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1 **Spatial mapping of key plant functional traits in terrestrial**

2 **ecosystems across China**

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Abstract

Trait-based approaches are of increasing concern in predicting vegetation changes and linking ecosystem structure to functions at large scales. However, a critical challenge for such approaches is acquiring spatially continuous plant functional trait distribution. Here, eight key plant functional traits were selected to represent two-dimensional spectrum of plant form and function, including leaf area (LA), leaf dry matter content (LDMC), leaf N concentration (LNC), leaf P concentration (LPC), plant height, seed mass (SM), specific leaf area (SLA) and wood density (WD). A total of 52477 trait measurements of 4291 seed plant species were collected from 1541 sampling sites in China and were used to generate a spatial plant functional trait dataset (1 km), together with environmental variables and vegetation indices based on two machine learning models (random forest and boosted regression trees). The two models showed a good accuracy in estimating WD, LPC and SLA, with average R^2 values ranging from 0.45 to 0.66. In contrast, both the two models had a weak performance in estimating SM and LDMC, with average R^2 values below 0.25. Meanwhile, LA, SM and plant height showed considerable differences between two models in some regions. To obtain the optimal estimates, a weighted average algorithm was further applied to merge the predictions of the two models to derive the final spatial plant functional trait dataset. The optimal estimates showed that climatic effects were more important than those of edaphic factors in predicting the spatial distribution of plant functional traits. Estimates of plant functional traits in northeast China and the Qinghai-Tibet Plateau had relatively high uncertainties due to sparse samplings, implying a need of more observations in these regions in future. Our trait dataset could provide critical support for trait-based vegetation models and allows exploration into the relationships between vegetation characteristics and ecosystem functions at large scales. The eight plant functional traits datasets for China with 1 km spatial resolution are now available at https://figshare.com/s/c527c12d310cb8156ed2 (An et al., 2023).

1 Introduction

41 Climate change has been affecting vegetation distributions and biogeochemical cycling globally and
42 altering their feedbacks to the climate system (Kirilenko et al., 2000; Finzi et al., 2011; Jónsdóttir et
43 al., 2022). Dynamic global vegetation models (DGVMs) are powerful tools for predicting changes
44 in vegetation and ecosystem-atmosphere exchanges (e.g., water, carbon, and nutrient cycling) in a
45 changing climate (Foley et al., 1996; Peng, 2000). However, conventional DGVMs are still
46 insufficient realistic, largely due to their dependence on the plant functional types (PFTs) assumption
47 (Sitch et al., 2008; Yurova and Volodin, 2011; Scheiter et al., 2013). PFTs in conventional DGVMs
48 commonly have fixed attributes (mostly trait values) (Van Bodegom et al., 2012; Wullschleger et
49 al., 2014) that do not reflect plant adaptation to environments, limiting the quantification of carbon-
50 water-nutrient feedback between terrestrial ecosystems and the atmosphere (Zaehle and Friend,
51 2010; Liu and Yin, 2013). Trait-based approaches can provide robust theoretical basis for developing
52 the next generation of DGVMs (Van Bodegom et al., 2012; Sakschewski et al., 2015; Matheny et
53 al., 2017). Plant functional traits, which are closely associated with ecosystem functions (Diaz et al.,
54 2004; Yan et al., 2023), can effectively reflect response and adaptation of plants to environmental
55 conditions (Myers-Smith et al., 2019; Qiao et al., 2023).

56 Attempts to predict spatially continuous trait data have been conducted at regional to global
57 scales (Madani et al., 2018; Moreno-Martínez et al., 2018; Boonman et al., 2020; Loozen et al.,
58 2020). Webb et al. (2010) proposed that the environment creates a filtered trait distribution along an
59 environmental gradient, and such trait-environment relationships offer fundamental supports to
60 predict the spatial distribution of plant functional traits through extrapolating local trait
61 measurements. Boonman et al. (2020) mapped the global patterns of specific leaf area (SLA), leaf
62 N concentration (LNC), wood density (WD) and plant height based on a set of climate and soil
63 variables. As the number of available global trait databases increase (Kattge et al., 2011; Wang et
64 al., 2018), trait-environment relationships are becoming increasingly quantitative and accurate
65 (Bruelheide et al., 2018; Myers-Smith et al., 2019). Alternatively, remote sensing approaches, such
66 as empirical methods and physical radiative transfer models (e.g., partial least squares regression,
67 PROPECT model), have been developed to estimate plant physiological, morphological, and
68 chemical traits (e.g., leaf chlorophyll content, SLA, LNC and leaf dry matter content (LDMC))
69 (Darvishzadeh et al., 2008; Romero et al., 2012; Ali et al., 2016). Vegetation indices, such as the
70 normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI), have been
71 successful in estimating plant functional traits of crops, grasslands and forests (Clevers and Gitelson,
72 2013; Li et al., 2018; Loozen et al., 2018). Loozen et al. (2020) demonstrated that EVI was the most
73 important predictor for mapping the spatial pattern of canopy nitrogen in European forests.
74 Admittedly, recent studies have suggested that combining environmental variables and vegetation
75 indices can improve the predictive accuracy of canopy N compared to those based on vegetation
76 indices alone (Loozen et al., 2020).

77   Although there have been reports on plant functional trait distribution in China in some global
78   or regional research (Yang et al., 2016; Butler et al., 2017; Madani et al., 2018; Moreno-Martínez et
79   al., 2018; Boonman et al., 2020), they are still of large uncertainties in characterizing the spatial
80   distribution of plant functional traits in China. First, global studies generally have relatively few,
81   unevenly distributed sampling sites in China (Butler et al., 2017; Madani et al., 2018; Boonman et
82   al., 2020), impeding our understanding of the true spatial characteristics of trait variability. Second,
83   these studies are usually inconsistent. For example, Moreno-Martínez et al. (2018) and Madani et
84   al. (2018) demonstrated that SLA values were low in the southeast areas but high in the southwest
85   areas of China, whereas Boonman et al. (2020) found the opposite. Third, most studies mainly
86   focused on leaf traits (Yang et al., 2016; Loozen et al., 2018; Moreno-Martínez et al., 2018), whereas
87   traits associated with the whole-plant and reproductive strategies, such as WD and seed mass (SM),
88   were ignored. Therefore, mapping and verifying the spatial patterns of key functional traits that
89   reflect the whole plant economics spectrum in China is a top priority.

90   In this study, our main objective was to generate a spatial dataset for several key plant
91   functional traits, through combining field measurements, environmental variables and vegetation
92   indices. To achieve this goal, we used a processing routine to predict the spatial distribution of plant
93   functional traits. First, eight plant functional traits (i.e., SLA, LDMC, LNC, LPC, LA, plant height,
94   WD and SM) were selected because they reflect plant adaptation to environment constraints and
95   trade-offs between plant form and function (Reich and Cornelissen, 2014; Diaz et al., 2016). Second,
96   we used random forest and boosted regression trees to predict the spatial patterns of plant functional
97   traits by training the relationships between plant functional traits and environmental variables and
98   vegetation indices. To obtain the optimal estimates, an ensemble model (i.e., weighted average
99   algorithm) was further applied to merge the predictions of the two models. Finally, plant species
100   were aggregated to PFTs, and the spatial abundance of PFTs at 1 km resolution was calculated using
101   land cover map (100 m). We derived the spatial trait datasets via calculating community-weighted
102   trait values within grid cells (1 km) based on these abundances of each PFT and predicted trait
103   values.

2 Materials and Methods

2.1 Plant functional trait collection and data processing

106   Westoby (1998) proposed the 'leaf-height-seed' (LHS) strategy scheme that describes three
107   functionally different strategy axes in relation to SLA, plant height and SM, which are also included
108   in our study. As key leaf economics traits, LNC, LPC and LDMC were selected because they are
109   closely linked to plant growth rate, resource acquisition, and ecosystem function (Wright et al.,
110   2004). LA is indicative of the trade-off between carbon assimilation and water-use efficiency
111   (Wright et al., 2017), and WD reflects the trade-off between growth rate and support cost, with a
112   higher WD linked to a lower growth rate but a higher biomass support cost (King et al., 2006). The

113   information on the eight plant functional traits and their ecological meanings are described in Table
114   1.

115   Plant trait data was obtained and collected via two main sources. The first source was public
116   trait databases, including the TRY database (Kattge et al., 2020) and the China Plant Trait Database
117   (Wang et al., 2018). The second source was from literature (listed in Appendix A). To ensure data
118   quality and comparability, we only included trait observations that met the following five criteria:
119   1) Measurements must be obtained from natural terrestrial fields in order to minimize the influences
120   of management disturbance, and observations from cropland, aquatic habitat, control experiments
121   or gardens were excluded; 2) According to the mass ratio hypothesis, the effect of plant species on
122   ecosystem functioning is determined to an overwhelming extent by the traits and functional diversity
123   of the dominant species and is relatively insensitive to the richness of subordinate species (Grime,
124   1998). Thus, we only included studies that measured plant trait observations from all species or
125   dominant species within a community; 3) In order to account for the trait variation within and
126   between communities, we only considered real measurements of traits from individual plants, and
127   not species-level averages (Jung et al., 2010; Siefert et al., 2015); 4) Plant trait observations must
128   be made on mature and healthy plant individuals, so some specific growth stages (e.g., seedling)
129   and size classes (e.g., sapling) were excluded to reduce the confounding effect of ontogeny (Thomas,
130   2010); 5) We only included studies with clear geographical coordinates to ensure alignment with
131   predictor variables. The sampling location and sample time information from the original studies
132   were also included in the dataset.

133   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 shade-
136   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.

138 **Table 1** Description of plant functional traits selected in this study and their relevant ecosystem

139 functions.

Trait	Abbreviation	Description	Relevant ecosystem functions
Specific leaf area	SLA	As a core leaf economics trait (Wright et al., 2004), it is related to trade-off between leaf lifespan and C acquisition as well as light competition (Reich et al., 1991)	Productivity, litter decomposition, competitive ability (Bakker et al., 2011; Smart et al., 2017)
Leaf dry matter content	LDMC	Strongly related to resource availability and potential growth rate (Hodgson et al., 2011)	Productivity, litter decomposition, herbivore resistance, and drought tolerance (Bakker et al., 2011; Smart et al., 2017; Blumenthal et al., 2020)
Leaf N concentration	LNC	As a core leaf economics trait, it is strongly related to photosynthetic capacity (Wright et al., 2004)	Productivity, nutrient cycling, litter decomposition (LeBauer and Treseder, 2008; Bakker et al., 2011)
Leaf P concentration	LPC	As a core leaf economics trait, it is strongly related to photosynthetic capacity (Wright et al., 2004)	Productivity, nutrient cycling, litter decomposition (LeBauer and Treseder, 2008; Bakker et al., 2011)
Leaf area	LA	Trade-off between C assimilation and water use efficiency, it is related to energy balance (Wright et al., 2017)	Productivity (Li et al., 2020)
Plant height	/	A major determinant of a plant's ability to compete for light (Moles et al., 2009)	C storage, animal diversity (Conti et al., 2013; Roll et al., 2015)
Wood density	WD	A measure of carbon investment, representing the trade-off between growth and mechanical support (Martínez-Vilalta et al., 2010)	Drought tolerance, productivity (Hoeber et al., 2014; Liang et al., 2021)
Seed mass	SM	Closely related to seed dispersal and seed predation, as well as seedling establishment, growth, and survival (Leishman et al., 2000)	Competitive ability (Zepeda and Martorell, 2019)

140 The plant trait data was checked for possible errors and corrected as per three steps as follows.

141 First, species name and taxonomic nomenclature were corrected and standardized according to the

142 Plant List (http://www.theplantlist.org/) using the "plantlist" package. 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). Third, we

145 appended information on plant growth form (tree, shrub, and herb), leaf type (broadleaved and

146 needle-leaved) and leaf phenology (evergreen and deciduous) from the TRY categorical traits

147 database (https://www.try-db.org/TryWeb/Data.php#3) and *Flora Reipublicae Popularis Sinicae*

148 (http://www.iplant.cn/frps). After these treatments, we collected a total of 52477 trait measurements

149 from 1541 sampling sites for our database, representing 4291 species from 212 families and 1230

150 genera (Fig. 1). Information on the statistics for the eight plant functional traits collected in this

151 study is shown in Table B1 in Appendix B.
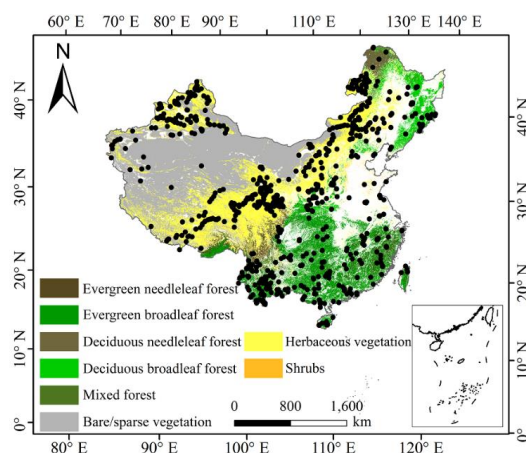
Figure 1. Location distribution and land cover map in China.

2.2 Environmental data

2.2.1 Climate data

Twenty-one climate variables were used in this study, including 19 bioclimate variables, solar radiation (RAD), and AI (Table B2 in Appendix B). The 19 bioclimate variables and RAD were obtained from the WorldClim dataset (version 2.1) for the period from 1970 to 2000 (https://www.worldclim.org/data/worldclim21.html). The AI data was extracted from the CGIAR Consortium of Spatial Information (CGIAR-CSI) website for the period from 1950 to 2000 (http://www.csi.cgiar.org) (Trabucco and Zomer, 2018). The spatial resolution of climate data was 1 km.

2.2.2 Soil data

Twelve soil variables were included in this study, representing the different aspects of soil properties, i.e. soil texture, bulk density (BD), pH, and soil nutrients (Table B2 in Appendix B). All soil variables were extracted from the Soil Database of China for Land Surface Modeling (http://globalchange.bnu.edu.cn/research/soil2) (Shangguan et al., 2013). Given the importance of topsoil properties on community composition (Bohner, 2005), the soil data was averaged to represent the top 30 cm of soil in our study. The spatial resolution was 1 km.

2.2.3 Topography

The topographic variable was elevation. Elevation data was extracted from the STRM 90m dataset in China, based on the SRTM V4.1 database (https://www.resdc.cn/data.aspx?DATAID=123). The spatial resolution was 1 km.

Given the collinearity among climate and soil variables, we reduced the number of environmental predictors based on Pearson's correlation coefficient (r) (Figs. B1 and B2 in Appendix B). Among a set of highly correlated variables (r > 0.75), only one variable was retained in subsequent analysis to ensure a combination of different environmental variables. The final selection of environment predictors included nineteen variables: mean annual temperature (MAT),

179   mean diurnal range (MDR), min temperature of coldest quarter (Tmin), max temperature of coldest

180   quarter (Tmax), temperature seasonality (TS), mean annual precipitation (MAP), precipitation

181   seasonality (PS), precipitation of wettest quarter (PEQ), precipitation of driest quarter (PDQ), AI,

182   RAD, elevation, soil sand content (SAND), pH, BD, soil total N (STN), soil total P (STP), soil

183   alkali-hydrolysable N (SAN), and cation exchange capacity (CEC).

2.3 Vegetation indices

185   Three categories of vegetation indices were included in this study (Table B2 in Appendix B). The

186   first selected was EVI, which was extracted from the MOD13A3 V006 product

187   (https://lpdaac.usgs.gov/products/mod13a3v006/). This product is available as a monthly average

188   with spatial resolution of 1 km, ranging from January 2000 to December 2018. Second, MODIS

189   reflectance data was also extracted from the MOD13A3 V006 product. This included MIR

190   reflectance, NIR reflectance, red reflectance, and blue reflectance. Third, the MERIS terrestrial

191   chlorophyll index (MTCI) was extracted from the Natural Environment Research Council Earth

192   Observation Data Centre (NERC-NEODC, 2005) (https://data.ceda.ac.uk/). MTCI data is available

193   globally as a monthly average at 4.63 km spatial resolution, and ranges from June 2002 to December

194   2011. It is noted that valid MTCI values should be greater than 1, so our study deleted any values

195   less than 1.

196   To avoid collinearity, we also reduced the number of vegetation indices based on Pearson's

197   correlation coefficient (r) (Figs. B3 in Appendix B). Furthermore, given that most plant functional

198   traits were measured during the growing season, the variables related to the growing season were

199   determined to be important predictors. The final selection included 36 variables: annual EVI, EVI

200   (May, June, July, August and September), MTCI, MIR, NIR, red and blue (all for January, June,

201   July, August and September).

202   Both environmental variables and vegetation indices variables were resampled to a consistent

203   spatial resolution of 1 km using the nearest neighborhood method.

204   PFT is also an important factor in influencing the variation of plant functional traits (Verheijen

205   et al., 2016; Loozen et al., 2020), thus PFT was included as a predictor in this analysis. We used the

206   2015 land cover map at a 100 m spatial resolution from the Copernicus Global Land Service (CGLS-

207   LC100, Version 3) (https://land.copernicus.eu/global/products/lc) (Buchhorn et al., 2020). We

208   focused on natural terrestrial vegetation, so all artificial or crop areas were thus eliminated in our

209   dataset. Seven categories were included: evergreen needleleaf forest (ENF), evergreen broadleaf

210   forest (EBF), deciduous needleleaf forest (DNF), deciduous broadleaf forest (DBF), shrubland

211   (SHL), grassland (GRL) and bare/sparse vegetation. Furthermore, in order to match species names

212   to PFTs, we associated each species (i.e., plant growth form, leaf type and leaf phenology) with a

213   corresponding PFT. For example, the information on *Salix matsudana* is: tree, deciduous and

214   broadleaf, thus, we were able to associate the PFT of deciduous broadleaf forest (DBF) to this

215   species. The species that did not correspond to any PFT were discarded.

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2.4 Model fitting and validation

216

217 To predict spatial patterns of plant functional traits, we used two machine learning models, i.e.,

218 random forest and boosted regression trees.

219 Random forest is an ensemble machine learning method based on classification and regression

220 trees using collections of regression trees to classify observations according to a set of predictive

221 variables (Breiman, 2001). This method repeatedly constructs a set of trees from random samples

222 of training data, and the final prediction is produced by integrating the results of all individual trees,

223 which makes it a robust method. The models are controlled by two main parameters: the number of

224 sampled variables (mtry) and the number of trees (ntree). The parameter mtry was set to range from

225 1 to 57 (at an interval of 1), and the ntree was set as 500, 1000, 2000, 5000 and 10000 in subsequent

226 runs. This analysis was performed using the 'randomForest' function in the 'randomForest' package

227 (Liaw and Wiener, 2002).

228 Boosted regression trees is a machine learning method based on generalized boosted regression

229 models, and using a boosting algorithm to combine many sample tree models to optimize predictive

230 performance (Elith et al., 2006). There is no need for prior data transformation or the elimination of

231 outliers, and this method can fit complex non-linear relationships while automatically handling

232 interaction effects between predictors (Elith et al., 2008). The four parameters to optimize in these

233 models are the number of trees, interaction depth, learning rate and bag fractions. We varied the

234 parameter settings to find the optimal parameter combination that achieves minimum predictive

235 error. The number of trees was set to 3000, the interaction depth varied from 1 to 7 (at an interval

236 of 1), the learning rate was set to 0.001, 0.01, 0.05 and 0.1, and the bag fraction was set to 0.5, 0.6,

237 0.7 and 0.75. PFT was used as a dummy variable in the boosted regression trees models. This

238 analysis was conducted using the 'gbm' function in the 'gbm' package (Ridgeway, 2006).

239 We used a 10-fold cross validation to select the optimal parameter combination and to evaluate

240 the final model performance for each trait. We spilt the data into two parts: 80% of the trait data was

241 used to train the models, and the remaining 20% was used to assess model's performance. The fitting

242 performances of the random forest and boosted regression trees methods were evaluated using

243 determinate coefficient (R^2), root-mean-square error (RMSE), and mean absolution error (MAE).

244 These scores are calculated following Eq. (1), Eq. (2) and Eq. (3):

245
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(p_i - o_i)^2}{\sum_{i=1}^{n}(p_i - \hat{o}_i)^2} \tag{1}$$

246
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - o_i)^2} \tag{2}$$

247
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|o_i - p_i| \tag{3}$$

248 where p_i and o_i are the predictive values and observed values, respectively, $\hat{o}_i$ is the mean of

249 the observed values.

250 To quantify the relative importance of each predictor consistently across the two models, we

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251 used the method proposed by Thuiller et al. (2009). The correlations between fitted values and

252 predictions were calculated using permuted values for the predictor of concern. This step was

253 repeated a user-defined number of times for each predictor, and the mean correlation coefficient

254 over runs was recorded. Then the relative importance of each predictor was quantified as one minus

255 the Spearman rank correlation coefficient (see Boonman et al. 2020). In addition, we used

256 generalized additive models to fit the relationships between plant functional traits and the most

257 important variables using the 'gam' function in the 'mgcv' package.

258 **2.5 Generation of plant functional trait maps and model performance**

259 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. To obtain the optimal estimates, the ensemble model was

263 further applied to merge the predictions of random forest and boosted regression trees according to

264 their cross-validated R^2 values. The accuracy of the ensemble model was calculated by regressing

265 the 20% of cross-validation data used for testing against the observed trait values.

266 To evaluate the model performance (i.e. the variability in the prediction across models), the

267 coefficient of variation (CV) was calculated as the difference between the predictions of random

268 forest and boosted regression trees methods and the ensemble prediction weighted by the predictive

269 performance of each of the models. CV is calculated following Eq. (4):

270
$$CV_t = \frac{\sqrt{\frac{\sum_{m=1}^{2}(pred_{m,t}-obs_t)^2 \,*r_{m,t}^2}{\sum_{m=1}^{2} r_{m,t}^2}}}{obs_t} \tag{4}$$

271 where $pred_{m,t}$ is the predictive values of t trait in m model, obs_t is the values of t trait in the

272 ensemble model, $r_{m,t}^2$ is the cross-validated R^2 of t trait in m model.

273 **2.6 Uncertainty assessments**

274 Multivariate environmental similarity surface analysis (MESS) was used to identify the range of the

275 extrapolated predictor values across the locations in the plant trait dataset (Elith et al., 2010). This

276 method is often used to evaluate the extent of extrapolation and the applicability domain. If the

277 values are negative, this indicates that at a given grid cell, at least one predictor variable is outside

278 the extent of referenced predictor layer. This analysis was conducted using the 'mess' function in

279 the 'dismo' package.

280 All analyses were performed in R 4.0.2 (R Core Team, 2020).

281 **3 Results**

282 **3.1 Performances of prediction models**

283 Cross-validation showed that the performance of the predictive models differed greatly among the plant

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284 functional traits (Table 2). WD had the best performance in all three models, with R^2 values of 0.64, 0.68

285 and 0.67 for random forest, boosted regression trees and ensemble model, respectively. LPC, height and

286 SLA had R^2 values greater than 0.45, while SM and LDMC performed the worst, with R^2 values

287 below 0.25. In addition, the ensemble model performed better than the random forest and boosted

288 regression trees alone (Tables C1 and C2 in Appendix C).

289 **Table 2** Results of plant functional traits for cross-validated R^2, RMSE and MAE for random

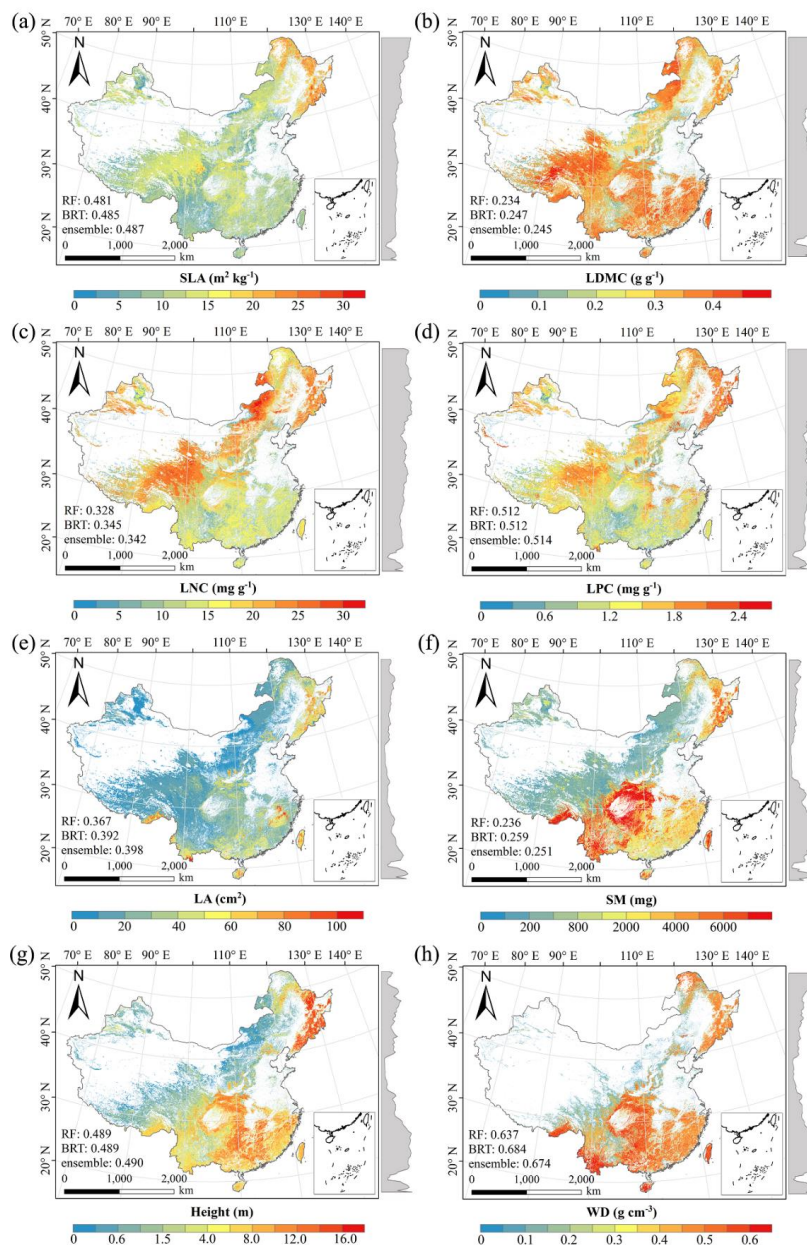290 forest, boosted regression trees, and ensemble model.

Traits	Random forest			Boosted regression trees			Ensemble model		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
SLA	0.48	7.02	5.10	0.48	6.99	5.08	0.49	6.98	5.07
LDMC	0.23	0.10	0.07	0.28	0.09	0.07	0.24	0.09	0.07
LNC	0.33	6.64	4.92	0.34	6.52	4.85	0.34	6.54	4.85
LPC	0.51	0.80	0.53	0.51	0.80	0.53	0.51	0.80	0.53
LA	0.37	68.94	26.76	0.39	67.69	27.47	0.40	67.28	26.59
SM	0.24	4547.22	1228.07	0.26	4478.88	1183.61	0.25	4499.67	1201.83
Height	0.49	2.89	2.09	0.49	2.89	2.10	0.49	2.89	2.10
WD	0.64	0.13	0.10	0.68	0.12	0.10	0.67	0.13	0.10

291 SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P

292 concertation; LA, leaf area; WD, wood density; SM, seed mass.

293 **3.2 Spatial patterns of predicted plant functional traits**

294 There were relatively consistent spatial patterns for SLA, LNC and LPC, with high values in the

295 northeastern and northwestern regions and the southeastern Qinghai-Tibet Plateau, and low values

296 in southwestern China (Figs. 2a, 2c and 2d, Figs. D1, D2 in Appendix D). SLA and LPC increased

297 with latitude, while LNC did not vary significantly along the latitudinal gradient. For SLA, LNC

298 and LPC, the variability was low among the random forest, boosted regression trees and ensemble

299 model, with an overall CV less than 0.3 (Figs. 3a, 3c, and 3d). LDMC values were relatively high

300 in most regions of China, and the low values were mainly located in eastern Yunnan and the Loess

301 Plateau (Fig. 2b, Figs. D1, D2 in Appendix D). LA and SM showed consistent spatial patterns, with

302 high values in the northeastern and southern regions (except for the Sichuan Basin), and the

303 southeastern Qinghai-Tibet Plateau (Figs. 2e and 2f, Figs. D1, D2 in Appendix D). The strong

304 latitudinal gradients were observed in LA and SM, where values decreased with latitude.

305 The CV values of LPC and SM decreased with latitude, but other traits did not show latitudinal

306 patterns (Figs. 3). The CV values were relatively high, especially in the northwestern region, the

307 Inner Mongolia Plateau-Loess Plateau region (only for LA) and Yunnan province (only for SM)

308 (Figs. 3e and 3f). Plant height and WD had consistent spatial patterns, with high values in the

309 northeastern and southern regions (Figs. 2g and 2h, Figs. D1, D2 in Appendix D). The CV values

310 across models for plant height were higher in northwestern China and Inner Mongolia Plateau-Loess

311 Plateau region, while CV values for WD in China were low throughout China (Figs. 3g and 3h).

Figure 2. Spatial patterns of predicted plant functional traits in China based on the ensemble model. The grey curves to the right of the maps display trait distribution along with latitude. RF, random forest; BRT, boosted regression trees; ensemble, ensemble model; SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.
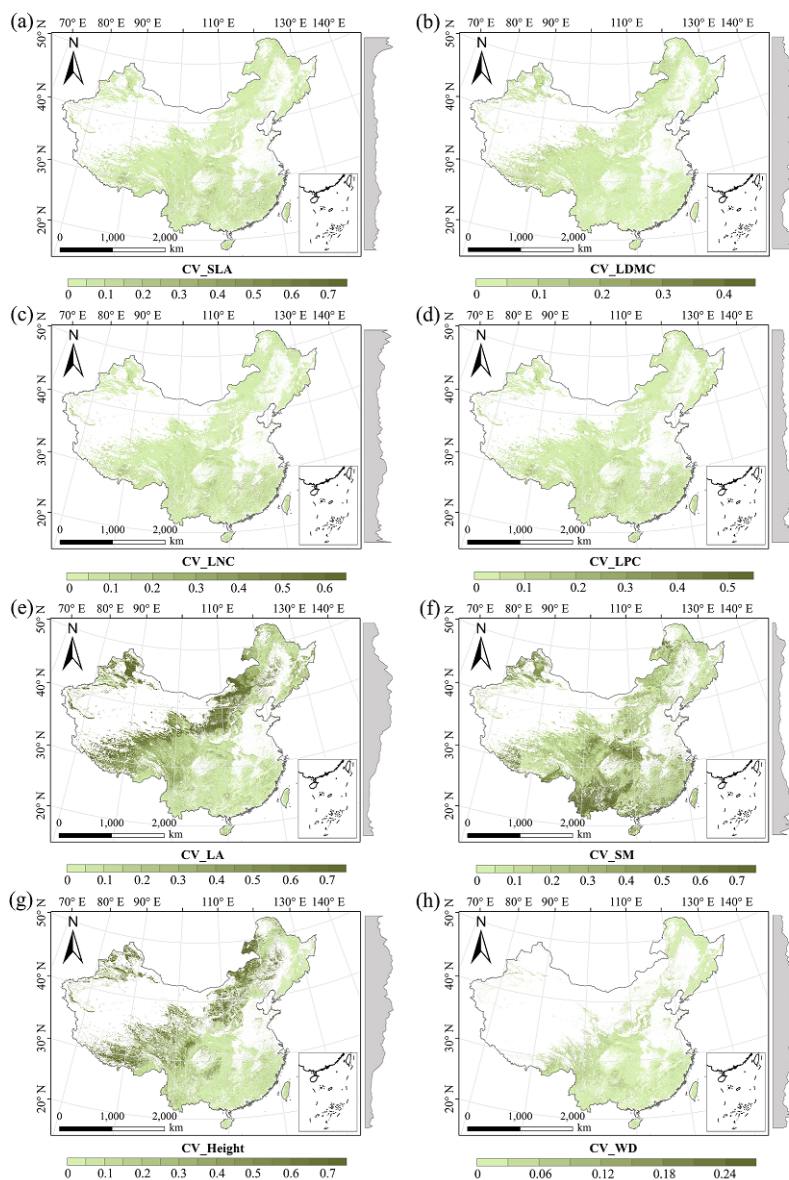
Figure 3. The variability in plant functional trait predictions among random forest, boosted regression trees and ensemble model. The grey curves to the right of the maps display coefficient of variation along with latitude. SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.

3.3 Relative importance of predictive variables

The dominant factors explaining spatial variation differed greatly among the eight plant functional

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326 traits (Table 3). Overall, climate variables were more important for predicting plant functional traits
327 than were soil variables. Temperature variables (i.e., MAT, MDR and TS) showed close
328 relationships with SLA, LDMC, LPC and WD, while precipitation variables (i.e., PS, PEQ, MAP
329 and PDQ) were more important for predicting the spatial patterns of LNC, LPC, LA and plant height.
330 RAD was the fourth most dominant factor in predicting the spatial patterns of SLA, SM, WD and
331 plant height. Elevation also play an important role in the LDMC and LPC predictions. Within soil
332 variables, soil nutrients [i.e., pH and soil available P (SAP)] showed close associations with SLA,
333 LNC and SM. In addition to the environmental variables, MTCI emerged as an important predictor
334 for explaining SLA, LDMC, LA and plant height. Finally, EVI was the most important predictor for
335 LA and SM, and MIR in January and May were the primary predictors of WD. The relationships
336 between plant functional traits and the most important variables were shown in Figs. E1 and E2 in
337 Appendix E.

338 **Table 3** List of the eight most important variables for plant functional trait predictions.

Rank	SLA	LDMC	LNC	LPC	LA	SM	Height	WD
1	SAP	MAT	PS	MDR	EVI5	EVI8	PEQ	MIR1
2	TS	Elevation	SAP	PDQ	PEQ	SAP	EVI6	TS
3	blue9	MTCI5	pH	Elevation	MTCI9	MAT	MTCI6	MIR5
4	RAD	blue8	MDR	MIR8	NIR9	RAD	RAD	RAD
5	MTCI4	MTCI4	MAP	Tmax	AI	NIR1	pH	MIR6
6	MTCI6	MTCI6	PEQ	MTCI6	MTCI6	NIR8	MAP	pH
7	Elevation	NIR1	MIR1	MIR7	MAP	SAND	red9	red5
8	MTCI7	CEC	Tmax	MIR9	red5	BD	red5	PS

339 SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf
340 P concertation; LA, leaf area; WD, wood density; SM, seed mass; SAP, soil available P; TS,
341 temperature seasonality; blue, blue reflectance; RAD, solar radiation; MTCI, MERIS terrestrial
342 chlorophyll index; MAT, mean annual temperature; NIR, near-infrared reflectance; CEC, cation
343 exchange capacity; PS, precipitation seasonality; MDR, mean diurnal range; MAP, mean annual
344 precipitation; PEQ, precipitation of wettest quarter of a year; MIR, middle infrared reflectance;
345 Tmax, max temperature of warmest month of a year; PDQ, precipitation of driest quarter of a year;
346 EVI, enhanced vegetation index; AI, aridity index; red, red reflectance; SAND, soil sand content;
347 BD, bulk density.

348 **3.4 Model performance**

349 The distributions of the predictive trait values based on random forest, boosted regression trees, and
350 ensemble model were consistent with the original trait observations, especially the peak values (Fig.
351 4). Except for SM, the mean values of trait observations were relatively higher than those of the
352 predictive values.

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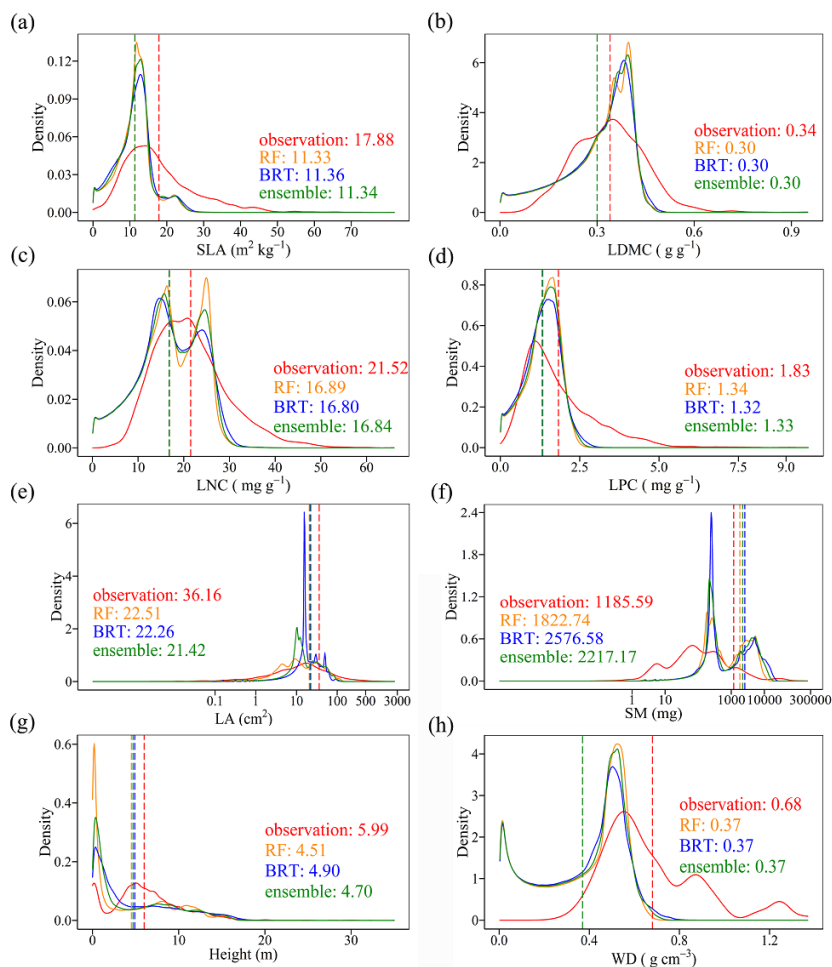
Figure 4. Comparison of trait distribution between observations and predictive values in each of the different models. Each panel depicts the distribution of observations in solid red, of the random forest (RF) model in yellow, of the boosted regression trees (BRT) model in blue, and of the ensemble model in green. The dashed vertical lines indicate mean values. SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.

3.5 Uncertainty assessments

The MESS values of five leaf traits and WD were positive in most regions, indicating a wide applicability domain of our models (Fig. 5). Nevertheless, trait predictions should be interpreted carefully for northeastern China and the Qinghai-Tibet Plateau due to the sparse samplings in these regions. In addition, spatial predictions for SM and plant height were extrapolated to a larger extent than were the other plant functional traits.

367
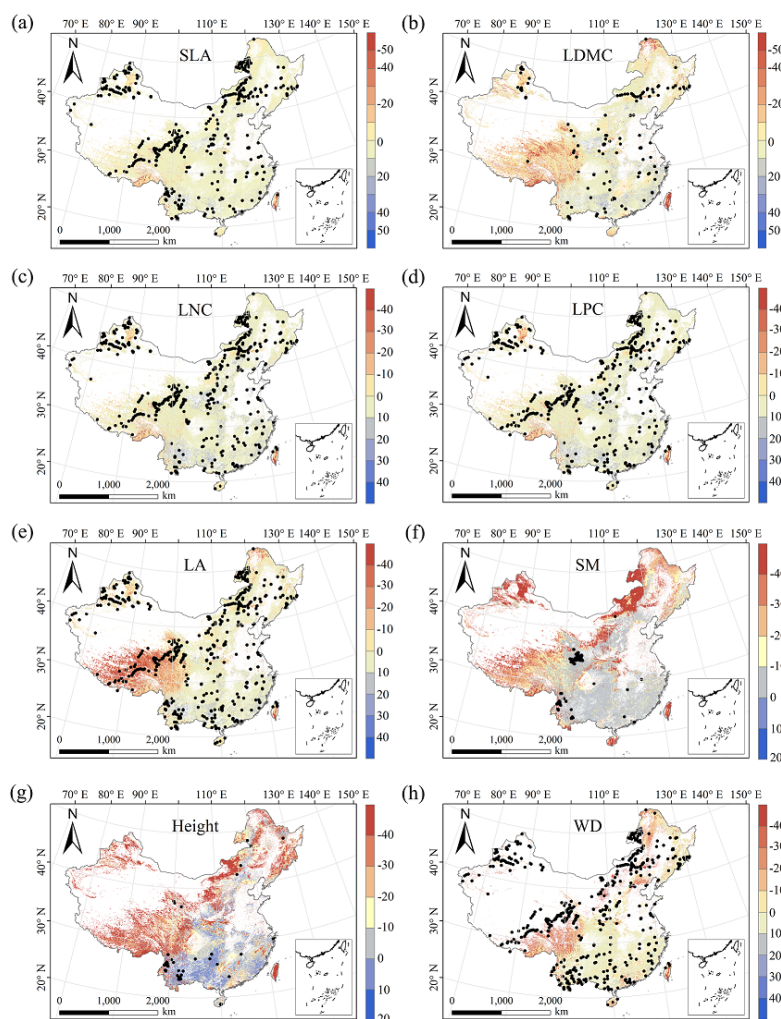
Figure 5. Multivariate environmental similarity surface (MESS) assessments for the eight plant functional traits. The black dots represented the locations of trait observations. More intense shades indicate greater similarity (blue) or difference (red) in environmental conditions of the location compared to the predictive factors covered by the training dataset. SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.

4 Discussion

4.1 Comparison with previous work

Our study predicted the spatial patterns of eight key plant functional traits across China using

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378　　machine learning methods and identified the applicability domain of the models. WD had the
379　　highest precision with an R^2 of 0.66, which was higher than the global WD prediction (Boonman et
380　　al., 2020). This improvement in precision may be attributed to the large number and dense
381　　occurrence of sample sites as well as the inclusion of vegetation indices in our study. In addition,
382　　SLA and LPC showed good accuracy with R^2 values of 0.50, which was higher than that of
383　　Boonman et al. (2020) and consistent with that of Martínez et al. (2018). Our study also predicted
384　　the spatial pattern of SM with an R^2 of 0.24, which was lower than in the global study of Madani et
385　　al. (2018) in which environmental variables explained 45.5% of SM variation. The low precision of
386　　SM may be explained in two ways. First, with few sampling sites included in our study, the
387　　environmental gradients were narrow. Second, previous studies and our unpublished study have
388　　suggested that SM variation is primarily controlled by a phylogenetic effect, whereas the
389　　environmental effect is weak (Moles et al., 2006). Therefore, phylogenetic relatedness among
390　　species should be considered to improve the predictive precision of the spatial pattern of SM in
391　　further work.

392　　　　There was no consensus in the spatial patterns of plant functional traits among the global
393　　studies. Thus, we compared our results to the other studies focused on China. Yang et al. (2016)
394　　predicted the spatial distribution of leaf mass per area (1/SLA) and LNC based on trait-environment
395　　relationships in China and had an R^2 of 0.13-0.16. The lower predictive precision may be because
396　　Yang et al. (2016) only used MAT, MAP, and RAD as predictors in estimating the spatial patterns
397　　of leaf mass per area and LNC, which likely led to poor performance and low heterogeneity. These
398　　results also demonstrate the advantage of our methods in mapping the spatial patterns of plant
399　　functional traits at a regional scale.

400 **4.2 Spatial patterns of plant functional traits in China**

401　　Our study revealed the spatial patterns of different plant functional traits across China, and the
402　　variability among the two machine learning methods was relatively low. In some regions, there were
403　　consistent patterns in plant functional traits between our study and the previous studies. For example,
404　　our study showed high SLA in the southeastern Qinghai-Tibet Plateau, which concurred with the
405　　global study of Boonman et al. (2020). Consistent with the global pattern (Wright et al., 2017), LA
406　　was larger in southern regions than in northern regions and showed a decreasing trend along a
407　　latitudinal gradient. Potapov et al. (2021) mapped global forest canopy height at a spatial resolution
408　　of 30 m by integrating GEDI and Landsat data, and their resulting spatial pattern of plant height in
409　　China was consistent with our study. This confirms the accuracy and reliability of predicting plant
410　　height through spatial extrapolation as in our study. However, in some regions there were
411　　contradictory patterns in the plant functional traits between our study and previous ones. Our study
412　　showed high LNC values in the northern Inner Mongolia Plateau-Loess Plateau-eastern Qinghai-
413　　Tibet Plateau and high heterogeneity in southern China, whereas Yang et al. (2016) predicted high
414　　LNC values in northeastern and northwestern China, northern Inner Mongolia Plateau, and the entire

415   Qinghai-Tibet Plateau, but low heterogeneity overall. In addition, Yang et al. (2016) predicted low

416   SLA variability in China, especially in the Qinghai-Tibet Plateau. These discrepancies may be

417   attributed to spatial extrapolation based on trait-climate relationships with a low predictive precision.

418   Moreover, our study also identified the applicability domain of our models for predicting the

419   spatial patterns of plant functional traits across China. Five leaf traits and WD appeared to have poor

420   applicability in northeastern China and the Qinghai-Tibet Plateau, primarily due to sparse samplings.

421   Although the predictions of plant height and SM were obtained in most regions through spatial

422   extrapolation, the results were consistent with previous studies. This demonstrates the reliability of

423   our methods. Future studies predicting plant functional traits across a large scale through remote

424   sensing observations or other supplementary data will be needed to re-evaluate our results.

425   4.3 The role of predictive variables

426   Our study indicates that environmental variables are important for predicting the spatial patterns of

427   plant functional traits, especially climate variables. Temperature variables were primary predictors

428   for SLA, LDMC, LPC and WD. The relationships between leaf traits and temperature have been

429   widely discussed in global and regional studies (Reich and Oleksyn, 2004; Bruelheide et al., 2018).

430   The positive linkage between WD and temperature may be driven by changes in the viscosity of

431   water. Plants can adapt to the low water viscosity at high temperatures by reducing the diameter and

432   density of their vessels and by thickening cell walls (Roderick and Berry, 2002; Thomas et al., 2004).

433   Precipitation variables were important predictors for leaf nutrient traits, LA, and plant height. Water

434   availability emerged as the primary predictor of plant height, which may be explained by the

435   hydraulic limitation hypothesis. Relative to shorter plants, taller plants tend to be at a higher risk of

436   embolisms due to their increased xylem length and conduit width. Thus, tall plants may be forced

437   to close their stomata and reduce the amount of photosynthesis (Renninger et al., 2009; Wang et al.,

438   2019). Although the effects of soil on trait predictions were relatively weak, we found that SAP and

439   pH played key roles in SLA, LNC and SM predictions. These results were similar with the previous

440   studies that reported that soil pH was an important driver of trait variation at the global scale and in

441   tundra regions (Kemppinen et al., 2021; Maire et al., 2015). Additionally, from the perspective of

442   cost-efficient theory, the strong effects of SAP reflected that high SLA and small seeds may be an

443   adaptation for facilitating soil exploration more efficiently in fertile soils (Freschet et al., 2010).

444   Vegetation indices have recently been proposed as important predictors of spatial patterns of

445   plant functional traits (Loozen et al., 2018). Our results corroborate these findings and further

446   suggest that EVI, MTCI and MIR reflectance are important predictors in models. Here, the

447   underlying mechanisms between vegetation indices and plant functional traits are not further

448   discussed due to their complexity and uncertainty. However, our results indicated that vegetation

449   indices and NIR reflectance are not key predictors of LNC estimation, which contrasts the findings

450   from global and regional studies (Loozen et al., 2018; Moreno-Martínez et al., 2018; Wang et al.,

451   2016). This may be related to the multitude of factors that influence the relationship between LNC

452 and vegetation indices and NIR reflectance, such as forest type and canopy structure (Dahlin et al.,
453 2013).

4.4 Uncertainties

455 Although our study mapped the spatial patterns of key functional traits of seed plants in China
456 through large-scale field investigations and compared the predictions with previous studies
457 performed at global and regional scales, there persist some uncertainties in the interpretation of these
458 results. First, the predictive ability of machine learning methods was relatively worse for certain
459 traits, especially for SM and LDMC. Beyond the environmental effects, the variation in plant
460 functional traits is also regulated by phylogenetic structure among plant species (e.g., family, order
461 and phylogenetic clade) (Li et al., 2017). Consequently, incorporating the phylogenetic information
462 will be a promising avenue in future studies for further improving the accuracy of spatial predictions
463 of plant functional traits (Butler et al., 2017). A second potential issue is sampling bias; there were
464 major spatial gaps in field investigation in both the northeastern China and the Qinghai-Tibet Plateau,
465 especially for SM and plant height. There are an increasing number of available datasets and studies
466 on SM and plant height, but many did not provide the corresponding geographic coordinates, thus
467 rendering the data unusable. 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),
469 and the overall quantity of WD data was much lower than that of leaf and reproductive traits, even
470 in the TRY database, which is the largest trait database in the world (Kattge et al., 2020). Finally,
471 additional key challenges in data availability must be resolved to scale up from the species to the
472 community levels, in particular with data surrounding species co-occurrence and their relative cover
473 or abundance in ecological communities (He et al., 2023). 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). In addition, integrating satellite remote sensing monitoring methods with
478 in situ data collection can also provide an effective way to estimate and assess the species diversity
479 at a large scale (Cavender-Bares et al., 2022).

4.5 Potential applications

481 Maps of these key functional traits of seed plants highlighted large-scale variability in space, which
482 will significantly advance ecological analyses and future interdisciplinary research. First, using the
483 spatially continuous trait datasets, one can optimize and develop trait-flexible vegetation models,
484 which allows for the exploration of the community assembly rules based on how plants with
485 different trait combinations perform under a given set of environmental conditions (Berzaghi et al.,
486 2020). When trait-flexible vegetation models are available, incorporating trait maps into models
487 will bridge the gap for vegetation classifications and predictions of vegetation distribution under

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488 global change, which is not feasible in conventional vegetation models (Van Bodegom et al., 2012;
489 Yang et al., 2019). Second, the assessments of China's terrestrial ecosystem carbon sink have had
490 large uncertainties so far (Piao et al., 2022), but the spatial continuous trait datasets will provide an
491 effective way to link ecosystem characteristics to ecosystem carbon sink estimates in China (Madani
492 et al., 2018; Šímová et al., 2019). These analyses will help shed light on the mechanisms underlying
493 plant functional traits and terrestrial ecosystem carbon storage at a large scale.

5 Data availability

495 The original eight plant functional traits dataset collected in this study that were used for machine
496 learning models (named by Data file used for machine learning models.csv) and final maps of eight
497 plant functional traits in terrestrial ecosystems in a GeoTIFF format across China (named by plant
498 functional trait category) are now available for the private link
499 https://figshare.com/s/c527c12d310cb8156ed2 (An et al., 2023). Once the article is accepted, we
500 will publicly publish these datasets at the figshare website.

6 Conclusions

502 We created a set of spatial continuous trait datasets at a 1-km spatial resolution using machine
503 learning methods in combination with field measurements, environmental variables and vegetation
504 indices. Models for leaf traits (except for LDMC), WD and plant height showed good accuracy and
505 robustness, whereas models of SM and LDMC had relatively poor precision and robustness.
506 Temperature variables were the most important predictors for leaf traits (except for LA) and WD,
507 and precipitation variables were the most important predictors for leaf nutrient traits, LA and plant
508 height. We caution that plant functional trait predictions should be interpreted carefully for
509 northeastern China and the Qinghai-Tibet Plateau. The spatial continuous trait datasets generated in
510 our study are complementary to current terrestrial in-situ observations and offer new avenues for
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512 China.

513

Appendix A Data collection from literature

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Appendix B

Table B1 Summary of statistics in plant functional traits, environmental variables and geographical distribution in China.

Trait	Unit	Range	Mean	CV (%)	No. of species	Entries	Sites
SLA	$m^2\ kg^{-1}$	0.06–81.68	17.88	54.96	2463	8851	1032
LDMC	$g\ g^{-1}$	0.06–0.95	0.34	100.00	1582	3549	193
LNC	$mg\ g^{-1}$	3.41–66.02	21.52	37.44	2335	7060	567
LPC	$mg\ g^{-1}$	0.09–9.70	1.83	62.19	2074	5968	515
LA	cm^2	0.0033–2553.33	36.16	259.64	1838	5899	691
Height	m	0.01–35.00	5.99	67.58	1171	16324	636
WD	$g\ cm^{-3}$	0.25–1.37	0.68	33.16	768	1476	639
SM	mg	0.10–201300.00	1185.59	562.32	1163	3080	134
Altitude	m	-144–5454					1541
MAT	°C	-12.07–24.32					1541
MAP	mm	15–2982					1541
Soil total N	$g\ kg^{-1}$	0.11–10.25					1541
Bulk density	$g\ cm^{-3}$	0.83–1.45					1541

SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass; MAT, mean annual temperature; MAP, mean annual precipitation.

835 **Table B2** List of all the predictors including environment and remote sensing variables used in this study.

Type of variables	Variable name	Abbreviations	Units	Time periods	Spatial resolution	Source
Climate	Mean annual temperature	MAT	°C	1970-2000	1 km	WorldClim version 2.1
	Mean diurnal range	MDR	°C	1970-2000	1 km	WorldClim version 2.1
	Temperature seasonality	TS	°C	1970-2000	1 km	WorldClim version 2.1
	Max temperature of warmest month	Tmin	°C	1970-2000	1 km	WorldClim version 2.1
	Min temperature of coldest month	Tmax	°C	1970-2000	1 km	WorldClim version 2.1
	Temperature annual range	TAR	°C	1970-2000	1 km	WorldClim version 2.1
	Isothermality	IS	%	1970-2000	1 km	WorldClim version 2.1
	Mean temperature of wettest quarter	MTEQ	°C	1970-2000	1 km	WorldClim version 2.1
	Mean temperature of driest quarter	MTDQ	°C	1970-2000	1 km	WorldClim version 2.1
	Mean temperature of warmest quarter	MTWQ	°C	1970-2000	1 km	WorldClim version 2.1
	Mean temperature of coldest quarter	MTCQ	°C	1970-2000	1 km	WorldClim version 2.1
	Mean annual precipitation	MAP	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation of wettest month	PEM	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation of driest month	PDM	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation seasonality	PS	%	1970-2000	1 km	WorldClim version 2.1
	Precipitation of wettest quarter	PEQ	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation of driest quarter	PDQ	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation of warmest quarter	PWQ	mm	1970-2000	1 km	WorldClim version 2.1
	Precipitation of coldest quarter	PCQ	mm	1970-2000	1 km	WorldClim version 2.1
	Aridity index	AI	/	1970-2000	1 km	Global CGIAR-CSI
	Solar radiation	RAD	kJ m^{-2} day^{-1}	1970-2000	1 km	WorldClim version 2.1
Topography	Elevation	/	m		1 km	SRTM 90m V4.1
Soil	Soil sand content	SAND	%	/	1 km	Shangguan et al. (2013)
	Soil silt content	SILT	%	/	1 km	Shangguan et al. (2013)
	Soil clay content	CLAY	%	/	1 km	Shangguan et al. (2013)
	Bulk density	BD	g cm^{-3}	/	1 km	Shangguan et al. (2013)
	Soil pH	pH	/	/	1 km	Shangguan et al. (2013)

Continued

| Type of variables	Variable name	Abbreviations	Units	Time periods	Spatial resolution	Source
	Soil organic matter	SOC	g kg^{-1}	/	1 km	Shangguan et al. (2013)
	Soil total N	STN	g kg^{-1}	/	1 km	Shangguan et al. (2013)
	Soil total P	STP	g kg^{-1}	/	1 km	Shangguan et al. (2013)
	Soil alkali-hydrolysable N	SAN	mg kg^{-1}	/	1 km	Shangguan et al. (2013)
	Soil available P	SAP	mg kg^{-1}	/	1 km	Shangguan et al. (2013)
	Soil available K	SAK	mg kg^{-1}	/	1 km	Shangguan et al. (2013)
	Cation exchange capacity	CEC	me kg^{-1}	/	1 km	Shangguan et al. (2013)
EVI	MODIS EVI long-term monthly averages		/	2001-2018	1 km	MOD13A3 V006
NIR	MODIS NIR long-term monthly averages		/	2001-2018	1 km	MOD13A3 V006
MIR	MODIS MIR long-term monthly averages		/	2001-2018	1 km	MOD13A3 V006
Red	MODIS red long-term monthly averages		/	2001-2018	1 km	MOD13A3 V006
Blue	MODIS blue long-term monthly averages		/	2001-2018	1 km	MOD13A3 V006
MTCI	MTCI long-term monthly averages		/	2003-2011	4.63 km	MTCI level 3 product
Land cover	Land cover map		/	2015	100 m	Copernicus Global Land Service Collection 3

836 The remote sensing variables are calculated as long-term monthly averages from 2001 to 2018. Thus 12
837 variables of each remote sensing category are obtained.
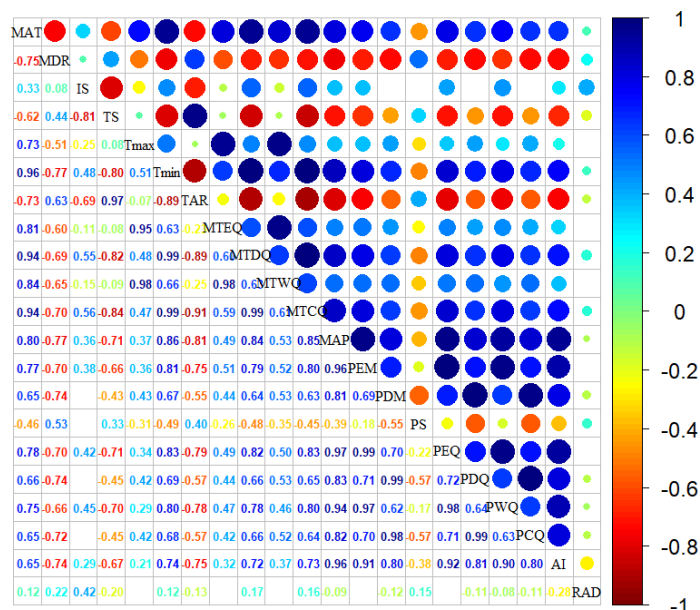
Figure B1. Correlations among climate variables. The blank indicates that the correlations are not significant ($P > 0.05$). The size of the circles is proportional to the correlation coefficient. The abbreviation of climate variables is seen in Table B2.

842
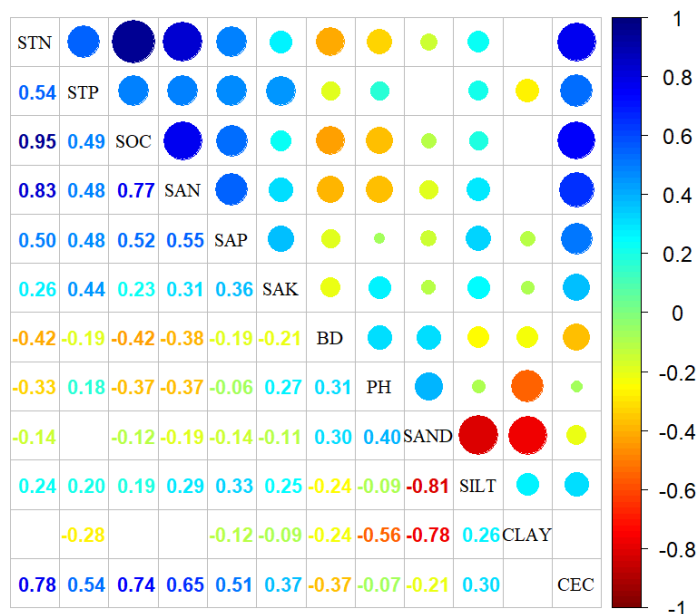
Figure B2. Correlations among soil variables. The blank indicates that the correlations are not significant

844 (*P* > 0.05). The size of the circles is proportional to the correlation coefficient. The abbreviation of soil

845 variables is seen in Table B2.
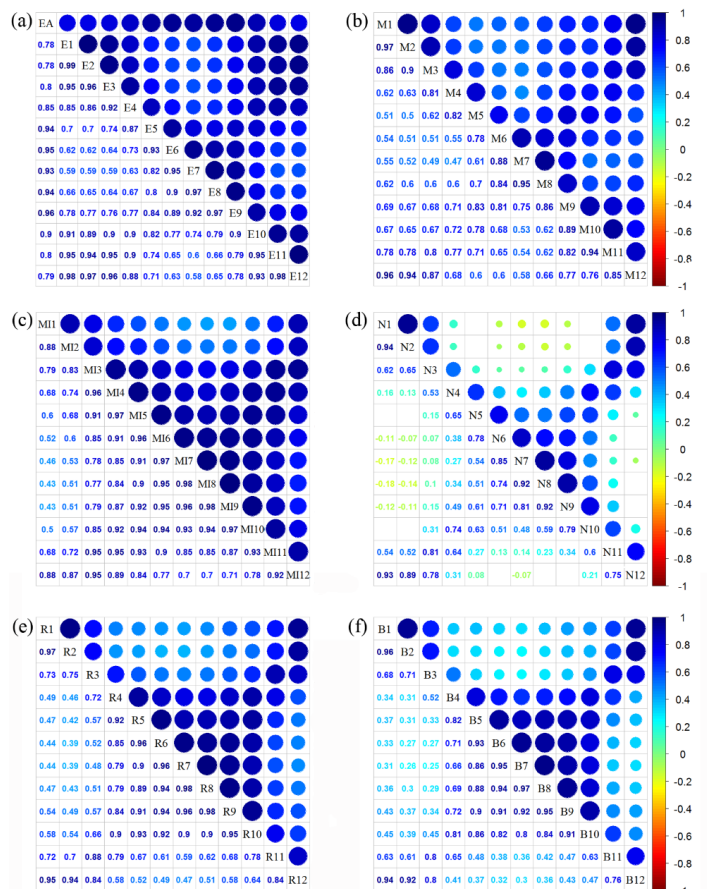
Figure B3. Correlations among monthly remote sensing variables. The blank indicates that the correlations are not significant ($P > 0.05$). The size of the circles is proportional to the correlation coefficient. (a) enhanced vegetation index (EVI); (b) MERIS terrestrial chlorophyll index (MTCI); (c) MIR reflectance; (d) NIR reflectance; (e) red reflectance; (f) blue reflectance.

Appendix C

Table C1 Optimal parameter combination and model performance of random forest (RF) for plant functional traits

| Traits	ntree	mtry	R²	RMSE	MAE
SLA	1000	24	0.476	7.049	5.134
LDMC	1000	11	0.234	0.095	0.072
LNC	1000	57	0.392	0.129	0.098
LPC	1000	20	0.587	0.176	0.129
LA	1000	18	0.278	72.996	26.622
Height	1000	38	**0.871**	0.234	0.178
WD	1000	9	0.531	0.092	0.072
SM	1000	22	**0.197**	6043.95	1290.866

SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.

Table C2 Optimal parameter combination and model performance of boosted regression trees (BRT) for plant functional traits

Traits	n.tree	interaction. depth	shrinkage	learning rate	bag fractions	R²	RMSE	MAE
SLA	3000	6	0.01	10	0.75	**0.486**	6.986	5.082
LDMC	3000	2	0.01	10	0.75	**0.247**	0.094	0.071
LNC	3000	6	0.01	10	0.70	**0.414**	0.126	0.096
LPC	3000	7	0.01	10	0.75	**0.591**	0.175	0.129
LA	3000	3	0.001	10	0.75	**0.282**	72.308	27.556
Height	3000	3	0.05	10	0.6	0.871	0.234	0.178
WD	3000	4	0.01	10	0.70	**0.627**	0.082	0.066
SM	3000	7	0.001	10	0.50	0.192	6070.703	1268.386

SLA, specific leaf area; LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density; SM, seed mass.

861   **Appendix D**

862
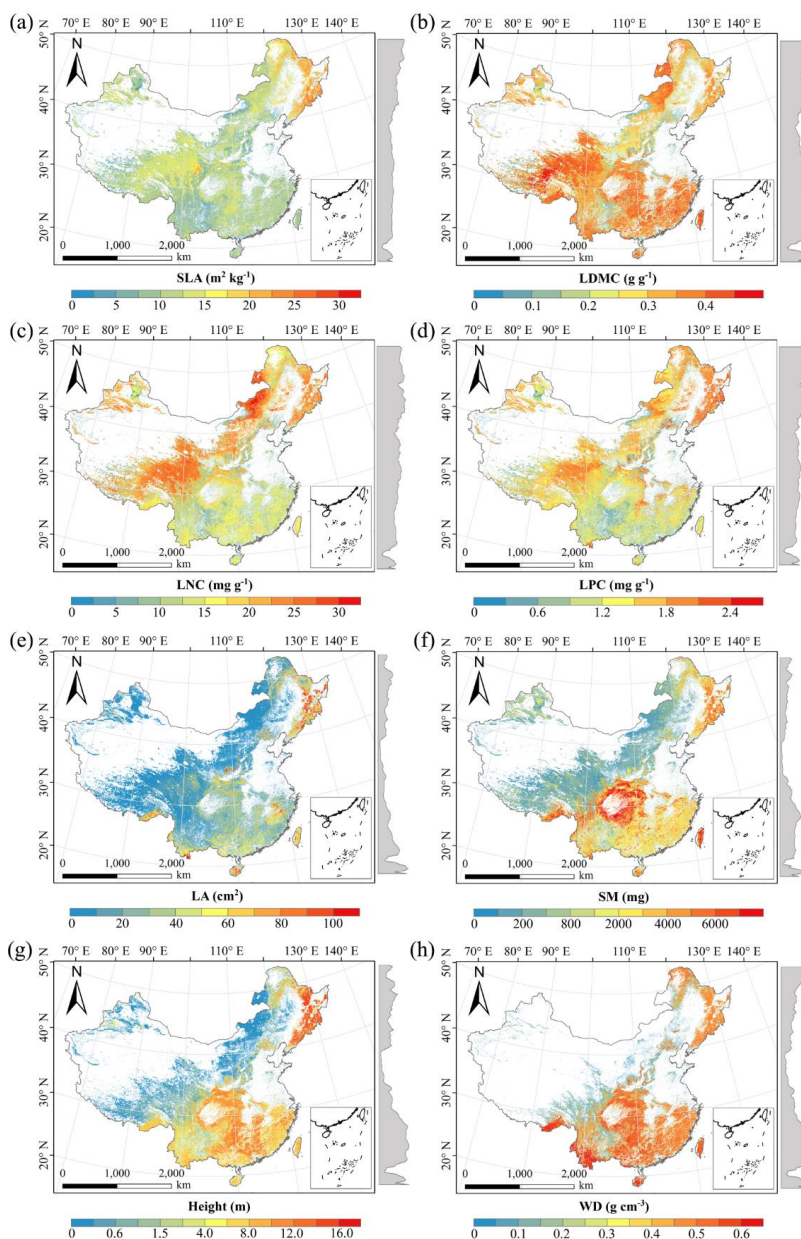
Figure D1. Spatial distribution of plant functional traits based on random forest (RF). The grey curves
on the right of maps were trait distribution along with latitude. SLA, specific leaf area; LDMC, leaf dry
matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD, wood density;
SM, seed mass.
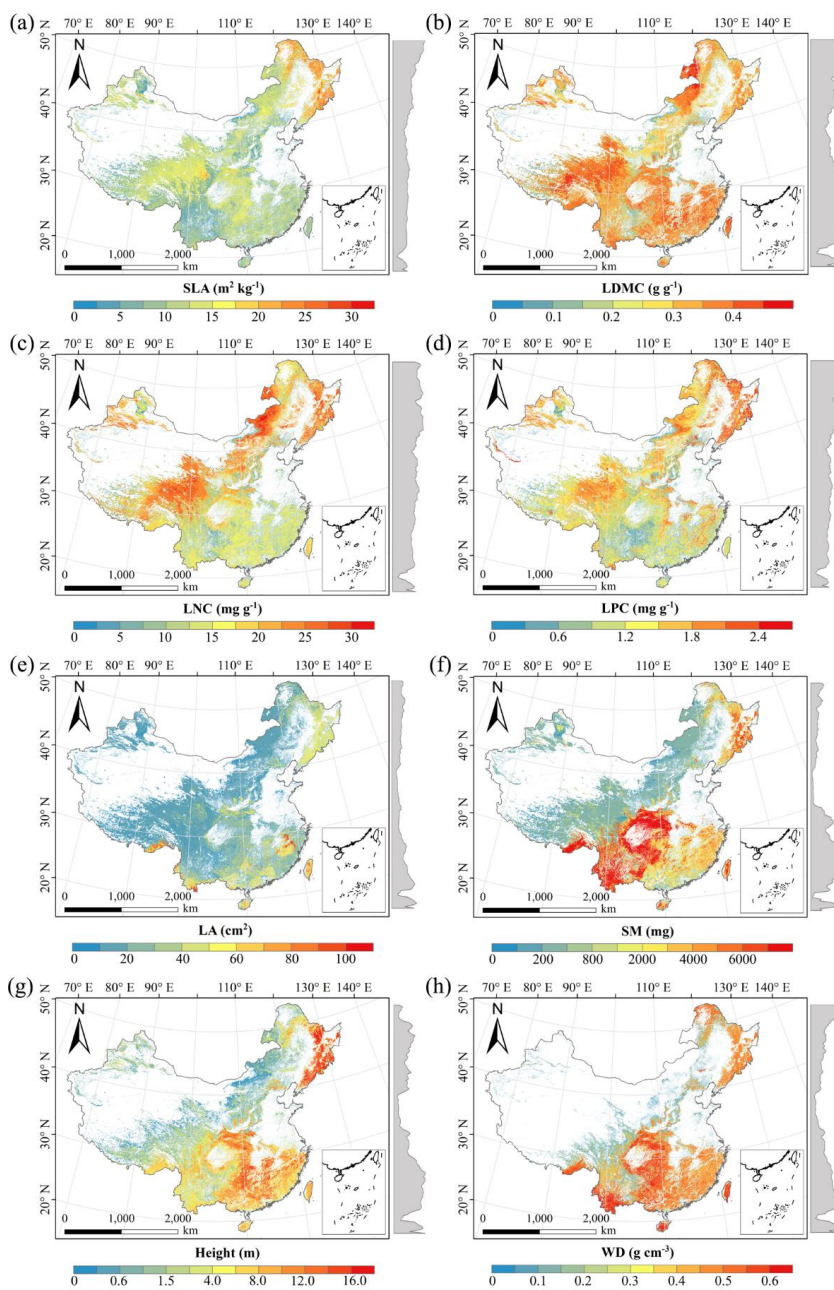
867

868 **Figure D2.** Spatial distribution of plant functional traits based on boosted regression trees (BRT). The

869 grey curves on the right of maps were trait distribution along with latitude. SLA, specific leaf area;

870 LDMC, leaf dry matter content; LNC, leaf N concertation; LPC, leaf P concertation; LA, leaf area; WD,

871 wood density; SM, seed mass.

Appendix E
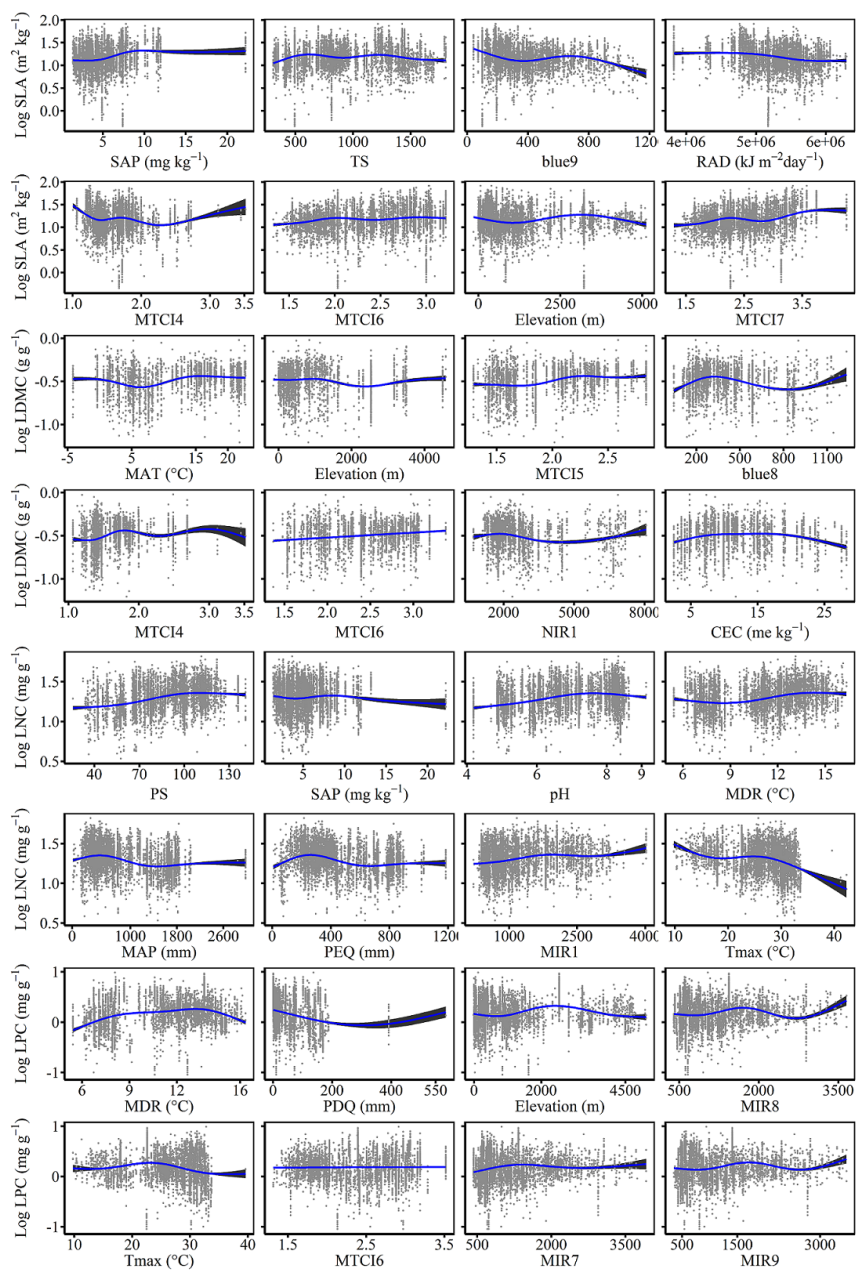
Figure E1. The relationships between SLA, LDMC, LNC, LPC and their eight most important predictors.

875
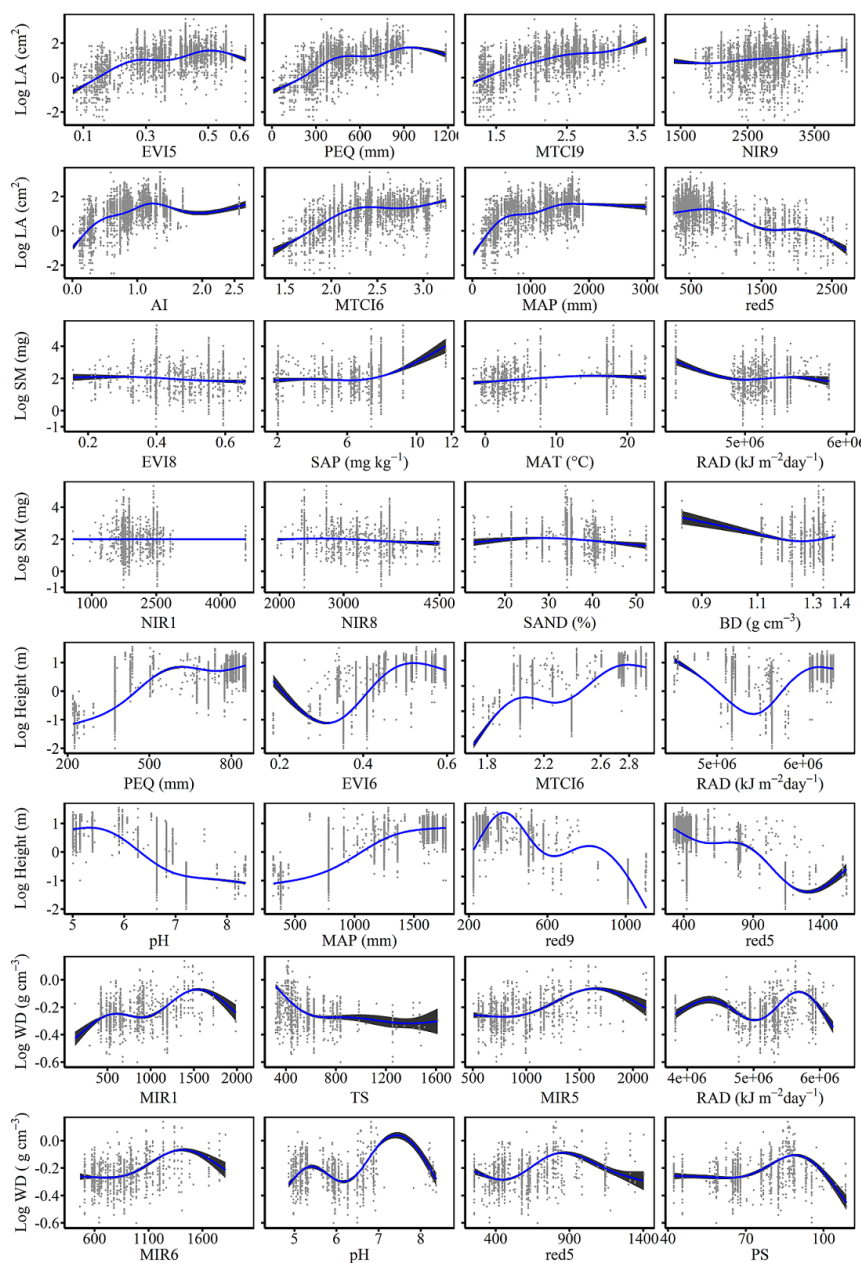
Figure E2. The relationships between LA, SM, Height, WD and their eight most important predictors.

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