Referee #1

This manuscript describes an effort to make a global reference map of leaf inclination angle by combining leaf angle observations (from the TRY database and extracted from images) with ancillary data (including plant functional/crop types, reflectance, BRDF, climate, topography) and a random forest approach. Results are compared to other available data related to leaf angle distributions from the GBOV and DIRECT databases.

The clearly written manuscript provides a compelling justification for why consistent global leaf angle data would be widely useful. The authors note the challenge of sparse leaf angle observations, and while they have devised some creative ways to expand those observations to train the random forest model, some elements of the methods and evaluation have the potential to create consequential bias.

We thank the referee for the recognition and insightful comments that help us improve the manuscript. We have noted the biases in Fig. 13 and discussed their causes in section 4.1 (Line 346-359).

> *Due to the lack of high-resolution reference MLA, the global MLA was evaluated through a comparison of the MLA-derived G(0) with the high-resolution reference G(0) (Fig. 13). The result shows medium consistency but MLA-derived G(0) overestimates at low values (< 0.60), especially for CRO, PAS, SHR, and WET.* ***The overestimation may be partly caused by the underestimation of MLA at high values that is related to the errors introduced in the sample expansion and upscaling. These errors are mainly caused by a lack of LIA measurements, vegetation structural complexity, and seasonal variation. In addition, the uncertainties in the reference G(0) may have contributed to the overestimation.*** *The reference G(0) was derived from the Beer-Lambert law (Eq. (4)) which assumes that the canopy is a* ***turbid medium.*** *The turbid medium assumption is unrealistic for complex vegetation (Widlowski et al., 2014).* ***The angular variation of CI and the mixture of branches and leaves*** *in generating high-resolution G(0) can also lead to the overestimation. Previous studies have shown that CI increases with the view zenith angle (Fang 2021), which means that the whole CI > CI(0) and can lead to the underestimation of the reference G(0) (Eq. (6) and (7)). The mixture of branches and leaves may result in the underestimation of the reference G(0) due to the usually higher inclination angle of the trunks (Liu et al. 2019b). Compared with the previous G(0) derived from global vegetation biophysical products (Eq. (7)) (R2 = 0.11, RMSE = 0.53) (Li et al. 2022), the MLA-derived*

> *G(0) performs better (R2 = 0.38, RMSE = 0.15).*

In addition, Since G(θ) varies most significantly in the nadir direction for different MLA (Wilson 1959), the uncertainty of G(θ) derived from the global MLA in other directions is smaller than that of G(0).

Specific comments:

1. The method from Pisek et al. (2011) to derive leaf angle from images requires that images are leveled. It's not possible to know whether images taken from Google are leveled, and whether images systematically describe distribution within a plant, and this can create bias in the dataset.

The referee is correct that the canopy pictures taken from Google do not contain the level information directly. In this study, the level state of the canopy images was determined from the background information, such as the ground level and plant stems. For each species, more than 75 leaves from different images were collected (Line 110), reducing the uncertainties from non-leveled photography.

2. The TRY database was used to determine dominant species in an area to select species for manual classification from images. No details were given about how this was done, but datasets from TRY were not designed for this purpose and may not be representative.

Thanks to the referee's reminder, we have added more details regarding the species selection procedure to the manuscript (Line 108).

> *The TRY species location data (848,919, Fig. S3b) (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.*

Most species distribution databases, e.g., the Global Biodiversity Information Facility (GBIF) (Yesson et al. 2007), only consider the appearance of species but not their spatial representativeness. The TRY species location database consists of trait measurements for common species which represent a hundreds-of-square-meters area around the location. The dominant species was artificially identified by investigators and the spatial representativeness is vital for following LIA upscaling. Therefore, the TRY species location database was utilized after throughout consideration.

3. Leaf angle can be highly variable within a species, depending on factors like leaf age, plant water status, and canopy position. The manuscript does not report distributions of replicates per species, and given the large expansion of spatial coverage from TRY data locations (where leaf angles were not directly observed) it's possible that training data may not be representative of their species.

We agree with the referee about the leaf angle variation from a plant physiological perspective. It is understood that LIA is influenced by the environment and varies within a species.

In this study, LIA is the mean leaf inclination angle (MLA) of all leaves at the canopy or pixel scale, not for a single leaf. For a site, the LIA of multiple leaves at different heights and orientations are obtained and averaged to obtain a robust MLA (Chianucci et al. 2018; Pisek and Adamson 2020). The MLA partly mitigates the impact of canopy position, sunlit and shaded leaves, branching patterns, stem elongation, and species-specific genetic traits like phototropism and heliotropism. This kind of mean LIA is desperately wanted in many remote sensing and land surface modeling studies (Lawrence et al. 2019; Li et al. 2023; Majasalmi and Bright 2019; Tang et al. 2016; Zhao et al. 2020). In those studies, LIA is commonly assumed constant (spherical distribution, 57.3 degrees) or biome type-specific (assigning a constant value for each biome). Indeed, these assumptions may not represent the true field measurements (Tables 3 and 4). Our objective is to provide a more realistic global MLA map for remote sensing and land surface modeling studies.

In this study, the LIA seasonal variations were not considered in the global LIA map because of the lack of seasonal LIA measurements. As a matter of fact, temporal LIA variations are usually small, except under extreme situations (unusual). For example, the LIA variations of European beech forest and eucalyptus in different successional stages are less than 10 degrees (le Maire et al. 2011; Liu et al. 2019; Raabe et al. 2015). Crops generally show higher LIA variations than non-crops (Biskup et al. 2007; Zhang et al. 2017). Therefore, many studies have considered LIA as a species-specific static trait when there are no seasonal field measurements (Pisek et al. 2022; Raabe et al. 2015; Toda et al. 2022).

The global LIA map derived in this study is consistent with field measurements (Tables 3 and 4). This is a significant improvement compared to existing static simplifications (Lawrence et al. 2019; Li et al. 2023; Majasalmi and Bright 2019; Tang et al. 2016; Zhao et al. 2020). In a forthcoming study, we plan to retrieve LIA from remote sensing and the temporal LIA variation will be considered.

Thanks to the referee's comment, we have revised the manuscript (Line 151).

> *Many studies have treated LIA as a species-specific static trait and ignored within-species variations when LIA measurements are limited (Pisek et al., 2022; Toda et al., 2022; Raabe et al., 2015). Following the rationale, the spatial coverage of LIA measurements was expanded, and those records without location information were utilized (section 2.1.1).*

In addition, we counted the number of locations for different species and found the LIA replicates per species range from 1 to 330, and most replicates (98%) are less than 50. We added this information to the manuscript (Line 118).

4. Some of the products used for upscaling and evaluation themselves depend on assumptions about leaf angle, including MODIS LAI which was used to upscale the mean leaf angle data produced here to compare to GBOV and DIRECT data. I expect that GBOV and DIRECT LAI products also depend on leaf angle assumptions (as almost all methods of estimating LAI do).

In the MODIS LAI algorithm, a biome-specific static LIA was used as a priori (Myneni et al. 2002). The LIA is partly considered in the LAI retrieval algorithm and the MODIS LAI has been widely validated and shows good consistency (Brown et al. 2020; Yan et al. 2021). Therefore, it was used to upscale LIA in the evaluation procedure.

In GBOV and DIRECT, the high-resolution reference LAI is estimated by the empirical relationship between reflectance and LAI measurements. The LAI measurements were obtained with the Miller method (Eq. (1)) which does not require any leaf angluar information (https://gbov.land.copernicus.eu/products/).

$$LAI = 2\sum_{i=1}^{n} -\overline{\ln\ P(\theta_i)}\, \cos(\theta_i)\, \sin(\theta_i) d_{\theta_i} \qquad (1)$$

Where $P(\theta_i)$ is the gap fraction value in viewing zenith ring i. Therefore, the GBOV and DIRECT data do not dependent on leaf angle assumptions.

Technical comments:

1. Line 10: I recommend “trait” instead of “parameter” here when discussing ecological processes.

We have revised it.

2. Line 103: I was confused by the statement “The majority of existing LIA measurements are located in the mid-latitudes of the Northern Hemisphere.” Because Figure 1 looks like a huge amount of data are in the American tropics?

Two different versions of TRY data (V5 and V6) were used and the V6 data provide a large amount of LIA measurements in the Southern Hemisphere. The original sentence was deleted.

3. Line 159: Coefficient of variation in reflectance or something else?

Yes, it represents the coefficient of variation in reflectance. We have revised it in the manuscript.

4. Line 194: The single-parameter ellipsoidal leaf angle distribution seems like a big assumption. Where there are data to test this, does it seem reasonable?

Compared to other leaf angle distribution 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; Kuusk 2001; Verhoef et al. 2007; Wang et al. 2007). Therefore, the single-parameter ellipsoidal leaf angle distribution was also used in this study and its parameter χ, the ratio of the horizontal and vertical axes of an ellipsoid, was first derived from MLA. We have rephrased the original sentence (Line 201).

> *Assuming a single-parameter ellipsoidal leaf angle distribution (Campbell, 1990), the parameter χ, the ratio of the horizontal and vertical axes of an ellipsoid, was first derived from MLA. 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 (Kuusk 2001; Verhoef et al. 2007; Wang et al. 2007).*

5. Figure 12: Are the distinct peaks in the reference data for different crops in panels b and c?

The distinct peaks in the reference sample data are caused by the MLA assignment manner and the homogeneity of cropland. The crop MLA samples were generated by assigning typical MLAs (Table S2) for different crops with high-resolution crop maps, followed by the upscaling (section 2.3.2 Line 188). In the upscaling, the homogeneity of cropland may result in low sample diversity and distinct peaks.

We have clarified it in Lines 180 and 188.

> *Different mapping strategies were employed for noncrops and crops (Fig. 3b) considering the small number of valid crop samples (Fig. 4) and the lack of location information for most crop samples.*
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> *For crops, the measured MLA values were averaged for different crop types as a typical MLA (Table S2). After assigning typical MLAs for different crops with high-resolution crop maps (Table 1), the high-resolution crop MLA were upscaled to 500 m as training samples (Eq. (1)).*

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