. L., Minden, V., Laughlin, D. C., Sack, L., Allred, B., Baraloto, C., Byun, C., Soudzilovskaia, N. A., and Running, S. W.: A methodology to derive global maps of leaf traits using remote sensing and climate data. Remote Sens. Environ., 218, 69–88, https://doi.org/10.1016/j.rse.2018.09.006, 2018.

Apart from this, I have three minor comments:

2. Figure 2: What are the white areas? Please add in the label or caption.

[Response]: Thanks. We focused on natural terrestrial vegetation in this study, so all artificial or crop areas were thus eliminated in our dataset. So, the white areas are the eliminated areas including all artificial areas. We have added the relevant explanation

in the caption of all figures in the revised manuscript.

3. L 261: Probably not 'mean absolution error' but 'mean absolute error'

[Response]: Thanks. We have corrected 'mean absolution error' to 'mean absolute error' in the revised manuscript.

4. For vegetation modelling, it would be excellent to provide separate maps (datasets) for the predicted trait values for each PFT (in supplementary materials) because the models would use PFT-specific model input.

[Response]: Thanks. We have added separate maps for the predicted trait values for each PFT as Figs. D3-D8 in Appendix D in the revised manuscript.
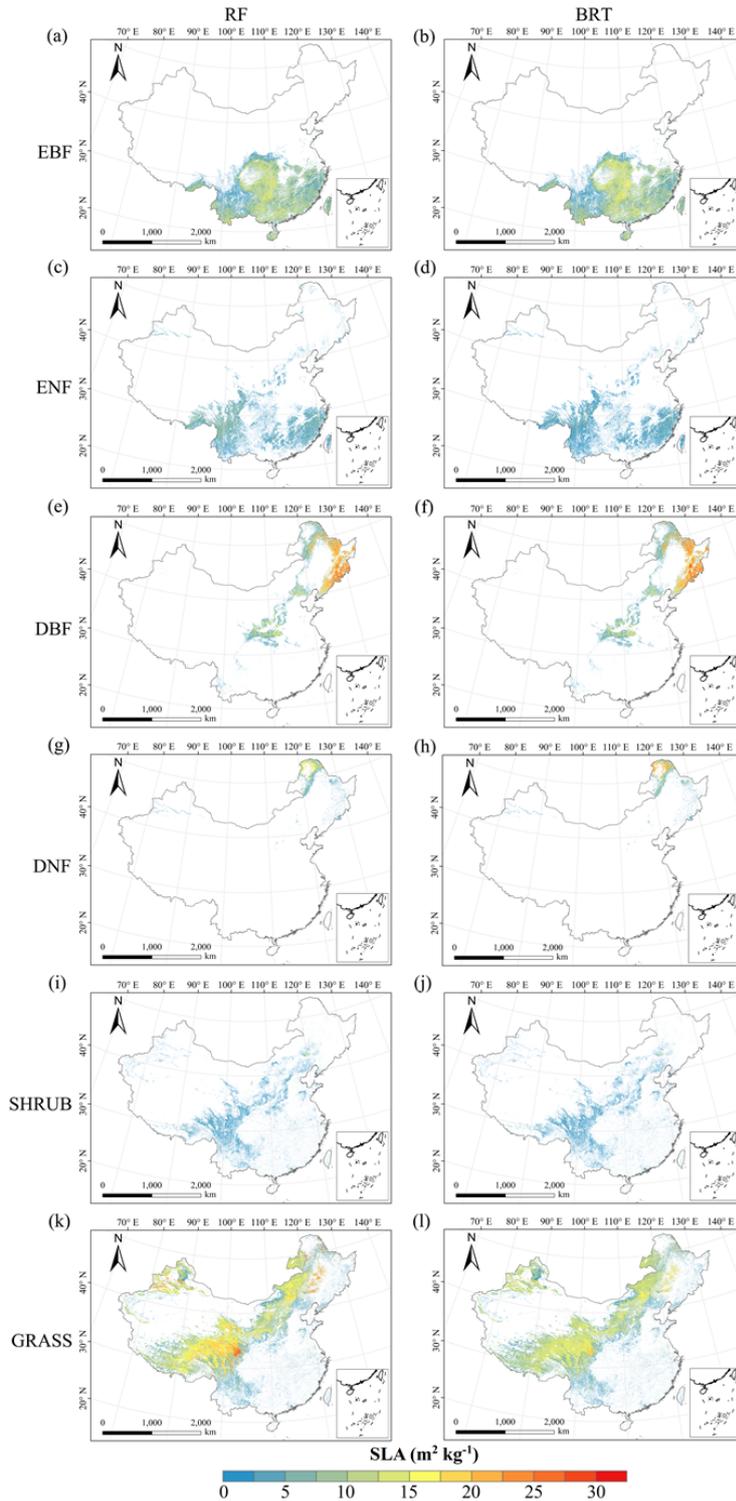
Figure D3. Spatial distribution of specific leaf area (SLA) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland; GRASS, grassland.
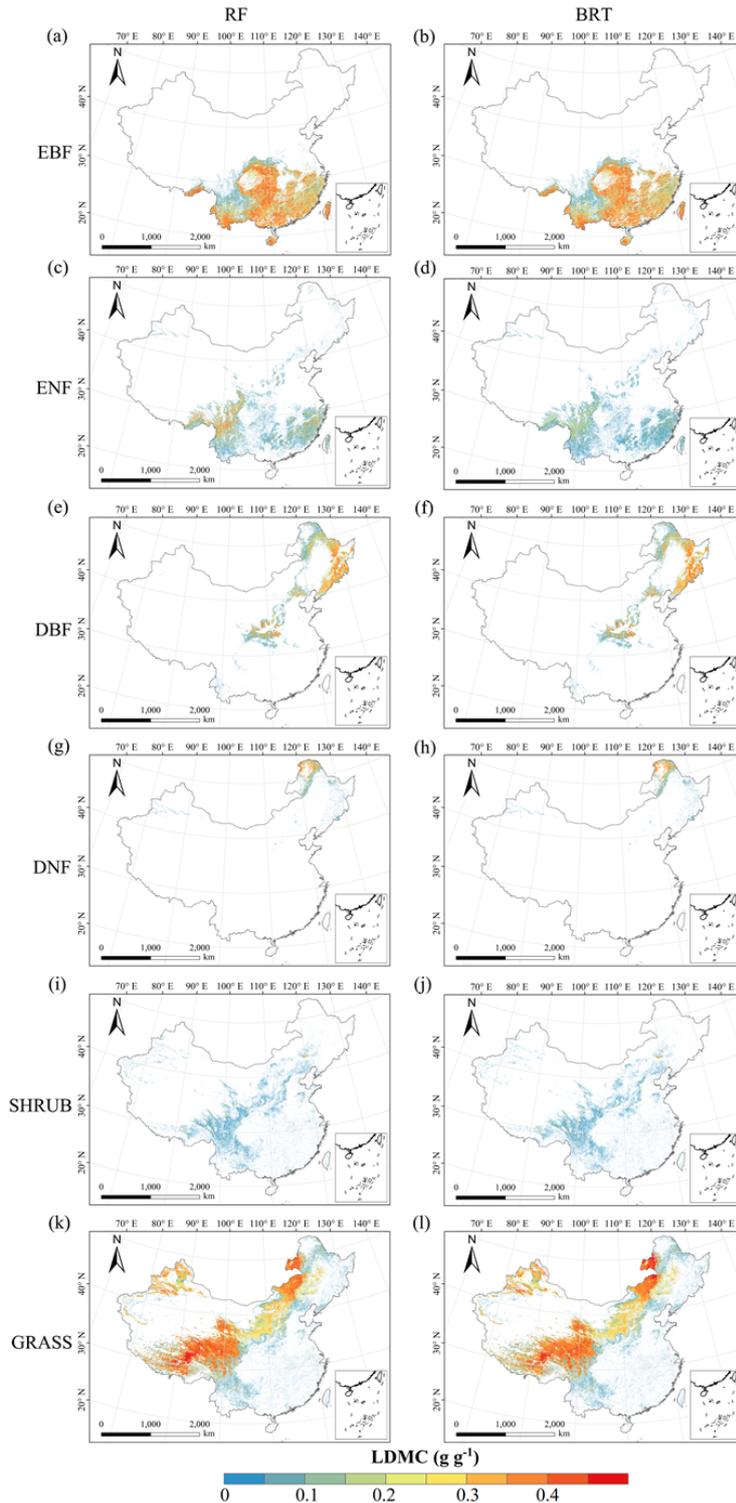
Figure D4. Spatial distribution of leaf dry matter content (LDMC) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland; GRASS, grassland.
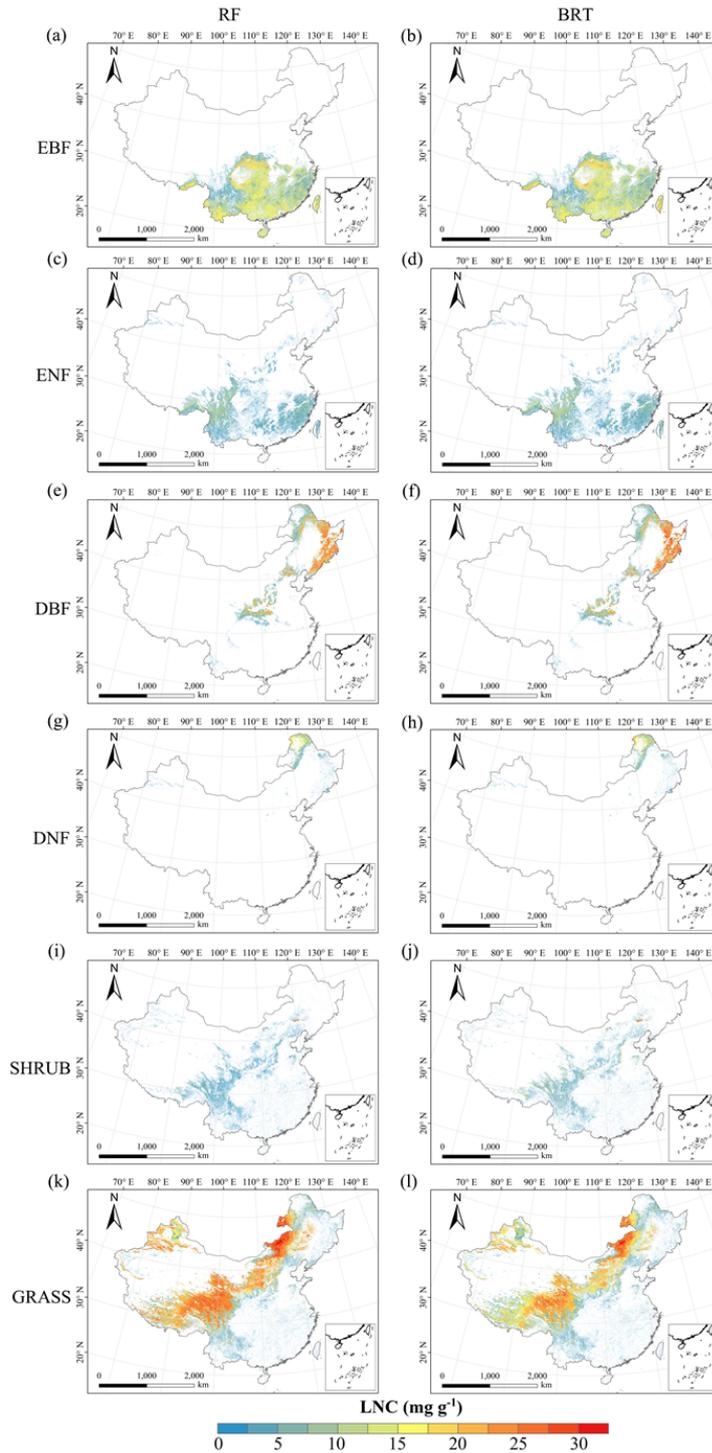
Figure D5. Spatial distribution of leaf N concentration (LNC) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland; GRASS, grassland.
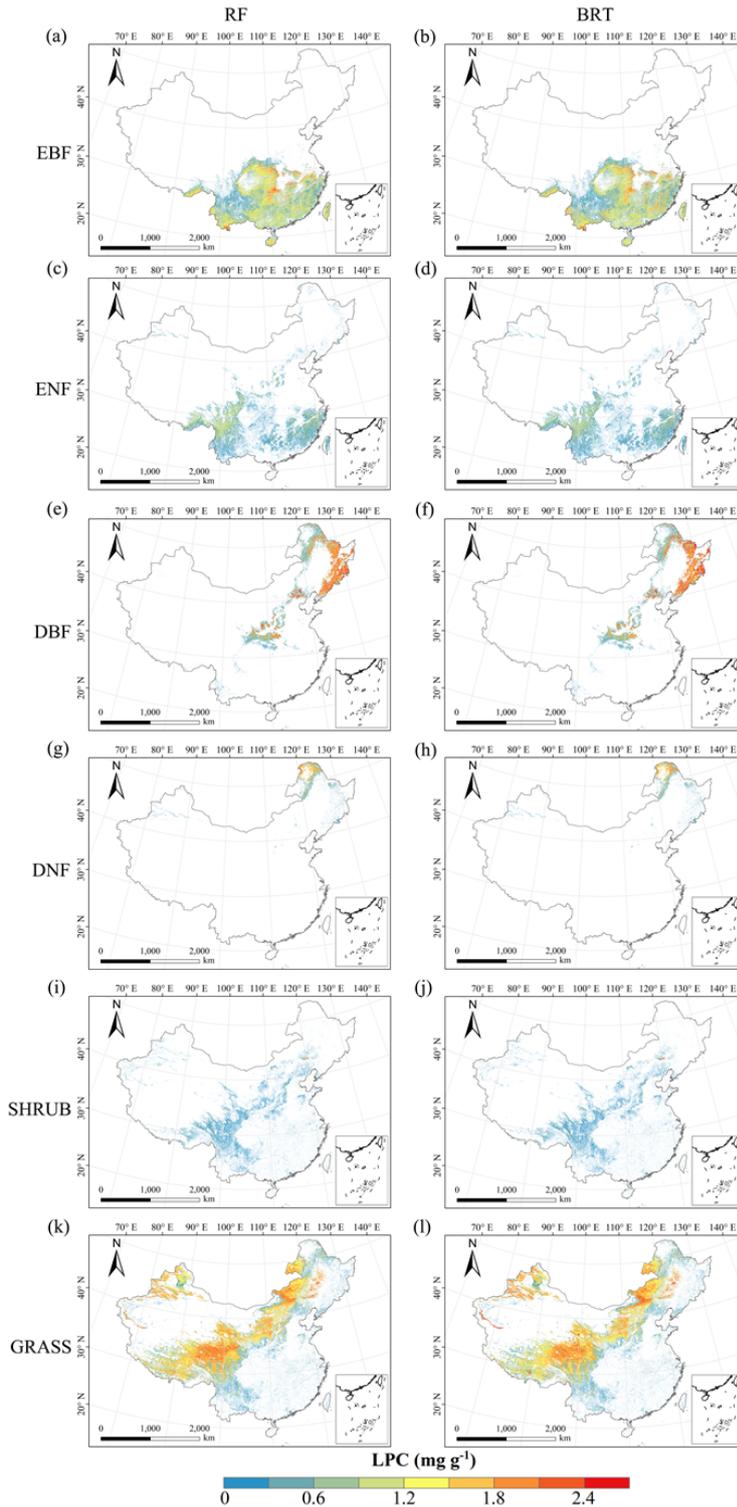
Figure D6. Spatial distribution of leaf P concentration (LPC) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland; GRASS, grassland.
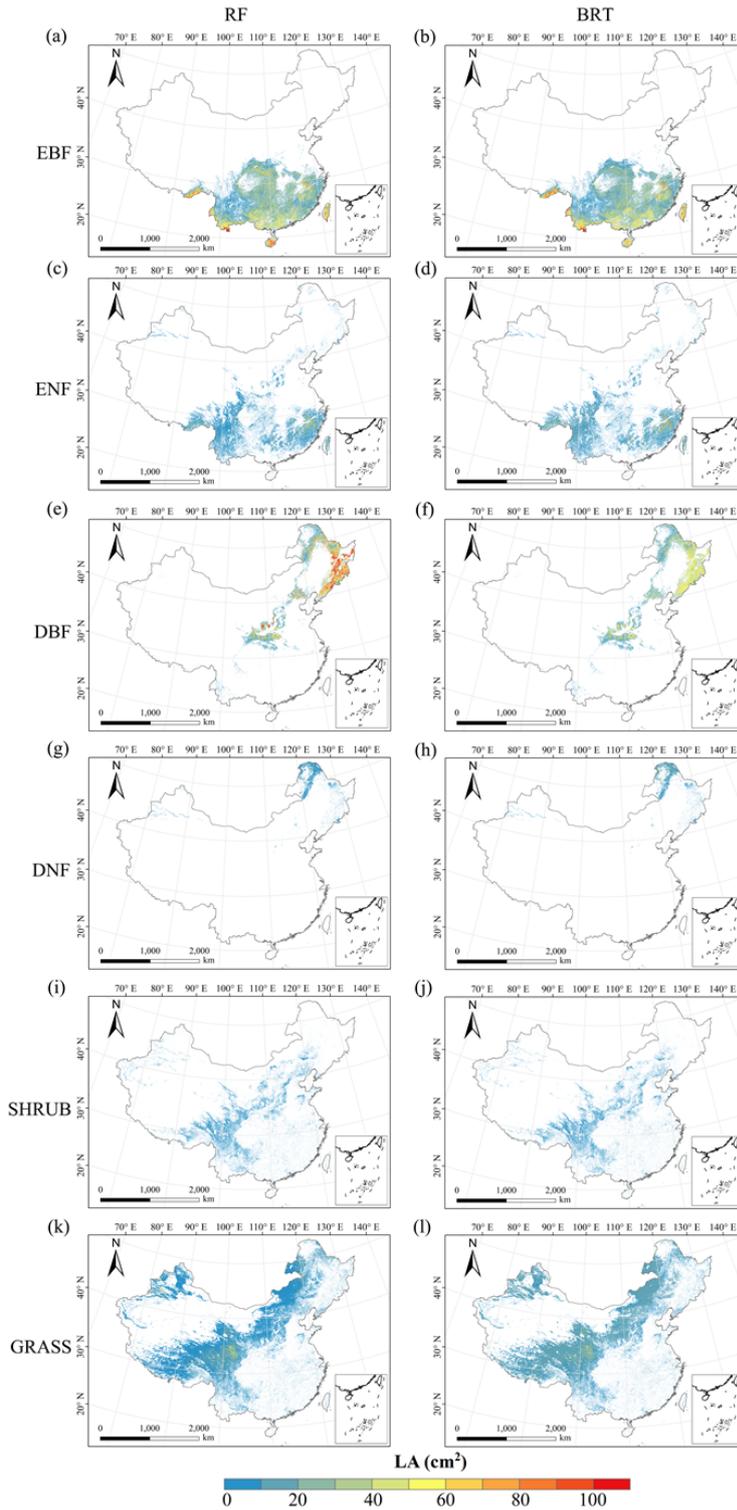
Figure D7. Spatial distribution of leaf area (LA) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland; GRASS, grassland.
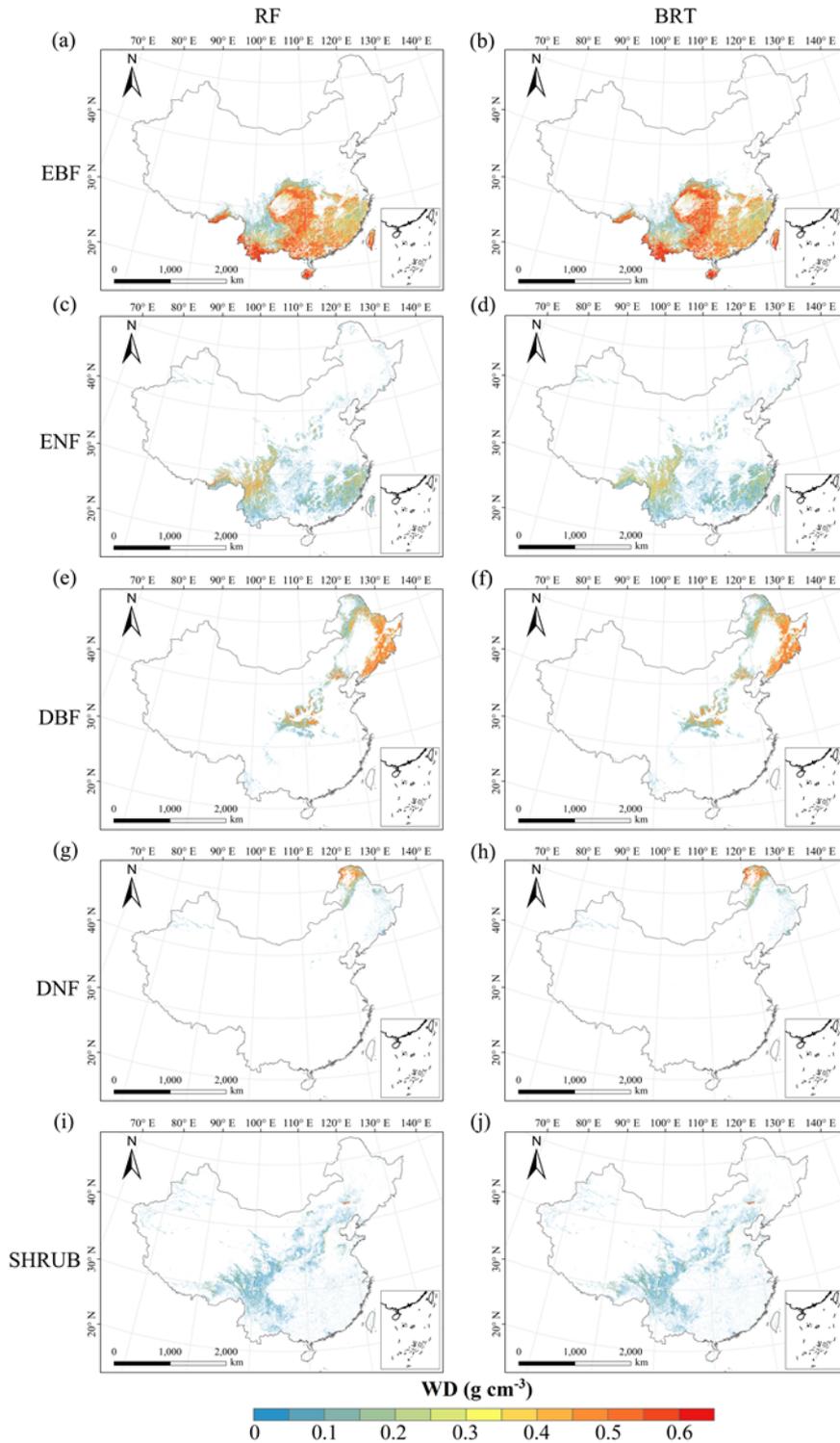
Figure D8. Spatial distribution of wood density (WD) for each plant functional type. The left penal was obtained from RF method (random forest), the right penal was obtained from BRT method (boosted regression trees). The white areas represent other natural vegetation types and artificial land cover types. EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; DBF, deciduous broadleaf forest; DNF, deciduous needleleaf forest; SHRUB, shrubland.