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Maps with 1 km resolution reveal increases in above- and belowground forest biomass carbon pools in China over the past 20 years

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Supplementary text

Text S1. Reasonability of the selected predictors in the random forest for BGB estimation

When forest type (FOR_T) is excluded, the BGB's predicting R^2 according to the ten-fold cross validation will be slightly reduced to 0.85±0.02, while the RMSE will be slightly elevated to 7.3±0.6 t/ha. On the other hand, if stand age information is not added as a supplementary predictor, the simulation R^2 and RMSE of BGB in China will be 0.86±0.01 and 7.1±0.5 t/ha, respectively. The seasonality of temperature and precipitation (Tsea and Psea) both have significant impacts on BGB. Without Tsea and Psea, the predicting efficiency of BGB in Chinese forests will be significantly reduced to 0.84±0.01 in R^2 and 7.5±0.4 t/ha in RMSE. These analyses proved the reasonability of adding these predictors in the RF designed for BGB estimation.

Soil properties, e.g., soil sand content are reported to have an impact on root biomass allocation (Ma et al., 2021). However, compared to the climatic impacts on forest RSR, the direct edaphic effect is usually much weaker (Mokany et al., 2006; Luo et al., 2012). To prove this assumption, here we chose the 'soil database of China for land surface modeling' which was derived from 8979 soil profiles and the Soil Map of China using polygon linkage method (Shangguan et al., 2013). The basic edaphic variables with large quantities of soil profile records are selected, including soil texture (sand and clay fractions), pH value, soil organic matter, total nitrogen and soil total phosphorus. After adding these six edaphic predictors, the predicting R^2 and RMSE for BGB according to ten-fold cross validations are 0.88±0.01 and 6.5±0.5 t/ha, respectively, compared to an R^2 of 0.89±0.02 and an RMSE value of 6.3±0.5 t/ha when edaphic factors are excluded. Accordingly, the incorporation of soil property maps as predictors will not improve the simulation efficiency of forests' BGB in China. As shown in Figure S4b, the contributions of edaphic factors are quite limited. By comparison between the contribution fractions of all predictors when edaphic factors are added and not added (see Figure S4), we may conclude that although soil conditions can slightly affect BGB, they are highly correlated with the plots' climatic and biotic conditions, making the edaphic factors no longer an essential input of the random forest models.

In fact, the currently available large-scale soil property maps are interpolated from site-scale measurements, or estimated through machine learning with climatic variables applied as key predictors, rather than directly observed. So, it is supposed to have much lower quality than climatic background data. Hence, to avoid over-fitting by the RF model, as well as introducing errors embedded in the soil property maps, we did not incorporate edaphic factors as predictors of the RF model for BGB mapping in China.

Text S2. Open data adopted in this study and the related references

AGB data in (Liu et al., 2015) is available at: http://wald.anu.edu.au/data_services/data/global-above-ground-biomass-carbon-v1-0/;

Biomass dataset in (Xu et al., 2021) is available at: https://doi.org/10.5281/zenodo.4161694;

GlobBiomass product is from: https://globbiomass.org/wp-content/uploads/GB_Maps;

MODIS Vegetation Continuous Fields is from: https://lpdaac.usgs.gov/products/mod44bv061/;

LPDR VOD dataset is available from: http://files.ntsg.umt.edu/data/LPDR/LPDR_v3/;

ESA's 300 m annual land cover are from: http://maps.elie.ucl.ac.be/CCI/viewer/download.php;

Annual 30m land cover data in China are available at: https://doi.org/10.5281/zenodo.4417810;

WorldClim bioclimatic background is from: https://www.worldclim.org/data/worldclim21.html;

Soil property maps for China are available at: http://globalchange.bnu.edu.cn/research/soil2;

Additional references

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Supplementary Figures

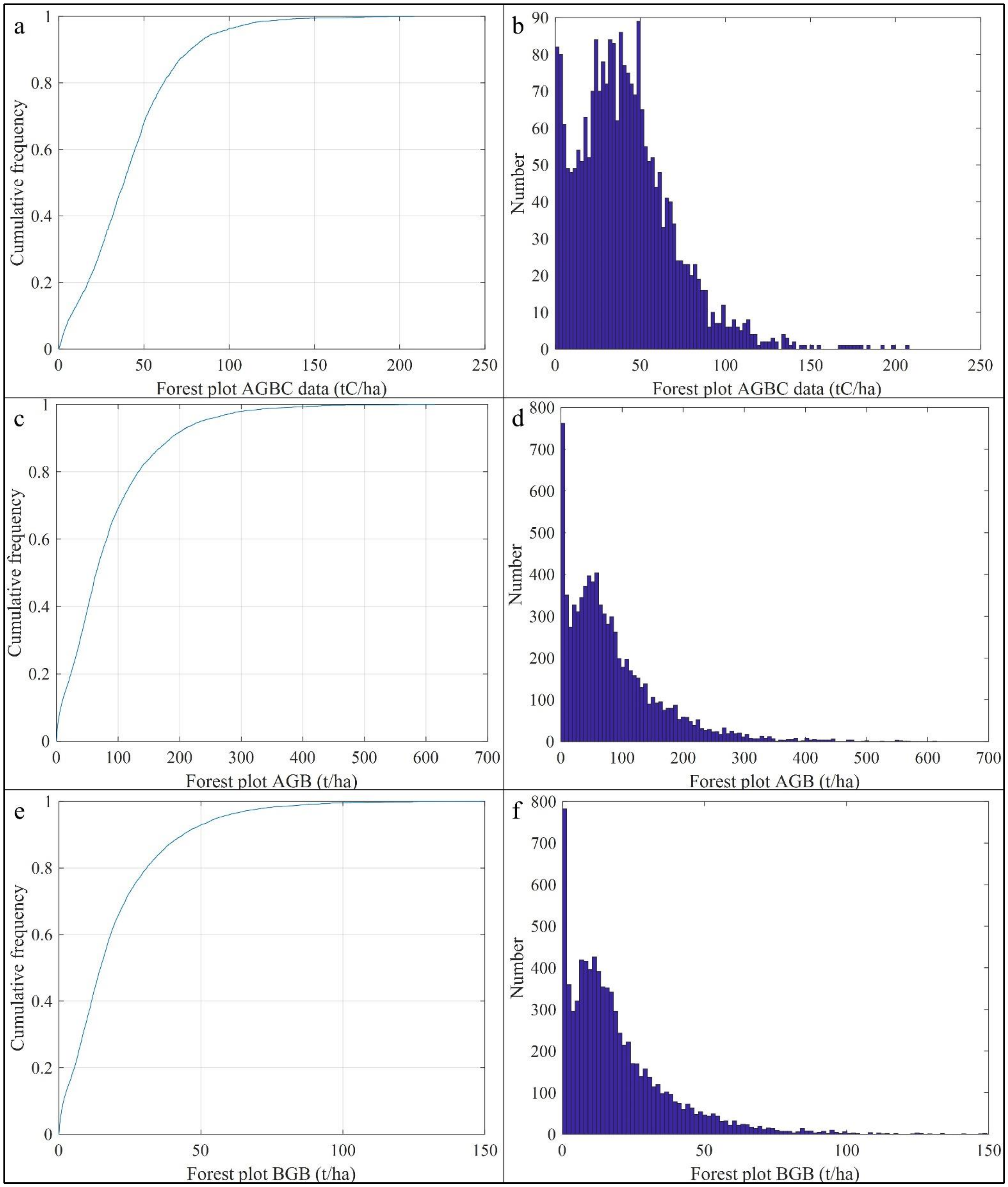

Figure S1. The (a, c, e) cumulative frequency curves and (b, d, f) histogram of (a~b) AGB carbon stock measurements at 2444 homogeneous forest plots; (c~d) AGB data at 8182 forest plots with both AGB and BGB records; (e~f) BGB data at 8182 forest plots with both AGB and BGB records.

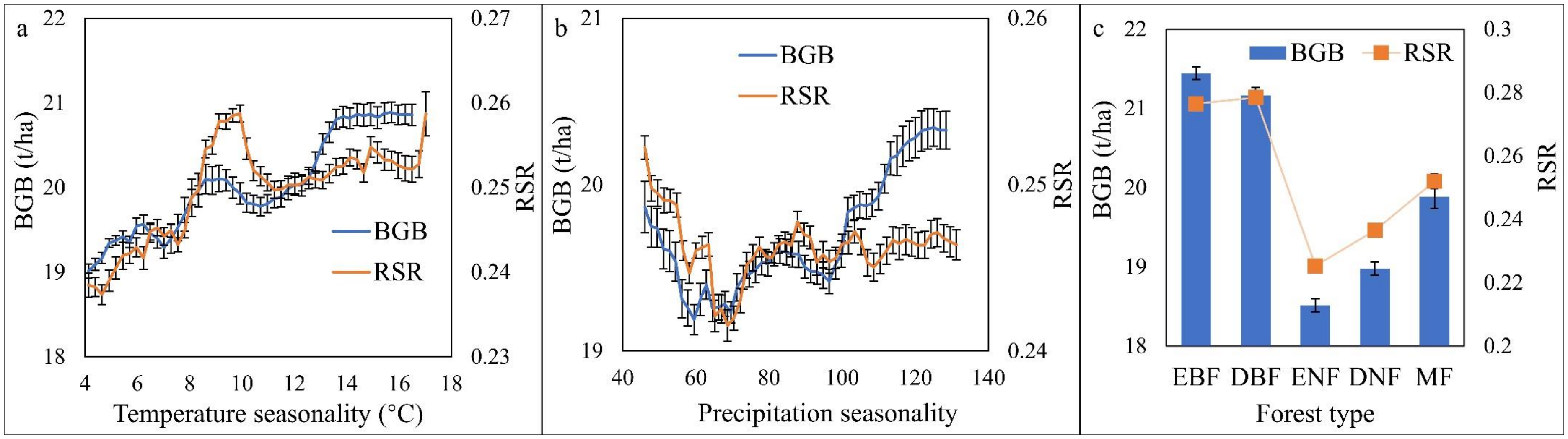

Figure S2. The partial dependence plots (PDP) between BGB or RSR and some supplementary predictors: (a) the PDP for temperature seasonality; (b) the PDP for precipitation seasonality; (c) the PDP for forest type (the partial impact of forest type on BGB or RSR). The lines are the mean PDP values, while the error bars are the standard deviation values of the ten-fold trainings.

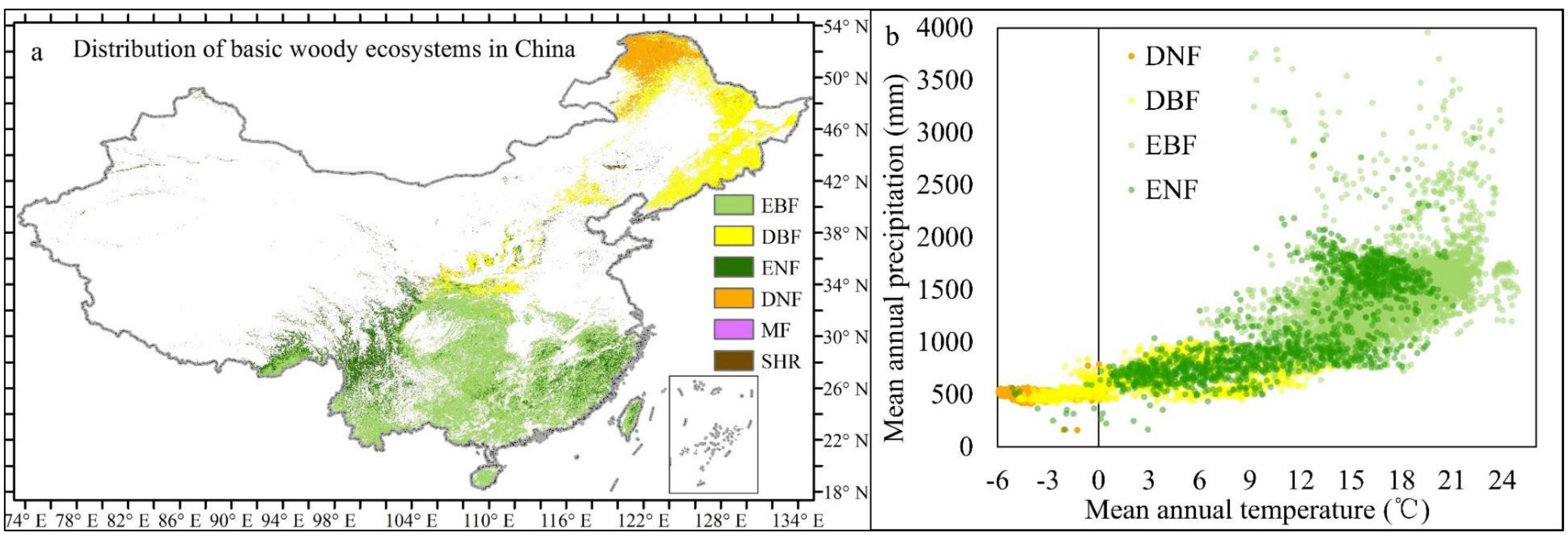

Figure S3. Classification of woody vegetation ecosystems in China. (a) the map of the distribution of six different woody ecosystems in China (EBF: evergreen broadleaf forest ecosystem; DBF: deciduous broadleaf forest ecosystem; ENF: evergreen needleleaf forest ecosystem; DNF: deciduous needleleaf forest ecosystem; MF: mixed forest ecosystem; SHR: shrubland ecosystem); (b) the basic climatic backgrounds of four major woody ecosystems in China, indicated by mean annual temperature and mean annual precipitation of 10000 1/120° pixels that are randomly chosen.

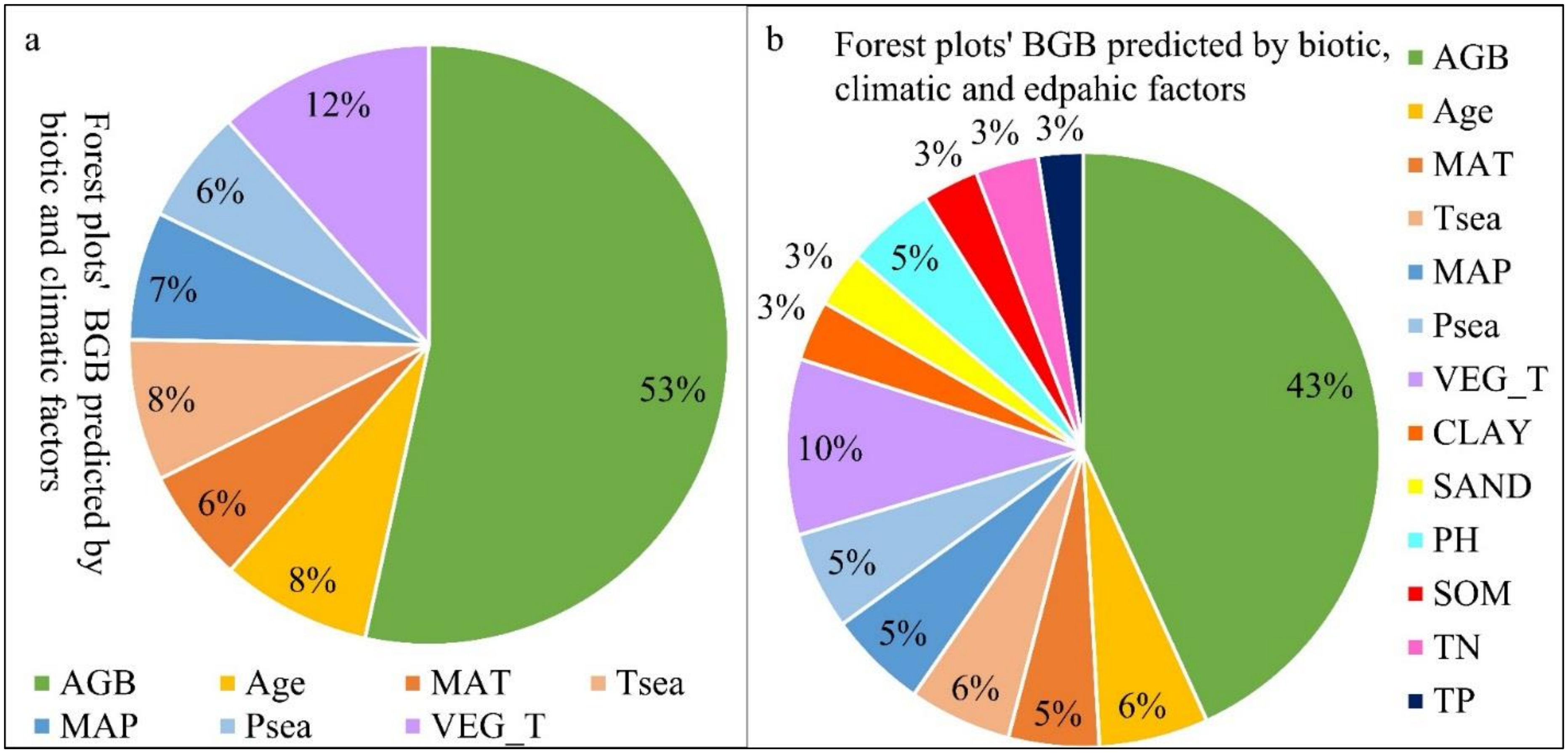

Figure S4. Each predictor's contribution to the simulation efficiency of BGB based on random forest model. (a) The contribution fraction of each climatic or biotic factor when soil property factors are not incorporated; (b) the contribution factions of all predictors when biotic, climatic, and edaphic factors are all incorporated. Abbreviations to some predictors: Tsea: temperature seasonality; Psea: precipitation seasonality; CLAY: soil clay fraction; SAND: soil sand fraction; PH: soil pH; SOM: soil organic matter content; TN: soil total nitrogen; TP: soil total phosphorus.