

Mapping global leaf inclination angle (LIA) based on field measurement data

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Abstract. Leaf inclination angle (LIA), the angle between leaf surface normal and zenith directions, is a vital trait in radiative transfer, rainfall interception, evapotranspiration, photosynthesis, and hydrological processes. Due to the difficulty in obtaining large-scale field measurement data, LIA is typically assumed to follow the spherical leaf distribution or simply considered constant for different plant types. However, the appropriateness of these simplifications and the global LIA distribution are still unknown. This study compiled global LIA measurements and generated the first global 500 m mean LIA (MLA) product by gap-filling the LIA measurement data using a random forest regressor. Different generation strategies were employed for noncrops and crops. The MLA product was evaluated by validating the nadir leaf projection function ($G(0)$) derived from the MLA product with high-resolution reference data. The global MLA is $41.47^\circ \pm 9.55^\circ$, and the value increases with latitude. The MLAs for different vegetation types follow the order of cereal crops (54.65°) > broadleaf crops (52.35°) > deciduous needleleaf forest (50.05°) > shrubland (49.23°) > evergreen needleleaf forest (47.13°) $\approx$ grassland (47.12°) > deciduous broadleaf forest (41.23°) > evergreen broadleaf forest (34.40°). Cross-validation shows that the predicted MLA presents a medium consistency ($r = 0.75$, RMSE = 7.15°) with the validation samples for noncrops, whereas crops show relatively lower correspondence ($r = 0.48$ and 0.60 for broadleaf crops and cereal crops) because of the limited LIA measurements and strong seasonality. The global $G(0)$ distribution is out of phase with that of the MLA and agrees moderately with the reference data ($r = 0.62$, RMSE = 0.15). This study shows that the common spherical and constant LIA assumptions may underestimate the interception of most vegetation types. The MLA and $G(0)$ products derived in this study would enhance our knowledge about global LIA and should greatly facilitate remote sensing retrieval and land surface modeling studies.

The global MLA and $G(0)$ products can be accessed at:

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30 1 Introduction

31 Vegetation regulates terrestrial carbon and water cycles through a series of biophysical processes such as photosynthesis,
32 respiration, and transpiration (Foley et al., 1996; Chen et al., 2019). These biophysical processes are mainly carried by leaves
33 and the characterization of leaves within canopies is vital for remote sensing and earth system modeling (Ross, 1975; Lawrence
34 et al., 2019). Leaf inclination angle (LIA) denotes the inclination of the leaf or needle to the horizontal plane or the angle
35 between the leaf surface normal and zenith (Wilson, 1960). LIA is a key canopy structural trait that determines radiative
36 transfer, rainfall interception, evapotranspiration, photosynthesis, and hydrological processes (Sellers, 1985; Ross, 1981;
37 Mantilla-Perez and Salas Fernandez, 2017; Xiao et al., 2000; Maes and Steppe, 2012). LIA has been used in radiative transfer
38 modeling (RTM), remote sensing inversion, and land surface modeling (LSM) studies (Tang et al., 2016; Wang and Fang,
39 2020; Lawrence et al., 2019; Ross, 1975).

40 At the canopy scale, the probability density of LIA or the fraction of leaf area per unit LIA is expressed as the leaf angle
41 distribution (LAD) (De Wit, 1965). De Wit (1965) summarized six theoretical LADs, including planophile, erectophile,
42 extremophile, plagioophile, uniform, and spherical distributions. Specifically, the spherical distribution assumes that the relative
43 probability density of the LIA is proportional to the area of the corresponding sphere surface element and its mean leaf
44 inclination angle (MLA) equals 57.3° ($MLA = 57.3^\circ$) (De Wit, 1965). Furthermore, Ross (1981) defined the inclination index
45 (χ_L) to describe the departure of LAD from the spherical distribution. For the planophile distribution, $\chi_L = 1$; for the erectophile
46 distribution, $\chi_L = -1$; and for the spherical distribution, $\chi_L = 0$. In the radiative transfer regime, LIA is generally represented by
47 the leaf projection function ($G(\theta)$), which is defined as the average projection ratio of unit leaf area in the illumination or
48 viewing direction θ (Ross, 1981; Nilson, 1971). The spherical distribution is characterized by an isotropic leaf projection
49 function ($G \equiv 0.5$) (De Wit, 1965).

50 In the field, LIA can be measured directly based on the leaf's geometrical structure or using indirect optical methods (Lang,
51 1973; Ryu et al., 2010; Norman and Campbell, 1989; Weiss and Baret, 2017). Using these methods, several LIA measurements
52 have been carried out and some LIA datasets were constructed (Kattge et al., 2020; Chianucci et al., 2018; Hinojo-Hinojo and
53 Goulden, 2020; Pisek and Adamson, 2020). These field methods are usually time-consuming and labor-intensive and are
54 typically difficult to acquire large-scale LIA (Li et al., 2023). In addition, the existing LIA datasets have not been
55 comprehensively analyzed. LIA has also been estimated from satellite imagery through empirical relationships or radiative
56 transfer model inversions (Zou and Mörtus, 2015; Bayat et al., 2018; Goel and Thompson, 1984). Remote sensing methods
57 are used primarily for crops in local regions, and the generality of these algorithms is limited (Li et al., 2023). Due to the
58 difficulty in large-scale LIA measurements and estimations, our knowledge about the global LIA remains lacking.

59 Because our understanding of the global LIA is limited, different LIA simplification strategies have been adopted in various
60 studies. For example, LIA is typically assumed to follow the spherical distribution (Tang et al., 2016; Zhao et al., 2020; Wang
61 and Fang, 2020). However, this assumption may decrease the accuracy of radiative transfer modeling, significantly
62 underestimate the radiation interception (Stadt and Lieffers, 2000), and cause large errors ($>50\%$) in leaf area index (LAI)

63 measurements and inversions (Yan et al., 2021). The spherical LIA assumption may introduce greater error in the nadir
64 direction than other viewing geometries (Yan et al., 2021), considering the large G variation in this direction (Wilson, 1959).
65 The lack of global LIA knowledge also limits the retrieval of other vegetation structural parameters (Li et al., 2023). In many
66 LSMs, LIA is commonly treated as a fixed value for different plant function types (PFT) (Lawrence et al., 2019; Majasalmi
67 and Bright, 2019). Field LIA measurements have demonstrated that the spherical distribution is not appropriate for forests,
68 and the PFT-dependent LIA ignores LIA variation within the PFT (Pisek et al., 2013; Yan et al., 2021; Majasalmi and Bright,
69 2019).

70 This study aims to generate the first global MLA map from existing LIA field measurements using a data-driven gap-filling
71 method. This method involves spatial expansion and upscaling of LIA measurements, and a random forest regressor using
72 input spectral, climate, and PFT data. Based on the global MLA map, we tested whether the spherical LIA assumption is
73 appropriate at the global scale. The new MLA map was validated by comparing the nadir G ($G(0)$) derived from the MLA with
74 high-resolution reference data. Section 2 outlines the materials and methods employed to generate and evaluate the global
75 MLA. Section 3 presents the global LIA measurements, global MLA and $G(0)$, and evaluation results. Section 4 discusses the
76 performance of the global MLA and $G(0)$, the usage of the new MLA map, and the limitations of the study. Section 5 presents
77 the main conclusions.

78 **2 Materials and methods**

79 **2.1 LIA measurement data**

80 **2.1.1 TRY LIA dataset**

81 TRY is a network of vegetation scientists headed by Future Earth, the Max Planck Institute for Biogeochemistry, and German
82 Centre for Integrative Biodiversity Research, providing a global database of curated plant traits (the TRY database)
83 (<https://www.trydb.org/TryWeb/Home.php>). Since its establishment in 2007, the TRY database has continuously evolved and
84 has become one of the most widely used vegetation trait databases. The latest V6 version (released on October 13, 2022)
85 employed in this study contains 15,409,681 trait records covering 305,594 plant taxa (Kattge et al., 2020). In this database,
86 LIA was recorded as a numerical or categorical variable. After data extraction and checking, 31,043 valid records were used,
87 which include numerical LIA, locations, and species. Many measurements lack location information, whereas, for some
88 locations, there are many measurements for individual species. The spatial distribution map appears relatively sparse despite
89 a large volume of data (Fig. 1). The LIA measurements in South America are mainly from palms while the LIA measurements
90 of most species are located in the Northern Hemisphere.

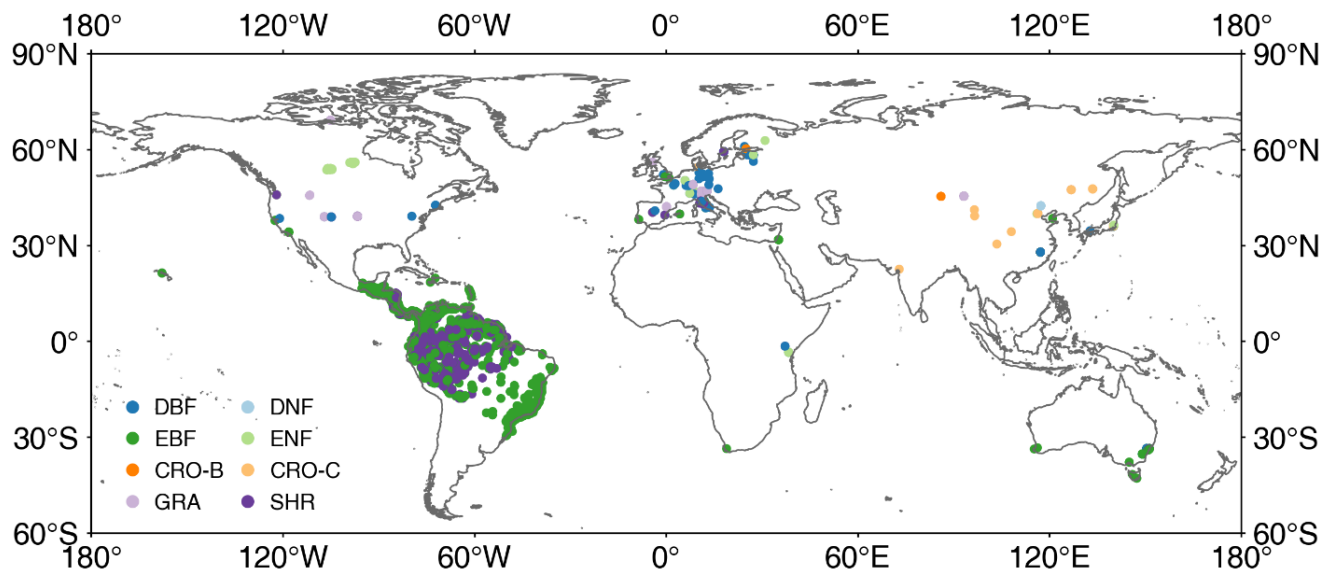


Figure 1. Locations of global leaf inclination angle measurements collected from TRY and the literature. DBF: deciduous broadleaf forest, DNF: deciduous needleleaf forest, EBF: evergreen broadleaf forest, ENF: evergreen needleleaf forest, CRO-B: broadleaf crops, CRO-C: cereal crops, GRA: grassland, SHR: shrubland.

2.1.2 LIA data from the literature

To fully utilize distributed and considerable LIA measurement data in the published literature, several keyword searches (leaf angle, leaf inclination angle, and leaf tilt angle) were performed in the Web of Science, Google Scholar, Google, and Chinese documentary databases. The LIA, location, and species information were manually extracted from the literature (Fig. 1). Several LIA measurements were already included in the TRY database (Chianucci et al., 2018; Pisek and Adamson, 2020). After aggregating LIA measurements for the same species at the same location, 780 LIA records were accessed from previous studies (Hinojo-Hinojo and Goulden, 2020; Pisek et al., 2022; Chen et al., 2021).

2.1.3 Manual LIA extraction

Only a few measurements in the northern tundra region were obtained, and the measurements in tropical regions are dominated by palm trees (Fig. 1). Therefore, LIA data for the northern tundra and tropical regions were extracted from horizontal side-view photographs searched from Google (Fig. S1). ImageJ software (<https://imagej.nih.gov/ij/>) was used to process the leveled photographs and derive LIA following the method of Pisek et al. (2011). The TRY species location data (848,919, Fig. S2b) (Jan 03, 2022) were used to obtain the dominant species information in tropical rainforests and the northern tundra. The species location points in these two vegetation types were spatially filtered and the frequency of occurrence for each species was counted. The species with a high frequency of occurrence were selected to measure the LIA. For each species, more than 75

110 leaves perpendicular to the viewing direction were selected and processed based on visual judgment to ensure the stability and
111 reliability of the MLA (Pisek et al., 2013). In total, the MLA of 104 species was manually derived.
112 In this study, most LIA measurements are obtained with protractor and level digital photogrammetry, especially for needleleaf
113 species. Therefore, the distinction between branches and leaves is considered. The diverse LIA records from different sources
114 were sorted to match the TRY species and to get the PFT based on the TRY Categorical Traits Dataset 2018 ([https://www.try-](https://www.try-db.org/TryWeb/Data.php#3)
115 [db.org/TryWeb/Data.php#3](https://www.try-db.org/TryWeb/Data.php#3)). LIA measurements from different sources were unified into canopy-level MLA with average
116 operation by leaf number (see Appendix A). If there were multiple LIA records for the same species, the mean value was
117 computed for the same location and species. In total, 5,554 LIA records of 1,194 species were collected, covering the growing
118 season from 2001 to 2022. LIA location replicates per species range from 1 to 330, and most replicates (98 %) are less than
119 50. Considering the different numbers of records for each species, the LIA data was further aggregated by species.

120 **2.2 Remote sensing data**

121 **2.2.1 Ancillary data used for MLA mapping**

122 The ancillary data used for global MLA mapping and analysis are listed in Table 1. Most earth observation data were accessed
123 and processed in Google Earth Engine (GEE) (<https://earthengine.google.com/>). The PFT classification system in the MODIS
124 global 500 m land cover type product (MCD12Q1 C6) was used and mode-aggregated from 2001 to 2022 to match the LIA
125 measurements (Fig. S3) (Sulla-Menashe et al., 2019). The 2001–2022 Landsat surface reflectance (Level 2, Collection 2, Tier
126 1) (Crawford et al., 2023), including Landsat 5 (2001–2012), Landsat 7 (2012–2013), and Landsat 8 (2013–2022) was utilized
127 to generate a global 30 m PFT map (Section 2.3.1), which was subsequently employed for LIA upscaling. Considering the
128 sensitivity of directional reflectance variation to LIA (Jacquemoud et al., 2009; Li et al., 2023), the 2001–2022 MODIS
129 bidirectional reflectance distribution function (BRDF) model parameters dataset (MCD43A1 C6.1) (Schaaf and Wang, 2015b)
130 and nadir BRDF adjusted reflectance dataset (MCD43A4 V6 NBAR) (Schaaf and Wang, 2015a) produced daily using 16 days
131 of Terra and Aqua MODIS data at 500 m resolution and were utilized as predictive variables. We used MCD43A1 C6.1 and
132 MCD12Q1 and MCD43A4 C6 for MLA mapping as these data were available on GEE when this study was conducted. Only
133 minor calibration changes and polarization correction were adopted in the upgrading from Collection 6 to 6.1, while the
134 MCD12Q1 and MCD43A4 algorithms remain the same
135 (https://landweb.modaps.eosdis.nasa.gov/data/userguide/MODIS_Land_C61_Changes.pdf). In addition, the multi-year
136 aggregation of these products (Table 2) further mitigates the version impact. Due to the scarcity of crop LIAs and the lack of
137 location information for existing crop LIA measurements, fine-resolution (10/30 m) crop-type maps (Table 1) in 2018 were
138 employed to support crop LIA mapping. Other data include the ERA5-Land reanalysis data, the ALOS digital elevation model
139 (AW3D30 V3.2), and the 2001–2022 MODIS LAI product (MCD15A2H) (Myneni, 2015). The LAI product was averaged
140 and aggregated from 2001–2022.

141

142 **Table 1.** Remote sensing data for global MLA mapping. BRDF: bidirectional reflectance distribution function.

Category	Data	Year	Spatial resolution	Temporal resolution	Reference
Plant function type	MCD12Q1 C6	2001–2022	500 m	Yearly	(Sulla-Menashe et al., 2019)
Surface reflectance	Landsat collection 2	2001–2022	30 m	16 days	(Crawford et al., 2023)
	MCD43A4 V6 NBAR	2001–2022	500 m	Daily	(Schaaf and Wang, 2015a)
BRDF	MCD43A1 C6.1	2001–2022	500 m	Daily	(Schaaf and Wang, 2015b)
Crop type	Cropland Data Layers (CDL)	2018	30 m	Yearly	(Boryan et al., 2011)
	EUCROPMAP	2018	10 m	Yearly	(D’andrimont et al., 2021)
	AAFC Annual Crop Inventory	2018	30 m	Yearly	(Fisette et al., 2013)
	Northeast China crop-type map	2018	30 m	Yearly	(You et al., 2021)
	NESEA-Rice10	2018	10 m	Yearly	(Han et al., 2021)
	China maize map	2018	30 m	Yearly	(Shen et al., 2022)
	China winter wheat map	2018	30 m	Yearly	(Dong et al., 2020)
Climate	ERA5-Land	2001–2022	0.1°	Monthly	(Muñoz-Sabater et al., 2021)
Terrain	AW3D30 V3.2	—	30 m	—	(Tadono et al., 2014)

143 **2.2.2 High-resolution reference data**

144 The high-resolution reference datasets provided by Ground Based Observations for Validation (GBOV,
145 <https://land.copernicus.eu/global/gbov/dataaccessLP/>) and DIRECT 2.1 (<https://calvalportal.ceos.org/lpv-direct-v2.1>) were
146 used to evaluate the generated global MLA (Fig. 2). These datasets provide high-resolution (20/30 m) LAI, effective LAI
147 (LAIe), and fractional vegetation cover (FVC, the proportion of the vertical projection area covered by green vegetation
148 (Gitelson et al., 2002)) data over a 3 km × 3 km area centered on each site generated using empirical relationships between
149 various vegetation indices and ground measurements (Li et al., 2022; Brown et al., 2020). GBOV has provided continuous
150 high-resolution reference data since 2013 (Fig. 2).

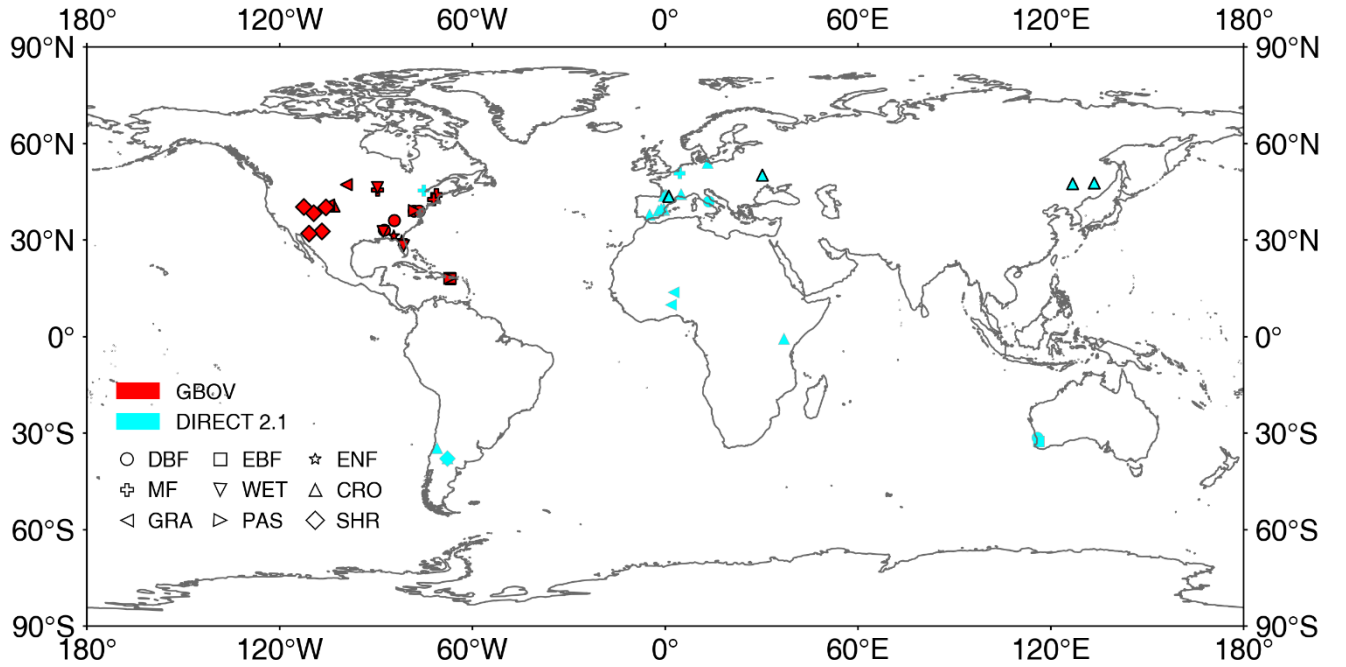


Figure 2. Locations of GBOV and DIRECT 2.1 sites used in this study. CRO: Cultivated crops, MF: Mixed forest, PAS: Pasture/hay, WET: Woody wetlands. See Fig. 1 for other acronyms. The black frame indicates those sites with >5 continuous records.

The global MLA map was indirectly evaluated by comparing the nadir leaf projection function derived from MLA with reference $G(0)$, because of the lack of high-resolution reference MLA. The high-resolution reference $G(0)$ was derived from high-resolution LAI, FVC, and clumping index (CI) ($=LAI_e/LAI$) with the Beer-Lambert law (Fig. S4) (Nilson, 1971).

$$P(\theta) = \exp \frac{G(\theta) * LAI * CI(\theta)}{\cos(\theta)} \quad (1)$$

Where $P(\theta)$, $CI(\theta)$, and $G(\theta)$ denote the gap fraction, CI, and G in direction θ , respectively. Specifically, the gap fraction in the nadir direction can be expressed by FVC.

$$P(0) = 1 - FVC \quad (2)$$

Therefore, the reference $G(0)$ was derived using the following formula.

$$G(0)_{CI(0)} = - \frac{\ln(1-FVC)}{CI(0) * LAI} \quad (3)$$

By using the whole CI as the nadir CI ($CI(0)$) in the above equation (Fang et al., 2021; Li et al., 2022), $G(0)$ was calculated as follows:

$$G(0)_{CI} \approx - \frac{\ln(1-FVC)}{CI * LAI} \quad (4)$$

166 2.3 Mapping global LIA

167 2.3.1 Data preparation

168 Many studies have treated LIA as a species-specific static trait and ignored within-species variations when LIA measurements
169 are limited (Pisek et al., 2022; Toda et al., 2022; Raabe et al., 2015). Following the rationale, the spatial coverage of LIA
170 measurements was expanded, and those records without location information were utilized (section 2.1.1). Under this
171 assumption, the LIA measurements were expanded through TRY species location data with species name matching. The
172 species location data comprises trait measurements for common species representing a hundreds-of-square-meter area around
173 the location. The dominant species was artificially identified by investigators and thus the spatial representativeness is
174 considered. When a species had multiple LIA observations at different locations, the nearest LIA was assigned to the TRY
175 species location. Visual inspections were conducted to remove potential TRY location biases, especially for non-vegetated
176 points such as water bodies and deserts. After spatial expansion, the number of LIAs reached 12,328 and its spatial distribution
177 became more uniform (Fig. S2c).

178 In this study, the scale gap between field measurements and satellite remote sensing data was fully considered. The canopy
179 level MLA measurement is regarded as equal to 30 m-MLA considering its spatial representativeness. To upscale the MLA
180 measurements from canopy level to the satellite resolution (500 m), a 30 m PFT map was first derived from Landsat reflectance
181 using a random forest classification method. The random forest was trained at a 500 m scale using the mode-aggregated
182 MODIS PFT classification map as training samples to generate a 30 m PFT map by hierarchically selecting homogeneous
183 pixels (with a coefficient of variation in reflectance < 0.2). The classification features were the same as those in the MODIS
184 classification algorithm (Sulla-Menashe et al., 2019). For a 500 m pixel with multiple PFTs (Fig. 3a), when one PFT had no
185 MLA measurement, the MLA of the PFT was assigned with the value of its nearest neighbor within 100 km with the same
186 PFT. This distance setting (100 km) was based on a previous study that derived global maps for various leaf traits from a
187 limited number of field measurements, remote sensing, and climate data (Moreno-Martínez et al., 2018). In field measurement,
188 the entire canopy MLA is commonly calculated as the average of all measured leaf LIAs weighted by leaf area (see Appendix
189 A) (Zou et al., 2014; De Wit, 1965; Yan et al., 2021). Leaves with larger areas have higher weights. Upscaling MLA from 30
190 m to 500 m follows the same rationale as that from leaf to canopy scale. For a 30 m pixel with a higher LAI, the weight of the
191 pixel is higher. Therefore, the 500 m MLA was computed as the weighted average of the enhanced vegetation index (EVI2)
192 assuming a linear relationship between LAI and EVI2 (see Appendix A) (Dong et al., 2019; Alexandridis et al., 2019).
193 Although previous studies have reported that vegetation index may be nonlinearly correlated to LAI because of the saturation
194 effect at medium and high LAI conditions, EVI2 is highly resistant to the saturation effect (Gao et al., 2023). The errors caused
195 by this slight nonlinearity were further analyzed in Section 4.4.

$$196 \quad MLA_{500m} = \frac{\sum MLA_{30m} \times EVI2_{30m}}{\sum EVI2_{30m}} \quad (5)$$

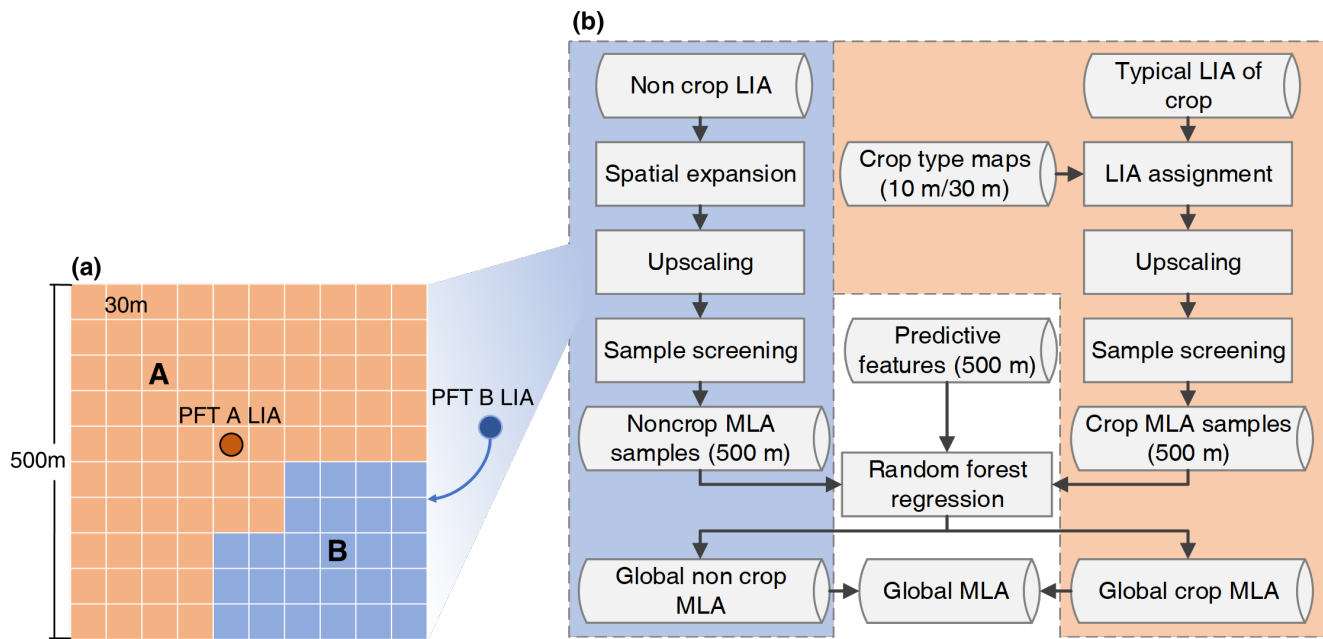


Figure 3. Leaf inclination angle (LIA) upscaling (a) and global mean LIA (MLA) mapping (b) strategies.

The 500 m upscaled MLA samples were further refined to select the most representative samples following three criteria: 1) the coefficient of variation of the 30 m EVI2 in the 500 m pixel is less than 0.2, 2) the vegetation proportion in the 500 m pixel is greater than 0.8, and 3) the proportion of PFTs represented by the MLA measurements in the 500 m pixel is greater than 0.4. The final number of samples after refinement is 3,013 with a uniform spatial distribution (Fig. 4).

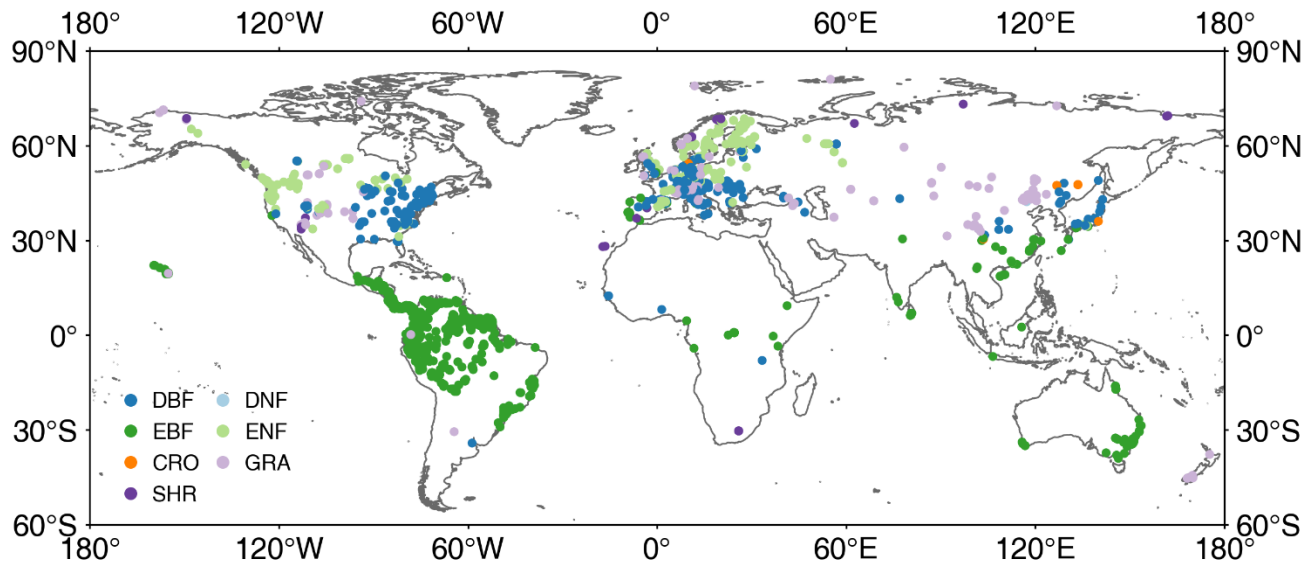


Figure 4. Distribution of global mean leaf inclination angle samples after screening. See Fig. 1 for acronyms.

205 **2.3.2 Global MLA mapping**

206 Different mapping strategies were employed for noncrops and crops (Fig. 3b) considering the small number of valid crop
207 samples (Fig. 4) and the lack of location information for most crop samples. For noncrops, the upscaled 500 m MLA samples
208 were used to train a random forest regressor to predict the global MLA from different features (Table 2). All input features
209 were unified to the 500 m resolution. Therefore, the derived MLA map corresponds to the average MLA at the 500 m scale.
210 Notably, this study used all MODIS BRDF and spectral reflectance data including low-quality ones that may be contaminated
211 by clouds. The multi-year aggregation (Table 2) can partly mitigate the influence induced by low-quality observations (Sulla-
212 Menashe et al., 2019). Normalized difference vegetation index (NDVI) was used as the predictive feature because it is strongly
213 coupled with LIA, especially under low and medium vegetation density conditions (Dong et al., 2019; Zou and Möttus, 2015).
214 To reduce computational complexity and potential overfitting, a feature selection process was conducted based on the variable
215 importance (the sum of the decrease in Gini impurity index over all trees in the forest) computed by the model, and only the
216 40 most important variables were used in the final prediction. During the training process, the out-of-bag error was minimized
217 to obtain the optimal hyperparameters. The prediction performance of the random forest regressor was evaluated using a ten-
218 fold cross-validation approach with upscaled MLA samples.

219 For crops, the measured MLA values were averaged for different crop types as a typical MLA (Table S2). After assigning
220 typical MLAs for different crops with high-resolution crop maps (Table 1), the high-resolution crop MLA were upscaled to
221 500 m as training samples (Eq. (5)). Only the samples with a crop area ratio > 80% within a 500 m pixel were selected for
222 training. The crops were further divided into broadleaf crops and cereal crops and processed with the same procedure used for
223 noncrops (Fig. 3b). All procedures were conducted on GEE under the WGS-84 geographic coordinate system.

224 Two quality layers were added to represent the quality of input data and the prediction model. The input data quality was
225 denoted by the proportion of high-quality BRDF inversions for each pixel. The prediction model quality was represented
226 qualitatively for each pixel considering whether the MLA was predicted by extrapolating beyond the range of the training
227 samples. The random forest model is typically regarded as a black-box and its uncertainty is difficult to quantify in the present
228 study.

229

230 **Table 2.** Predictive features in global MLA mapping.

Category	Features	Variables	Number
Spectral	Blue, green, red, near-infrared reflectance	10%, 33%, 50%, 67%, 90% quantiles and standard deviation	24
	NDVI	10%, 33%, 50%, 67%, 90% quantiles and standard deviation	6
BRDF	Kernel coefficients of the red band	10%, 33%, 50%, 67%, 90% quantiles and standard deviation	18
	Kernel coefficients of near-infrared band	10%, 33%, 50%, 67%, 90% quantiles and standard deviation	18
PFT	PFT	Constant	1

Climate	Solar downward radiation	Mean and standard deviation	2
	Temperature	Mean and standard deviation	2
	Precipitation	Mean and standard deviation	2
Terrain	Elevation	Constant	1
	Slope	Constant	1
	Aspect	Constant	1

2.4 Evaluation of global MLA

The global MLA map was indirectly evaluated using the nadir leaf projection function. The global $G(0)$ was derived from the MLA and evaluated with high-resolution reference (Section 2.2.2) following the upscaling scheme recommended by the Land Product Validation (LPV) Subgroup of the Committee on Earth Observation Satellites (CEOS) (<http://lpvs.gsfc.nasa.gov/>). Assuming a single-parameter ellipsoidal leaf angle distribution (Campbell, 1990; Wang et al., 2007), the parameter χ , the ratio of the horizontal and vertical axes of an ellipsoid, was first derived from MLA in radians. Compared to other models, the single-parameter ellipsoidal leaf angle distribution is a relatively more accurate and simpler model and has been used in many remote sensing studies (Campbell, 1990; Wang et al., 2007; Kuusk, 2001; Verhoef et al., 2007).

$$\chi = -3 + \left(\frac{MLA}{9.65}\right)^{-0.6061} \quad (6)$$

The $G(\theta)$ value in the nadir direction ($\theta=0^\circ$) was calculated using an analytical formula (Leblanc and Fournier, 2017).

$$G(\theta) = \frac{\sqrt{(\chi^2 + \tan^2 \theta) \cos \theta}}{\chi + 1.774(\chi + 1.182)^{-0.73}} \quad (7)$$

The MLA product was first upscaled to 3 km through a weighted averaging method using the MODIS LAI to derive $G(0)$ (Eq. (7)). The reference LAI, FVC, and CI were also upscaled to 3 km through simple averaging to compute the reference $G(0)$ (Eq. (4)). The MLA-derived $G(0)$ and the reference $G(0)$ were compared at the 3 km $\times$ 3 km area around each site. The correlation coefficient (r), bias, and root mean square error (RMSE) were calculated as the evaluation metrics, as follows:

$$r = \sqrt{1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (8)$$

$$Bias = \frac{1}{n} \sum_{i=1}^n (\hat{y} - y_i) \quad (9)$$

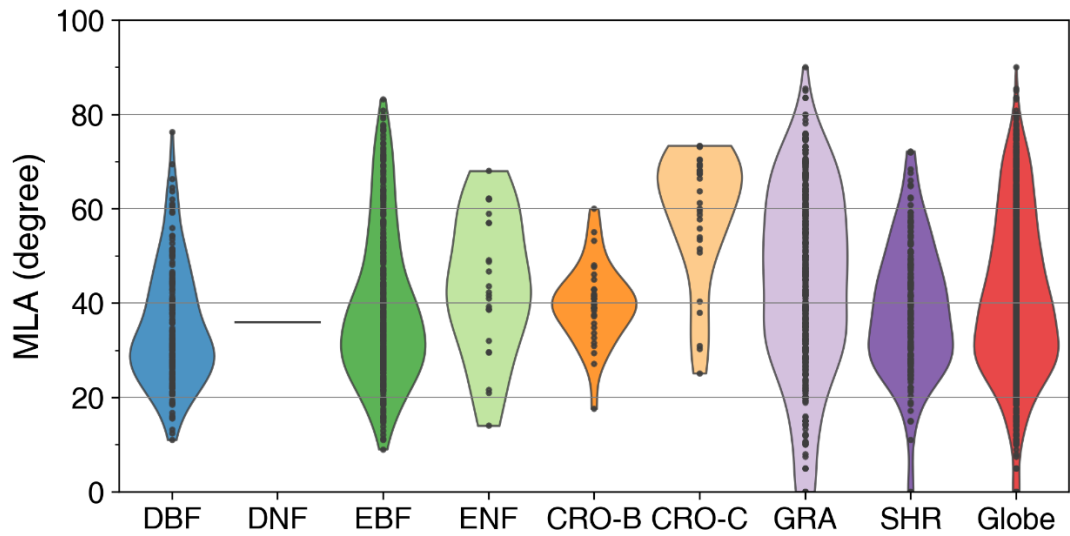
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y} - y_i)^2} \quad (10)$$

where $\hat{y}_i$, y_i , and n denote the MLA-derived $G(0)$, reference $G(0)$, and the number of $G(0)$, respectively.

250 **3 Results**

251 **3.1 Global measured LIA values**

252 The species-aggregated LIA was employed in the analysis of global LIA measurements. Fig. 5 shows the distributions of
253 global measured LIA values for different PFTs. The global measured MLA is 40.74° and generally follows the order of CRO-
254 C > GRA > ENF > CRO-B > EBF > SHR > DNF > DBF (Table 3). Cereal crops exhibit the highest MLA (59.11°), whereas
255 DBF has the most horizontal leaves (MLA = 34.94°). GRA and EBF show large LIA variations (Std = 20.44° and 17.17°),
256 whereas CRO-B exhibits a small range. The DNF LIA measurements are only for one species and show very little variation
257 (Fig. 5).



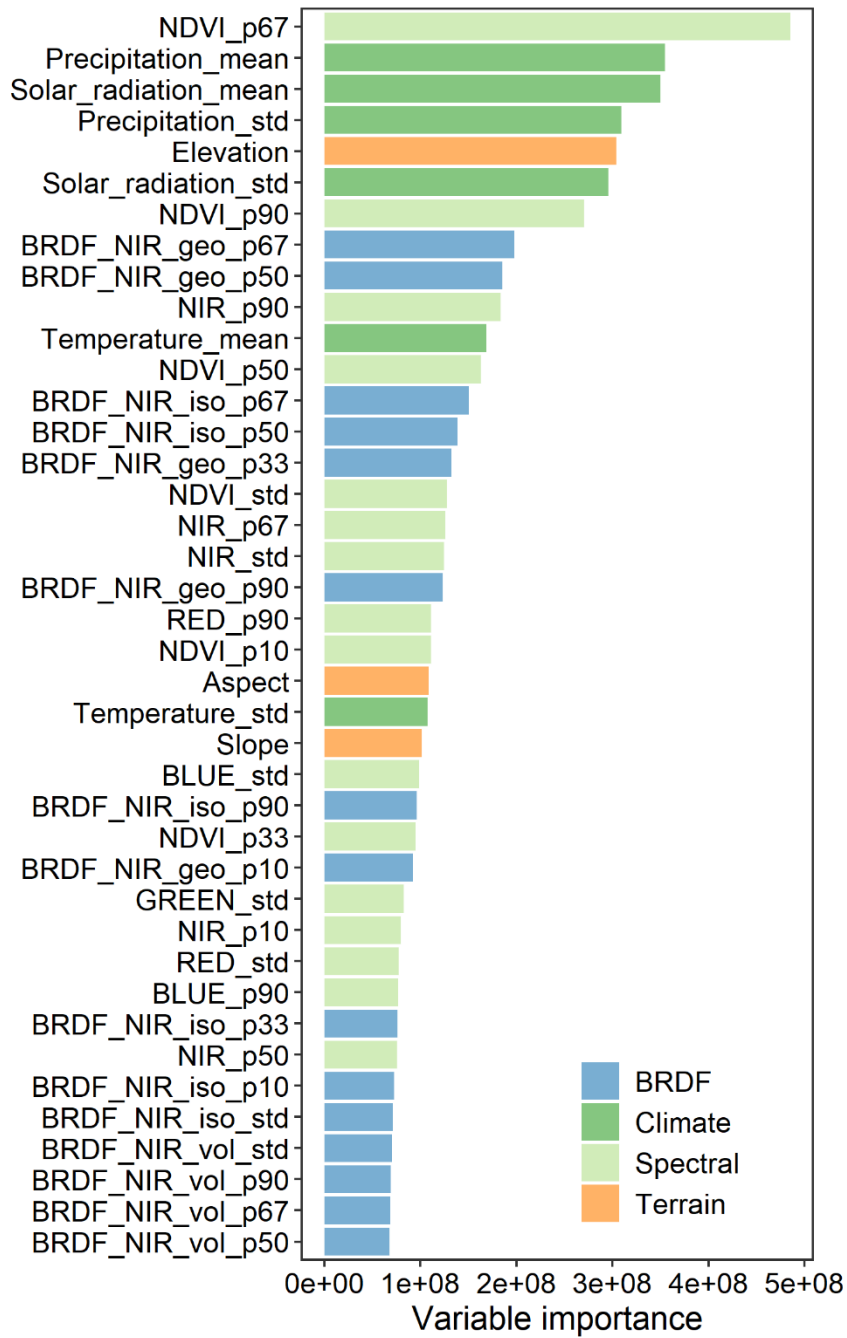
258
259 **Figure 5.** Distribution of global mean LIA (MLA) for different plant function types (see Fig. 1 for acronyms). The last shape shows the
260 global average. Statistics are conducted for each species as represented by points in the figure.

261
262 **Table 3.** Statistics of leaf inclination angle measured for different plant functional types (PFT). STD is the standard deviation. The inclination
263 index (χ_L) is converted from mean leaf inclination angle (MLA) ($\chi_L = 2\cos(MLA) - 1$) (Lawrence et al., 2019).

PFT	DBF	DNF	EBF	ENF	CRO-B	CRO-C	GRA	SHR	Globe
Number of species	171	1	347	23	32	31	399	190	1194
Mean(°)	34.94	35.88	39.30	43.69	39.71	59.11	44.13	38.32	40.74
STD (°)	12.40	0.00	16.11	14.40	8.11	13.28	20.17	13.80	17.12
χ_L	0.64	0.62	0.55	0.45	0.54	0.03	0.44	0.57	0.52

264 **3.2 The relationships between MLA and other variables**

265 Fig. 6 shows the importance of the top 40 variables in the MLA prediction obtained from the random forest regression model.
266 The importance of these 40 variables accounts for 78% of the total importance among all 76 variables. Spectral features account
267 for 30% of the importance, which is higher than that of other features. Among the spectral features, NDVI, near-infrared (NIR)
268 band, and red band reflectance are most critical for MLA prediction. The importance of BRDF features is comparable to that
269 of climatic variables (21% vs. 20%), followed by terrain features (7%). Among the BRDF features, the NIR BRDF information
270 shows a higher contribution than the red band, with importance in the following order: geometrically scattered kernel> isotropic
271 scattering kernel > volumetric scattering kernel. The importance ranking of the climatic variables follows the order of
272 precipitation $\approx$ solar radiation > temperature. In addition, elevation, slope, and aspect significantly impact on the MLA
273 prediction.



274

275 **Figure 6.** The importance of variables in the mean leaf inclination angle prediction. NIR, Red, Green, and Blue denote the nadir reflectance
 276 in near-infrared, red, green, and blue bands, respectively; geo, iso, and vol represent kernel coefficients of geometric-optical surface
 277 scattering, isotropic scattering, and volumetric scattering, respectively. The suffixes p××, mean, and std represent ××% quantile, mean, and
 278 standard deviation, respectively.

Fig. 7 illustrates the relationships between the upscaled MLA samples and the 16 most important variables. Overall, MLA decreases with the increase of NDVI, NIR reflectance, and NIR BRDF kernel parameters, whereas it increases with the standard deviation of NDVI. MLA is negatively correlated with solar radiation, precipitation, and temperature. Additionally, MLA increases with increasing the standard deviation of solar radiation (corresponding to mid-to-high latitude regions), while it decreases with the increase in the standard deviation of precipitation (corresponding to tropical and subtropical regions with high precipitation). MLA increases slightly with altitude and then decreases.

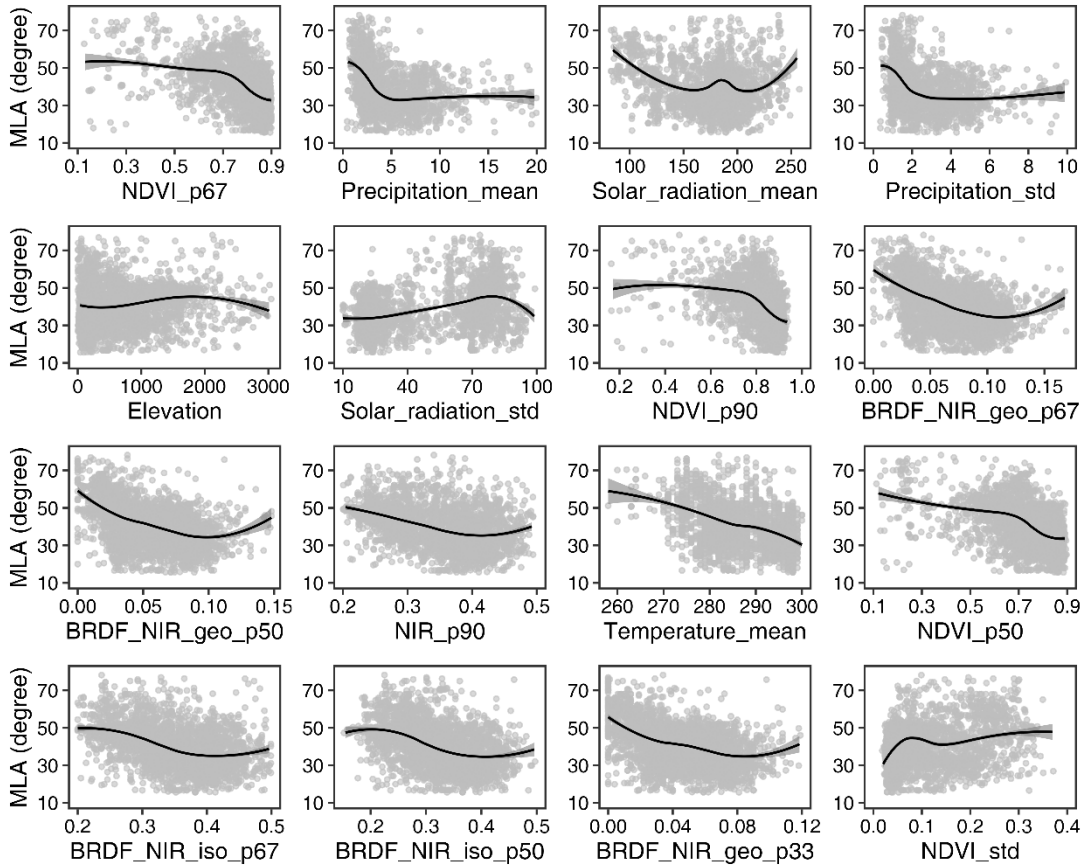
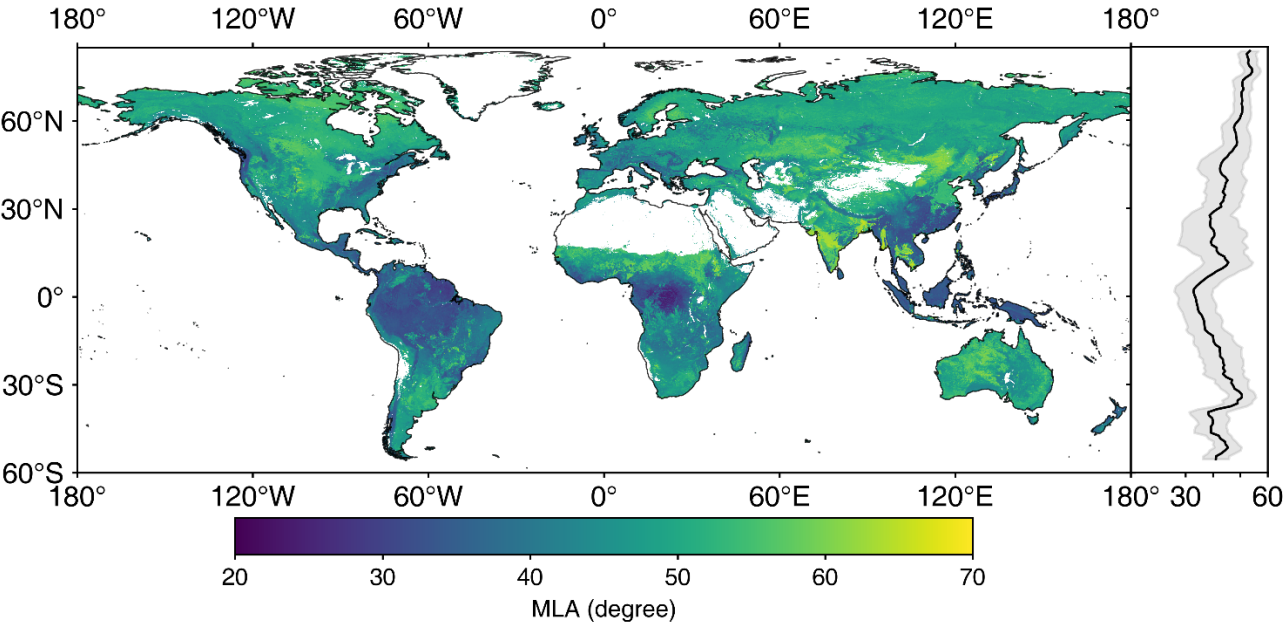


Figure 7. Relationships between mean leaf inclination angle (MLA) and different predictive variables. See Fig. 6 for different variables.

3.3 Global MLA and G(0) maps

Fig. 8 shows the spatial distribution of the global 500 m MLA product. Central Asia (grasslands), southern India (cereal crops), and the central United States (grasslands and cereal crops) show higher MLAs of approximately 60°, whereas the rainforests and Southeast Asia forests have more horizontal leaves with MLAs of around 30° (Fig. 8 and S2). MLA increases with latitude, from $32.93 \pm 7.03^\circ$ around the equator ($\sim 1.5^\circ$ N) to $53.48 \pm 3.20^\circ$ in the northern tundra ($\sim 76.5^\circ$ N). Variation in MLA decreases as latitude increases (Fig. 8). Among different PFTs, cereal crops show the highest MLA ($54.65 \pm 6.28^\circ$), while

293 evergreen broadleaf forest has the lowest MLA ($34.40 \pm 6.42^\circ$), and PFTs follow the order: CRO-C > CRO-B > DNF > SHR >
 294 ENF $\approx$ GRA > DBF > EBF (Table 4). Grassland, broadleaf forest, and evergreen needleleaf forests show larger MLA variations
 295 than other PFTs, whereas deciduous needleleaf forests show minimal variation. The global vegetation MLA is 41.47° , with a
 296 standard deviation of 9.55° , which is comparable to the MLA of DBF ($41.23 \pm 6.58^\circ$) (Fig. 9a and Table 4).

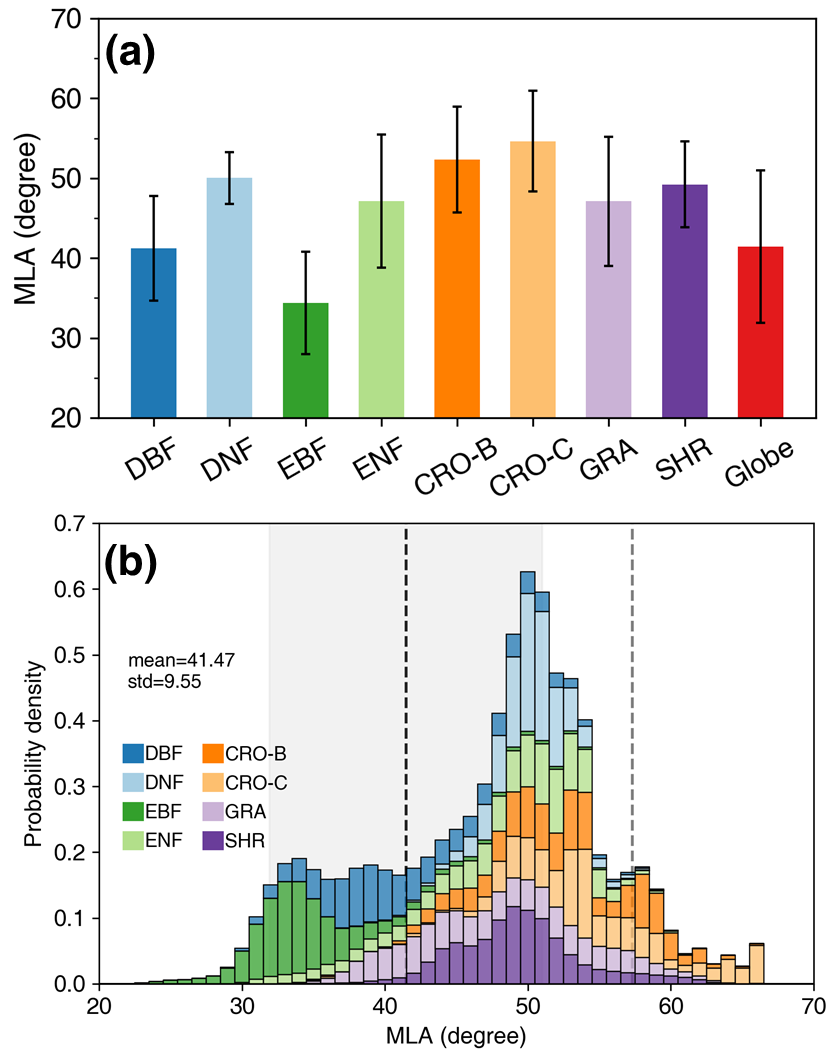


297
 298 **Figure 8.** The global mean leaf inclination angle (MLA) map. The right panel shows the MLA latitudinal mean (solid line) and the standard
 299 deviation values (shaded area) weighted by leaf area index.

300 **Table 4.** Statistics of global mean leaf inclination angle (MLA), nadir leaf projection function ($G(0)$), and inclination index (χ_L) for different
 301 plant functional types (PFT). STD is the standard deviation. The χ_L is converted from MLA ($\chi_L = 2\cos(MLA) - 1$) (Lawrence et al.,
 302 2019).

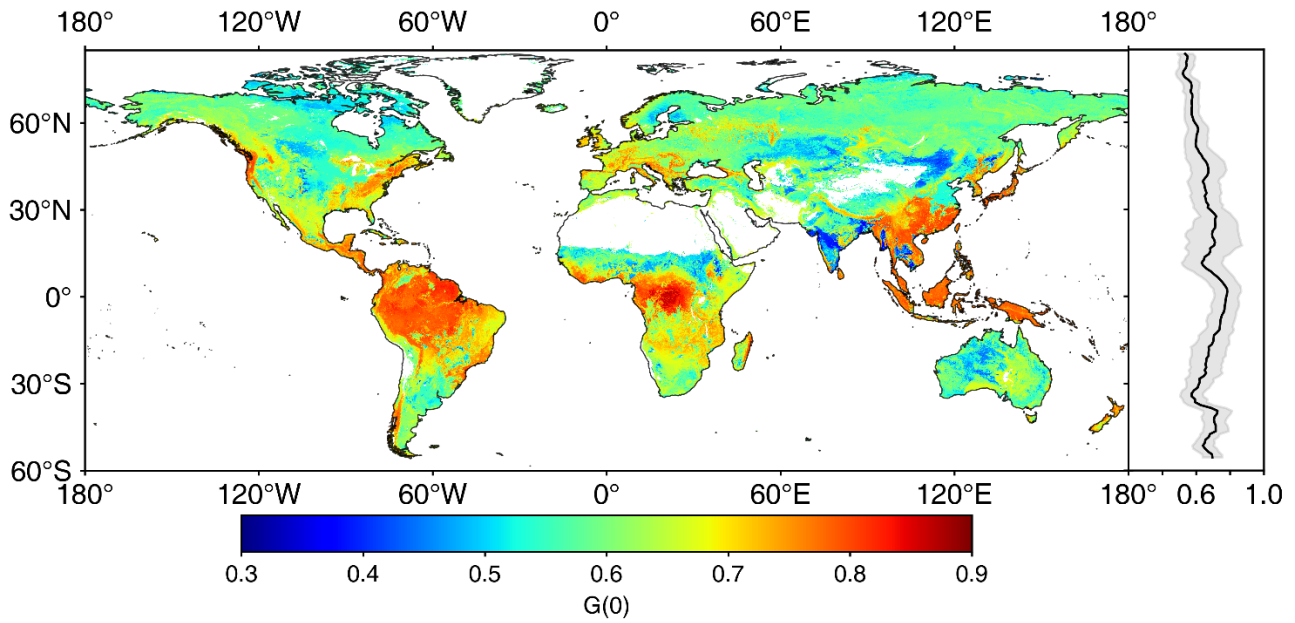
PFT	DBF	DNF	EBF	ENF	CRO-B	CRO-C	GRA	SHR	Globe
Area proportion(%)	14.02	6.32	15.08	11.42	2.99	6.84	28.45	14.88	100.00
MLA($^\circ$)	41.23	50.05	34.40	47.13	52.35	54.65	47.12	49.23	41.47
STD of MLA ($^\circ$)	6.58	3.24	6.42	8.35	6.63	6.28	8.08	5.35	9.55
$G(0)$	0.69	0.58	0.76	0.61	0.55	0.52	0.61	0.59	0.68
STD of $G(0)$	0.07	0.03	0.06	0.08	0.07	0.08	0.09	0.06	0.11
χ_L	0.50	0.28	0.65	0.36	0.22	0.16	0.36	0.31	0.50

303
 304 The global MLA exhibits an asymmetric probability density distribution toward the lower MLA (Fig. 9b). It roughly presents
 305 three peaks, with the highest peak ($\sim 51^\circ$) containing DNF, ENF, CRO, GRA, and SHR. The moderate peak ($\sim 35^\circ$) is mainly
 306 composed of EBF and DBF, while the third peak ($\sim 58^\circ$) is dominated by crops. The MLAs of crops and some grasslands are
 307 close to the MLA of the spherical distribution (57.30°). The global MLA (41.47°) is 15.83° (38%) smaller than the MLA of
 308 the spherical distribution because the vegetation MLA is mostly less than 57.30° (Fig. 9b).



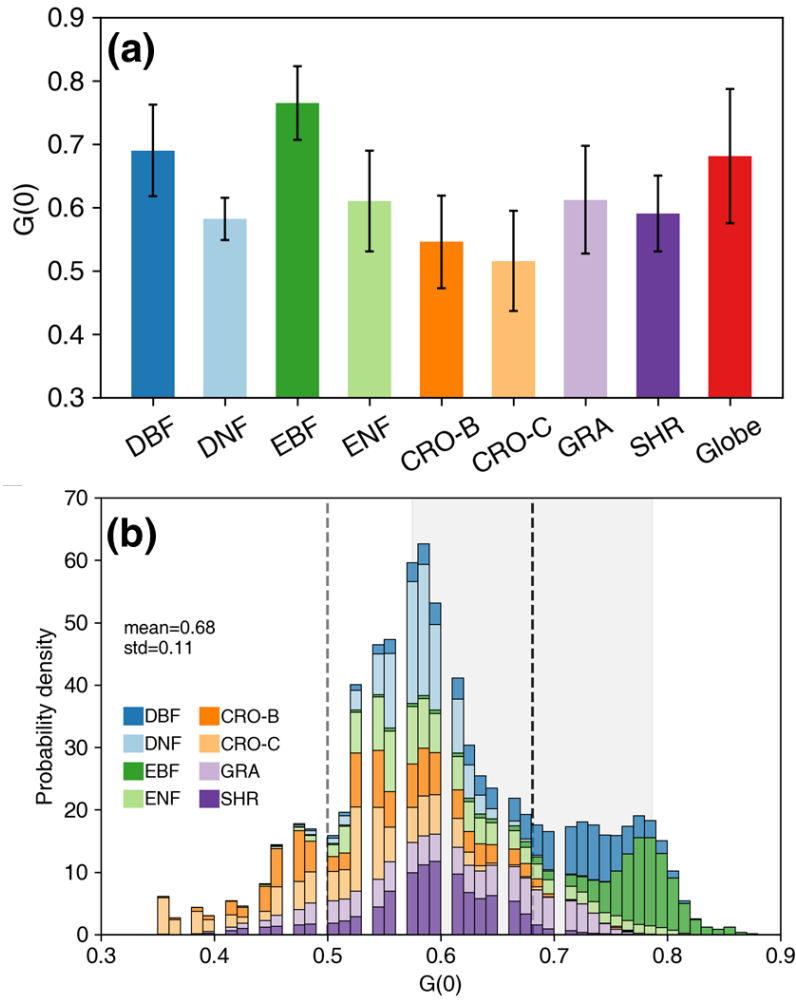
309
 310 **Figure 9.** Statistics (a) and probability density distributions (b) of the global mean leaf inclination angle (MLA) for different plant functional
 311 types. The error bars in (a) represent the standard deviation. The black dash line and shade area in (b) indicate the global MLA mean and
 312 standard deviation. The gray dashed line represents the MLA ($\approx 57.30^\circ$) of spherical leaf angle distribution. The mean, standard deviation,
 313 and probability density values are weighted by leaf area index. See Fig. 1 for the acronyms.

314 Fig. 10 displays the spatial distribution of global $G(0)$ generated from MLA. Overall, the global $G(0)$ shows an opposite pattern
 315 with the global MLA. The $G(0)$ values in Central Asia (grasslands, Fig. S3), southern India (cereal crops), and the central
 316 United States (grasslands and cereal crops) are relatively lower than those in tropical rainforests, forests in Southeast Asia, and
 317 forests in the eastern United States. $G(0)$ generally decreases slowly with latitude, from 0.78 ± 0.08 at the equator ($\sim 1.5^\circ$ N)
 318 to 0.52 ± 0.04 in the northern tundra ($\sim 76.5^\circ$ N).



319
 320 **Figure 10.** The global nadir leaf projection function ($G(0)$) map. The right panel shows the $G(0)$ mean (solid line) and standard deviation
 321 values (shaded area) weighted by leaf area index.

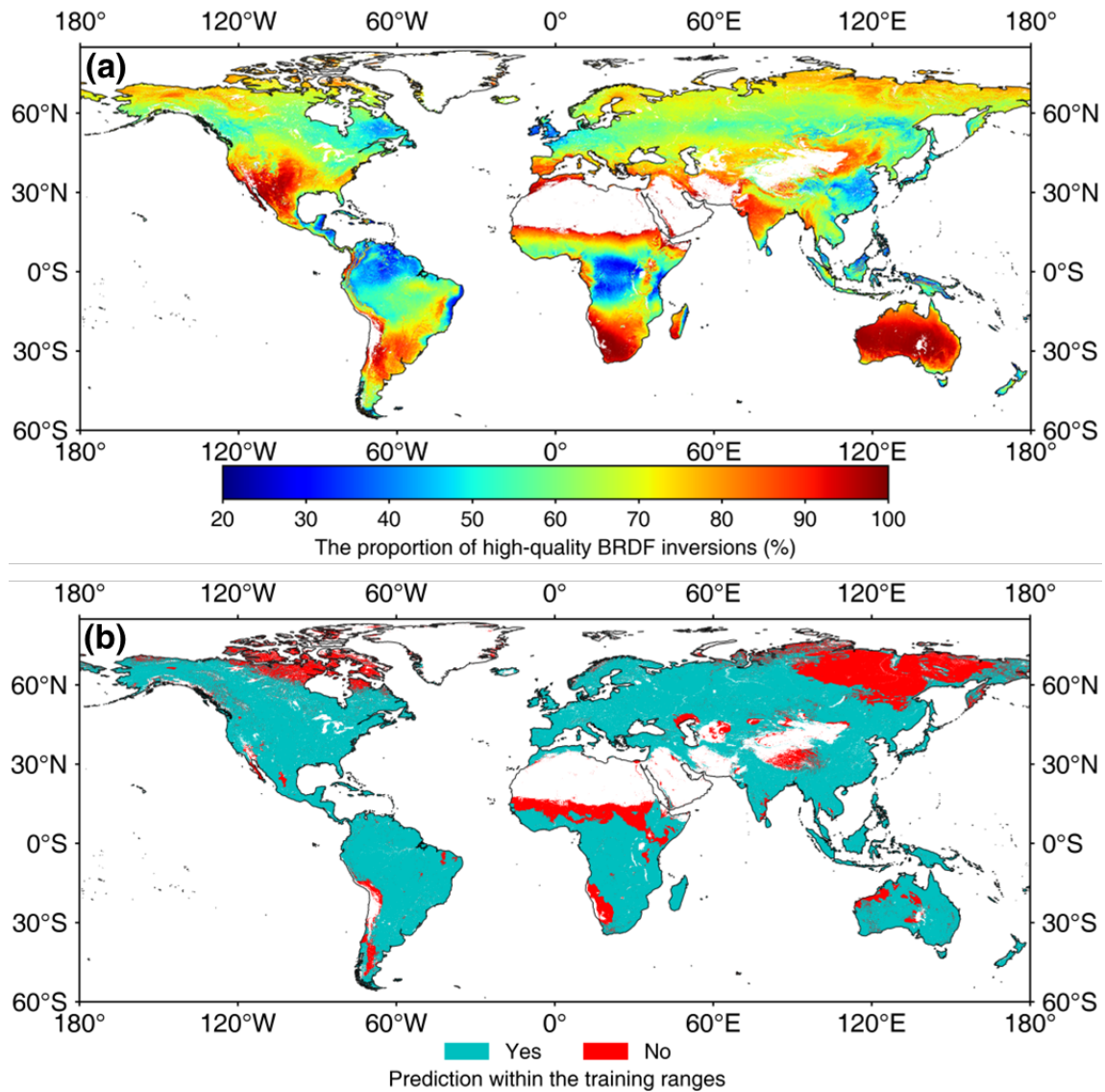
322 Among different PFTs, EBF has the highest $G(0)$, at approximately 0.76 ± 0.06 (Fig. 11a, Table 4), whereas cereal crops show
 323 the lowest value, at approximately 0.52 ± 0.08 . The DBF $G(0)$ is comparable to the global average. The $G(0)$ of broad-leaved
 324 forests is greater than that of other PFTs (Fig. 11a, Table 4). The global $G(0)$ probability density distribution peaks at 0.52–
 325 0.65, with an asymmetric distribution (Fig. 11b). The proportion on the right side of the peak is larger than that on the left. The
 326 peak of the global $G(0)$ distribution mainly contains DNF, ENF, CRO, GRA, and SHR. The left side of the peak is mainly
 327 composed of crops, while the right side is dominated by broad-leaved forests and some shrubs. The spherical distribution $G(0)$
 328 (0.50) is mainly represented by crops and a small amount of grassland, where $G(0)$ also shows a large variation (~ 0.35). The
 329 spherical distribution $G(0)$ is 0.18 (26%) less than the global average $G(0)$ (0.68), as most vegetation $G(0)$ is greater than 0.50
 330 (Fig. 11b).



331

332 **Figure 11.** Statistics (a) and probability density distributions (b) of the global nadir leaf projection function ($G(0)$) for different plant
 333 functional types. The error bars in (a) represent the standard deviation. The black dash line and shade area in (b) indicate the global $G(0)$
 334 mean and standard deviation. The gray dashed line represents the $G(0)$ ($=0.50$) of spherical leaf angle distribution. The mean, standard
 335 deviation, and probability density values are weighted by leaf area index. See Fig. 1 for the acronyms.

336 Fig. 12 demonstrates the global distributions of the MLA quality indicators. The global mean proportion of high-quality BRDF
 337 inputs is 68.03%. Northern South America and Central Africa have a low proportion of high-quality inputs (20%) because of
 338 cloud contamination (Fig. 12 (a)). Considering the large number of observations for each pixel (7904 from 2001 to 2022), this
 339 percentage (20%) of high-quality observations is sufficient to map MLA. In addition, 80.39% of the global MLA map was
 340 derived within the feature ranges of training samples, and the rest 19.61% were mainly located in high-latitude regions and
 341 Africa. For the latter areas, the MLA map was predicted with extrapolation and caution should be taken when using the map
 342 (Fig. 12 (b)).



343

344 **Figure 12.** Global distributions of quality indicators. (a) and (b) denote the proportion of high-quality BRDF inversions, and whether the
 345 prediction is within the ranges of training samples, respectively.

346

3.4 Evaluation of global MLA

347

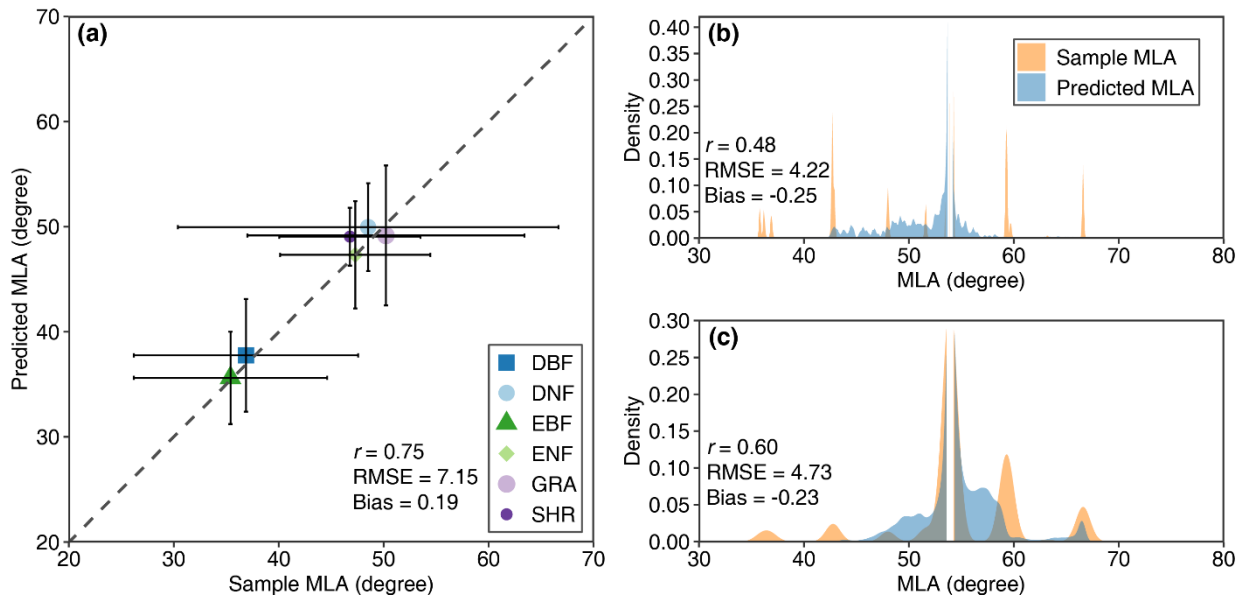
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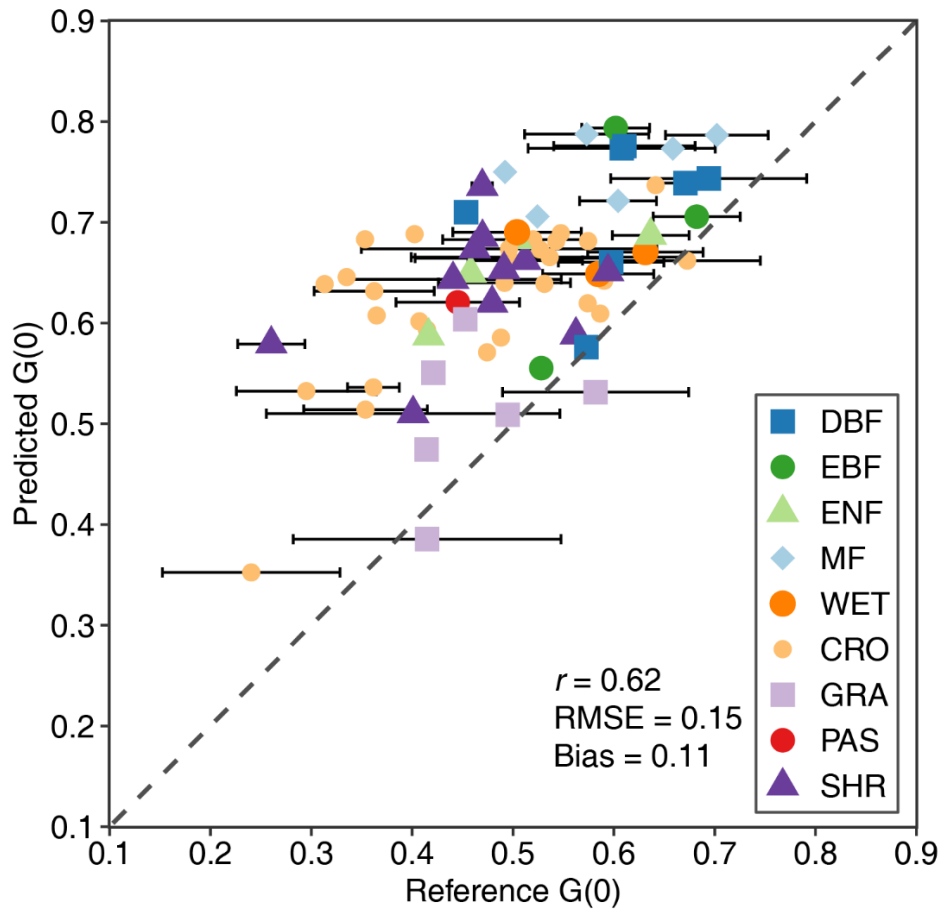
351

Fig. 13 shows the comparison between the predicted MLA and upscaled MLA samples using the ten-fold cross-validation method. For noncrops, the predicted MLA is moderately consistent with the upscaled sample MLA ($r = 0.75$, $RMSE = 7.15^\circ$), with 83% of samples having residuals $< 10^\circ$ and 94% of samples having residuals $< 15^\circ$. For DNF and SHR, the predicted MLA compresses the variation range of sample MLA (Fig. 13a). For crops, the predicted MLA of CRO-C shows higher consistency ($r = 0.60$) than that of CRO-B ($r = 0.48$). (Fig. 13b and c).



352
 353 **Figure 13.** Comparisons between predicted MLA and sample MLA for noncrop (a), broadleaf crops (b), and cereal crops (c) (See Fig. 1 for
 354 the acronyms). The error bar in (a) represents the standard deviation.

355 Fig. 14 compares $G(0)$ derived from the MLA and high-resolution reference data. The MLA-derived $G(0)$ shows moderate
 356 consistency with the reference $G(0)$ ($r = 0.62$), and 65% of the estimated $G(0)$ residuals are < 0.15 , and 84% of the residuals
 357 are < 0.20 . The estimated $G(0)$ generally overestimates ($bias = 0.11$), especially when $G(0)$ is low (< 0.60), mainly for crops,
 358 pasture, woody wetlands, and shrubs, whereas grasslands show better consistency. The estimated $G(0)$ is temporally more
 359 stable than the reference $G(0)$ which is generally greater than 0.50 and displays seasonal variation (horizontally distributed
 360 bars in Fig. 14).



361
 362 **Figure 14.** Comparisons of $G(0)$ derived from mean leaf inclination angle and high-resolution reference data for different plant functional
 363 types (see Fig. 2 for the acronyms). The error bar represents the standard deviation of reference $G(0)$ at different seasons.

364 4 Discussion

365 4.1 Global MLA and $G(0)$

366 This study compiled global LIA field measurements and generated the first global 500 m MLA and $G(0)$ maps (Figs. 8 and
 367 10). These maps show the average MLA and $G(0)$ conditions during the growing seasons from 2001 to 2022. Overall, the
 368 global MLA is lowest around the equator and increases with latitude (Figs. 8 and 10). This accords with the MLA latitude
 369 variation derived from model simulations (Huemmrich, 2013). Crops have higher MLA than broadleaf forests whose leaves
 370 are relatively horizontal. The global MLA and $G(0)$ maps enhance our understanding of the global distribution of MLA and
 371 $G(0)$ and should be useful in radiative transfer modeling, remote sensing of vegetation parameters, land surface modeling, and
 372 ecological studies.

373 The global MLA shows good consistency with validation samples (Fig. 13) and the statistics of LIA field measurements
 374 (Tables 3 and 4), demonstrating its reliability. The globally derived MLA is 41.47°, which is consistent with the LIA
 375 measurements (40.74°, Tables 3 and 4). However, the derived MLAs of DBF, DNF, CRO-B, and SHR are approximately 10°
 376 greater than the measured MLAs. It is noted that the number and spatial distribution of LIA measurements for these biomes
 377 are limited. For example, the global CRO-B areas are dominated by soybeans with higher LIA (Table S2), and the LIA
 378 measurements for soybeans are limited, which caused the CRO-B MLA in the global map to be greater than that in the
 379 measurement statistics (Tables 3 and 4). The poor crop MLA prediction (Fig. 13b) is mainly caused by a small number of
 380 samples and the strong seasonal variation. It is difficult to consider within-crop LIA variation when typical MLA values are
 381 assigned to different crops.

382 Due to the lack of high-resolution reference MLA, the global MLA was evaluated through a comparison of the MLA-derived
 383 $G(0)$ with the high-resolution reference $G(0)$ (Fig. 14). This practice was adopted because both MLA and $G(0)$ are closely
 384 related. $G(0)$ is typically calculated from the LIA distribution function based on Nilson's algorithm (Nilson, 1971). We
 385 calculated $G(0)$ from MLA assuming an ellipsoidal LIA distribution (De Wit, 1965) and found that the calculated $G(0)$ is
 386 highly consistent with the reference $G(0)$ calculated from the Nilson's algorithm for different theoretical LIA distributions
 387 (Fig. S5). The MLA-calculated $G(0)$ also shows a monotonic decreasing relationship with MLA (Fig. S6).

388 The result shows medium consistency but MLA-derived $G(0)$ overestimates at low values (< 0.60), especially for CRO, PAS,
 389 SHR, and WET. The overestimation may be partly caused by the underestimation of MLA at high values that is related to the
 390 errors introduced in the sample expansion and upscaling. These errors are mainly caused by a lack of LIA measurements,
 391 vegetation structural complexity, and seasonal variation. In addition, the uncertainties in the reference $G(0)$ may have
 392 contributed to the overestimation. The reference $G(0)$ was derived from the Beer-Lambert law (Eq. (1)) which assumes that
 393 the canopy is a turbid medium. The turbid medium assumption is unrealistic for complex vegetation (Widlowski et al., 2014).
 394 The angular variation of CI and the mixture of branches and leaves in generating high-resolution $G(0)$ can also lead to the
 395 overestimation. Previous studies have shown that CI increases with the view zenith angle (Fang, 2021), which means that the
 396 whole $CI > CI(0)$ and can lead to the underestimation of the reference $G(0)$ (Eq. (3) and (4)). The woody materials may
 397 introduce biases into the reference $G(0)$ as they were not separated in the high-resolution FVC and LAI products. The mixture
 398 of woody materials and leaves may have caused the underestimation of the reference $G(0)$ because trunks usually have higher
 399 inclination angles (Liu et al., 2019). The MODIS LAI product used for LIA upscaling in the $G(0)$ validation (section 2.4) is
 400 known to have issues such as internal inconsistency, backup algorithm accuracy, and spatiotemporal gaps (Kandasamy et al.,
 401 2013; Pu et al., 2023; Zhang et al., 2024). In the future, new improved MODIS LAI can be used in the $G(0)$ validation (Pu et
 402 al., 2024; Yan et al., 2024). Compared with the previous $G(0)$ derived from global vegetation biophysical products (Eq. (4))
 403 ($R^2 = 0.11$, $RMSE = 0.53$) (Li et al., 2022), the MLA-derived $G(0)$ performs better ($r = 0.62$, $RMSE = 0.15$). In addition, the
 404 $G(0)$ data obtained from our study can be used to derive the $G(\theta)$ for any arbitrary angle. One method of getting $G(\theta)$ is based
 405 on single-parameter ellipsoidal leaf angle distribution (Campbell, 1990) (Eq. (7)). Another method is to make use of both $G(0)$
 406 and $G(57.3^\circ) (\equiv 0.5)$ and derive $G(\theta)$ using a simple linear ($G(\theta) = a \cdot \theta + b$) or sinusoidal ($G(\theta) = a \cdot \sin(\theta) + b$)

407 interpolation method. Since $G(\theta)$ varies most significantly in the nadir direction for different MLA (Wilson, 1959), the
408 uncertainty of $G(\theta)$ derived from the global MLA in other directions will be smaller than that of $G(0)$.

409 **4.2 The relationship between MLA and other variables**

410 Analysis of the relationships between MLA and other features in the MLA mapping process reveals that MLA is negatively
411 correlated with NDVI, NIR reflectance, and NIR BRDF kernel coefficients (Fig. 7). These findings are consistent with other
412 simulation and experimental studies (Zou and Möttus, 2015; Liu et al., 2012; Dong et al., 2019; Jacquemoud et al., 1994).
413 Higher MLA generally means lower canopy interception and higher transmission for high solar altitude and more soil
414 background can be detected in the nadir direction (Liu et al., 2012). This results in lower (higher) canopy NIR (red) reflectance
415 because of the generally lower (higher) NIR (red) soil reflectance than that of the leaf components (Siegmund and Menz, 2005)
416 and negative correlations between MLA and NIR reflectance and NDVI (Liu et al., 2012). The negative relationships between
417 MLA and radiation, precipitation, and temperature (Fig. 7) are related to the vegetation adaptation mechanism. Under suitable
418 climate conditions (radiation, precipitation, and temperature), horizontal leaves are formed to absorb more radiation and
419 increase the photosynthesis rate (Van Zanten et al., 2010; King, 1997). The positive correlation between MLA and the standard
420 deviation of radiation and temperature (Fig. 7) indicates that the MLA is more vertical in areas with significant seasonal
421 changes in radiation and temperature (mid to high-latitude areas) because vertical leaves maximize intercepted radiation under
422 low solar altitudes at mid to high-latitude areas (Huemmrich, 2013).

423 Plant function type was initially used as a predictive variable (Tables 1 and 2), but relatively low importance was found for
424 LIA prediction (Fig.6, ranked 47 out of 76). This may be because the biome information is implicitly included in the spectral
425 features as the former is frequently derived from the latter (Sulla-Menashe et al., 2019). Previous studies have demonstrated
426 that the LIA variation within PFTs may be larger than that between PFTs. This indicates that the PFT is not a good predictor
427 (Prentice et al., 2024). To avoid overfitting, only the most important 40 features were used for MLA prediction (Fig. 6). To
428 explore the regional differences of the variable importance, an analysis was conducted for the tropical (23.5°S-23.5°N),
429 northern temperate (23.5°N-60°N), northern polar (60°N-90°N), and the southern temperate (23.5°S-60°S) zones. The 40 most
430 important variables are similar among different regions although minor differences exist (Fig. S7). Among the 40 variables for
431 tropical, northern temperate, northern polar, and southern temperate zones, 32, 35, 30, and 31 of them, respectively, are the
432 same as the 40 global variables (Fig. S7). Climate and spectral variables are significant among all regions, whereas BRDF
433 features are the most important in the southern temperate zone. The 40 most important variables in the global MLA prediction
434 account for ~ 80% of total importance among different regions, which is similar to that in the global prediction.

435 **4.3 Use of the new MLA map**

436 The spherical LAD assumption has been widely adopted in the literature (Tang et al., 2016; Zhao et al., 2020; Wang and Fang,
437 2020). This study demonstrates that the spherical assumption is valid only for cereal crops, but not for broadleaf forests (Tables
438 3 and 4). This finding is consistent with previous local LIA measurements (De Wit, 1965; Pisek et al., 2013; Yan et al., 2021).

439 For crops, the spherical assumption may become invalid because of seasonal change and species diversity (Table S2, Figs. 5
440 and 9). In addition, most (72%) of the reference $G(0)$ values are greater than 0.50 (Fig. S8); in this case, the spherical
441 distribution would underestimate the radiation and rainfall interception because of the overestimated LIA and underestimated
442 $G(0)$ for most conditions (Figs. 9 and 11) (Stadt and Lieffers, 2000). In current LSMs, a constant LIA is commonly assigned
443 for each PFT (Majasalmi and Bright, 2019). For example, the Community Land Model V5 (CLM5) (Table S4) (Lawrence et
444 al., 2019) uses lower inclination indices and higher LIA values than our results (Tables 3 and 4) and thus may underestimate
445 canopy interception. The global LIA map generated in this study provides a more reasonable LIA parameterization strategy
446 for the application communities.

447 **4.4 Limitations and prospects**

448 The limitations of this study mainly relate to the small number of LIA measurements, especially continuous measurements.
449 First, within-species LIA variations were neglected in the spatial expansion due to limited spatial coverage of existing LIA-
450 measured data (Section 2.3.1). This may introduce some errors, especially for crops. Second, three different sources of LIA
451 measurements were gathered with different measurement schemes, and uncertainty may arise because of these differences.
452 The random forest algorithm is robust to these differences because part of the samples and features were randomly selected
453 and the algorithm ensembled the predictions from multiple decision trees (Svetnik et al., 2003). We manually inspected all
454 field LIA data and are confident in their data quality. Third, for forests, the contribution of the understory was not considered.
455 Typically, the understory is characterized by more horizontal leaves, and ignoring the understory may lead to an MLA
456 overestimation (Utsugi et al., 2006). Nevertheless, a previous study showed that the relative contribution of the understory to
457 the overall MLA is less than 10% (Li et al., 2022). Finally, only the growing season MLA was calculated, whereas the seasonal
458 and long-term variations of MLA were not considered due to the lack of continuous LIA measurements.

459 We assumed a linear LAI-EVI2 relationship ($LAI = a \cdot EVI2$) to upscale MLA from the canopy to 500 m scale (Section 2.3.1
460 and Appendix A). Global analysis of MODIS LAI and EVI2 products shows a slight non-linear relationship between them
461 (Fig. S9). The non-linear relationship was also used to upscale MLA (Eq. A2) in a side experiment, where the derived MLA
462 was found consistent with the original one (Fig. S10) because of the homogeneity of the 500 m pixel after rigorous sample
463 screening (section 2.3.1). This demonstrates the suitability of the linear assumption.

464 In the future, more efficient LIA observation systems should be developed to provide continuous LIA data (Kattenborn et al.,
465 2022). LIA measurements can be integrated into existing ground observation networks, such as the National Ecological
466 Observatory Network (NEON) (Kao et al., 2012), Integrated Carbon Observation System (ICOS) (Gielen et al., 2018), and
467 Terrestrial Ecosystem Research Network (TERN) (Karan et al., 2016), to enhance temporal LIA measurements in larger spatial
468 extent, especially for DNF and crops. Using standard LIA measurement protocols will certainly improve the LIA data
469 consistency. (Li et al., 2023). In addition, canopy structure parameters are interrelated, and introducing other structure
470 parameter products, such as LAI, FVC, CI, and canopy height as predictive variables may improve the MLA prediction.
471 Multiangle reflectance (Jacquemoud et al., 2009; Goel and Thompson, 1984; Jacquemoud et al., 1994) or light detection and

472 ranging (Zheng and Moskal, 2012; Bailey and Mahaffee, 2017; Itakura and Hosoi, 2019) are encouraging remote sensing tools
473 that can help to derive temporally continuous and high-resolution MLA data.

474 **5 Conclusion**

475 This study compiled existing global LIA measurements and generated the first global 500 m MLA and G(0) products by gap-
476 filling the LIA measurement data using a random forest regressor. The mean of global LIA measurements is 40.74° and cereal
477 crops show the highest MLA (59.11°). The global MLA shows an explicit spatial distribution and the value increases with
478 latitude. The global MLA is $41.47^{\circ} \pm 9.55^{\circ}$ and follows the order of CRO-C > CRO-B > DNF > SHR > ENF $\approx$ GRA > DBF >
479 EBF. The predicted MLA presents a medium consistency ($r = 0.75$, RMSE = 7.15°) with the validation samples for noncrops.
480 For crops, the results are relatively poorer ($r = 0.48$ and 0.60 for broadleaf crops and cereal crops) because of limited LIA
481 measurements and strong seasonality. The G(0) derived from MLA is moderately consistent with the reference G(0) ($r = 0.62$).
482 The MLA and G(0) products obtained in this study would enhance our understanding of global LIA and assist remote sensing
483 retrieval and land surface modeling studies. These products provide a more realistic parameterization strategy than the
484 commonly used spherical LAD and PFT-specific MLA assignment. Note the global MLA and G(0) products mainly represent
485 the typical state during the growing season. These products can be further improved and temporal MLA data can be obtained
486 through continuous measurements and remote sensing retrieval.

487 **Data availability**

488 The global MLA and G(0) products (CAS-GLA) are available in: Li, S. and Fang, H. 2025,
489 <https://doi.org/10.5281/zenodo.12739662> (Li and Fang, 2025). The related code can be accessed at
490 https://code.earthengine.google.com/?accept_repo=users/SiJia/MTA.

491 **Author contributions**

492 HF and SL conceptualized this work. SL compiled global LIA measurements, generated global products, and curated the
493 datasets. SL and HF wrote the manuscript. HF was responsible for funding and supervision.

494 **Competing interests**

495 The contact author has declared that none of the authors has any competing interests.

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502 Appendix A. Upscaling LIA from leaf, canopy to ecosystem scale

503 From leaf to canopy scale, the entire canopy MLA is commonly calculated as the average of all measured leaf LIAs weighted
504 by leaf area (Eq. A1) (Zou et al., 2014; De Wit, 1965; Yan et al., 2021). In practice, because of the difficulty in leaf area
505 measurement, especially for a large number of leaves, the variability of leaf areas within a canopy is often ignored and the
506 areas of all leaves are assumed similar. In this case, the canopy LIA can be simplified as the average LIA weighted by leaf
507 number (Eq. A1) (Ryu et al., 2010; Pisek et al., 2011; Chianucci et al., 2018):

$$508 \quad MLA_{canopy} = \frac{\sum_i LIA_i * LA_i}{\sum_i LA_i} = \frac{LA_{mean} * \sum_i LIA_i}{LA_{mean} * N} = \frac{\sum_i LIA_i}{N} \quad (A1)$$

509 where MLA_{canopy} is the MLA at canopy scale, i is the i th leaf, LIA is leaf inclination angle, LA is single leaf area, LA_{mean} is
510 the mean leaf area by ignoring the variation of leaf area within a canopy, N is number of leaves within a canopy.

511 From the canopy to 30 m scale, the canopy level MLA is regarded as equal to 30 m-MLA because for MLA measurements,
512 the dominant species was artificially identified by investigators and the spatial representativeness at the extent of 30 m is
513 ensured.

514 From 30 m to 500 m, the 500 m MLA was formulated as the weighted average of 30 m MLA by the leaf area of the 30 m pixel
515 (Eq. A2), the same as that from the leaf to canopy scale. The leaf area of a 30 m pixel can be deduced from the product of leaf
516 area index (LAI) and the ground area of a 30 m pixel according to the definition of LAI (the half of green leaf area on the unit
517 of ground area) (Eq. A2) (Fang et al., 2019).

$$518 \quad MLA_{500} = \frac{\sum_j MLA_{30-j} * LA_{30-j}}{\sum_j LA_{30-j}} = \frac{\sum_j MLA_{30-j} * LAI_{30-j} * S}{\sum_j LAI_{30-j} * S} = \frac{\sum_j MLA_{30-j} * LAI_{30-j}}{\sum_j LAI_{30-j}} \quad (A2)$$

519 Where MLA_{500} and MLA_{30} represent MLA at 500 m and 30 m scales, j is the j th 30 m pixel, LA_{30-j} is the total leaf area of a
520 30 m pixel, LAI_{30-j} is leaf area index (m²/m²) of a 30 m pixel, S is the ground area of a 30 m pixel.

521 Assuming $LAI = a * EVI2 + b$ and $b \approx 0$ (as illustrated in Fig. S9), the MLA at 500 m scale can be calculated as:

522

$$MLA_{500} = \frac{\sum_j MLA_{30_j} * EVI2_{30_j}}{\sum_j EVI2_{30_j}}$$

(A3)

523

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