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.*
>
> *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)).*

Reference

Biskup, B., Scharr, H., Schurr, U., & Rascher, U. (2007). A stereo imaging system for measuring structural parameters of plant canopies. *Plant, Cell and Environment, 30*, 1299-1308

Brown, L.A., Meier, C., Morris, H., Pastor-Guzman, J., Bai, G., Lerebourg, C., Gobron, N., Lanconelli, C., Clerici, M., & Dash, J. (2020). Evaluation of global leaf area index and fraction of absorbed photosynthetically active radiation products over North America using Copernicus Ground Based Observations for Validation data. *Remote Sensing of Environment, 247*

Campbell, G. (1990). Derivation of an angle density function for canopies with ellipsoidal leaf angle distributions. *Agricultural and Forest Meteorology, 49*, 173-176

Chianucci, F., Pisek, J., Raabe, K., Marchino, L., Ferrara, C., & Corona, P. (2018). A dataset of leaf inclination angles for temperate and boreal broadleaf woody species. *Annals of Forest Science, 75*, 50-50

Kuusk, A. (2001). A two-layer canopy reflectance model. *Journal of Quantitative Spectroscopy and Radiative Transfer, 71*, 1-9

Lawrence, D.M., Fisher, R.A., Koven, C.D., Oleson, K.W., Swenson, S.C., Bonan, G., Collier, N., Ghimire, B., Van Kampenhout, L., & Kennedy, D. (2019). The Community Land Model version 5: Description of new features, benchmarking, and impact of forcing uncertainty. *Journal of Advances in Modeling Earth Systems, 11*, 4245-4287

le Maire, G., Marsden, C., Verhoef, W., Ponzoni, F.J., Lo Seen, D., Bégué, A., Stape, J.-L., &

Nouvellon, Y. (2011). Leaf area index estimation with MODIS reflectance time series and model inversion during full rotations of Eucalyptus plantations. *Remote Sensing of Environment, 115*, 586-599

Li, S., Fang, H., & Zhang, Y. (2023). Determination of the Leaf Inclination Angle (LIA) through Field and Remote Sensing Methods: Current Status and Future Prospects. *Remote Sensing, 15*, 946

Liu, J., Skidmore, A.K., Wang, T., Zhu, X., Premier, J., Heurich, M., Beudert, B., & Jones, S. (2019). Variation of leaf angle distribution quantified by terrestrial LiDAR in natural European beech forest. *ISPRS Journal of Photogrammetry and Remote Sensing, 148*, 208-220

Majasalmi, T., & Bright, R.M. (2019). Evaluation of leaf-level optical properties employed in land surface models – example with CLM 5.0. *Geoscientific Model Development Discussions*, 1-24

Myneni, R.B., Hoffman, S., Knyazikhin, Y., Privette, J.L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G.R., Lotsch, A., Friedl, M., Morisette, J.T., Votava, P., Nemani, R.R., & Running, S.W. (2002). Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment, 83*, 214-231

Pisek, J., & Adamson, K. (2020). Dataset of leaf inclination angles for 71 different Eucalyptus species. *Data Brief, 33*, 106391

Pisek, J., Diaz-Pines, E., Matteucci, G., Noe, S., & Rebmann, C. (2022). On the leaf inclination angle distribution as a plant trait for the most abundant broadleaf tree species in Europe. *Agricultural and Forest Meteorology, 323*

Raabe, K., Pisek, J., Sonnentag, O., & Annuk, K. (2015). Variations of leaf inclination angle distribution with height over the growing season and light exposure for eight broadleaf tree species. *Agricultural and Forest Meteorology, 214-215*, 2-11

Tang, H., Ganguly, S., Zhang, G., Hofton, M.A., Nelson, R.F., & Dubayah, R. (2016). Characterizing leaf area index (LAI) and vertical foliage profile (VFP) over the United States. *Biogeosciences, 13*, 239-252

Toda, M., Ishihara, M.I., Doi, K., & Hara, T. (2022). Determination of species-specific leaf angle distribution and plant area index in a cool-temperate mixed forest from UAV and upward-pointing digital photography. *Agricultural and Forest Meteorology, 325*

Verhoef, W., Jia, L., Xiao, Q., & Su, Z. (2007). Unified Optical-Thermal Four-Stream Radiative Transfer Theory for Homogeneous Vegetation Canopies. *IEEE Transactions on Geoscience and Remote Sensing, 45*, 1808-1822

Wang, W.M., Li, Z.L., & Su, H.B. (2007). Comparison of leaf angle distribution functions: Effects on extinction coefficient and fraction of sunlit foliage. *Agricultural and Forest Meteorology, 143*, 106-122

Wilson, J.W. (1959). Analysis of the spatial distribution of foliage by two-dimensional point quadrats. *New Phytologist, 58*, 92-99

Yan, K., Pu, J., Park, T., Xu, B., Zeng, Y., Yan, G., Weiss, M., Knyazikhin, Y., & Myneni, R.B. (2021). Performance stability of the MODIS and VIIRS LAI algorithms inferred from analysis of long time series of products. *Remote Sensing of Environment, 260*

Yesson, C., Brewer, P.W., Sutton, T., Caithness, N., Pahwa, J.S., Burgess, M., Gray, W.A., White, R.J., Jones, A.C., & Bisby, F.A. (2007). How global is the global biodiversity information facility? *PLoS ONE, 2*, e1124

Zhang, Y., Tang, L., Liu, X., Liu, L., Cao, W., & Zhu, Y. (2017). Modeling the leaf angle dynamics in rice plant. *PLoS ONE, 12*, 1-13

Zhao, J., Li, J., Liu, Q., Xu, B., Yu, W., Lin, S., & Hu, Z. (2020). Estimating fractional vegetation cover from leaf area index and clumping index based on the gap probability theory. *International Journal of Applied Earth Observation and Geoinformation, 90*, 102-112

Referee #2

This study compiled global Leaf Inclination Angle (LIA) field measurements and produced the first global 500 m LIA dataset using machine learning. The dataset was evaluated with the nadir leaf projection function, comparing it against high-resolution reference data, and the global LIA patterns across different biomes were further analyzed. While the study is intriguing and generally well-written, I have significant concerns regarding the reliability of this static, machine learning-based product, particularly due to the dynamic nature of LIA at the leaf level, limitations in scaling field measurements to the canopy and ecosystem level, and the lack of effective input data at the global scale. My specific concerns are outlined below:

We thank the referee for the insightful comments which help us to further improve the manuscript. We fully understand the referee's concerns and have provided detailed explanations below.

1. **Dynamic Nature of Leaf-Level LIA:** LIA is highly variable within a canopy, even for a single species. Observing a tree canopy, one can easily notice the variation in leaf inclination. To minimize self-shading or optimize light capture, sun and shade leaves on the same plant may have different inclinations. Moreover, LIA can change throughout the day to track the sun's movement, across growing seasons, and with leaf age and developmental stages. Under stress conditions, such as water scarcity or extreme temperatures, plants may adjust their leaf angles to reduce water loss or mitigate heat stress by altering turgor pressure. Additionally, variability in LIA is influenced by branching patterns, stem elongation, and species-specific genetic traits like phototropism and heliotropism. Given this variability, treating LIA as a static structural trait oversimplifies its inherently dynamic nature.

We agree with the referee's comments about the dynamic nature of leaf LIA. For plant physiologists, it is well known that LIA is influenced by environmental conditions and shows temporal variation.

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 height, 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).*

2. **Upscaling LIA Field Measurements:** The LIA field measurements from the TRY database seem to be primarily site-specific. The method used to upscale these measurements from the leaf level to the canopy and ecosystem scales is crucial for modeling accuracy, yet it is unclear in this study. The approach of using a weighted average of Enhanced Vegetation Index (EVI) to scale LIA from 30 m to 500 m, as

per equation (1), raises concerns. What is the solid physical or physiological rationale for this upscaling method? Without a clear justification, this approach appears problematic.

In field measurement, the entire canopy LIA is calculated as the average of all measured leaf LIAs weighted by leaf area (de Wit 1965; Zou et al. 2014). Leaves with larger areas have higher weights. Upscaling LIA from 30 m to 500 m follows the same rationale as that from leaf to canopy scale. For a 30 m pixel with a higher leaf area index (LAI), the weight of the pixel is higher. Considering that a linear relationship exists between LAI and enhanced vegetation index (EVI2) (Alexandridis et al. 2019; Dong et al. 2019), the LIA was upscaled by EVI2 (Eq. (1)).

Following the suggestion, we have explained in the manuscript (Line 165).

> *In field measurement, the entire canopy LIA is calculated as the average of all measured leaf LIAs weighted by leaf area (Zou et al., 2014; De Wit, 1965). Leaves with larger areas have higher weights. Upscaling LIA from 30 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 pixel is higher. Therefore, the 500 m MLA was computed as the weighted average of the enhanced vegetation index (EVI2) considering a linear relationship between LAI and EVI2 (Dong et al., 2019; Alexandridis et al., 2019).*

3. **Coarse Resolution and Low-Signal Inputs in the Model:** LIA provides detailed structural information at the leaf level. When using a machine learning model, how did the authors ensure that the global model inputs listed in Table 1 accurately represent such low-signal information (also the variations mentioned in comment #1) at a coarse spatial resolution, which is significantly larger than the leaf level? Importantly, the MODIS LAI product does not reliably capture LIA in its algorithm. Furthermore, as seen in Figure 6, NDVI and precipitation are identified as major factors controlling LIA. What is the specific basis for this, given that both factors exhibit strong seasonal dynamics? Overall, I think that current optical remote sensing systems, such as MODIS and Landsat, lack the capability to capture the subtle structural signal of LIA, as they were not designed for this purpose.

We agree with the referee that MODIS and Landsat are not designed for estimating LIA.

In this study, the MODIS LAI was only used for the upscaling evaluation of G(0) (Line 219). In the MODIS LAI algorithm, a biome-specific static LIA was used as a priori

(Myneni et al. 2002). This biome-specific LIA is very rough and should (and can) be improved. It is our goal to generate global pixel-scale LIA.

The correlation between LIA and NDVI or precipitation has been reported in many simulation and field studies (Dong et al. 2019; Jacquemoud et al. 1994; Liu et al. 2012; Zou and Mõttus 2015). This has been explained in section 4.2. Higher LIA means lower radiation interception, more NIR downward radiation, and lower NIR reflectance (Liu et al. 2012). This results in negative correlations between MLA and NIR reflectance and vegetation index. The negative correlation between MLA and precipitation relates to vegetation adaptation. Under suitable climate conditions, horizontal leaves can make better usage of precipitation and increase the photosynthesis rate (King 1997; van Zanten et al. 2010). Therefore, in this study, the mean and stand deviation of NDVI and precipitation time series were selected to predict LIA. The mean NDVI and precipitation represent the average situation for a specific area and correspond to the typical global LIA.

In canopy radiation transfer, canopy structure parameters, including leaf area index, LIA, and clumping index jointly determine the canopy reflectance (Liang 2005; Ross 1981; Verhoef 1984). Previous studies have shown that multi-angle reflectance is sensitive to LIA and can be used to derive the latter (Goel and Thompson 1984; Jacquemoud et al. 1994; Jacquemoud et al. 2009; Li et al. 2023). Since MODIS has multiangle observations, the multiangle information provided in the BRDF product (MCD43A1 C6.1) was used here as LIA predictors in this study. In contrast, Landsat lacks a multiangle view and was rarely used for LIA estimation.

Reference

Alexandridis, T.K., Ovakoglou, G., & Clevers, J.G.P.W. (2019). Relationship between MODIS EVI and LAI across time and space. *Geocarto International, 35*, 1385-1399

Biskup, B., Scharr, H., Schurr, U., & Rascher, U. (2007). A stereo imaging system for measuring structural parameters of plant canopies. *Plant, Cell and Environment, 30*, 1299-1308

Chianucci, F., Pisek, J., Raabe, K., Marchino, L., Ferrara, C., & Corona, P. (2018). A dataset of leaf inclination angles for temperate and boreal broadleaf woody species. *Annals of Forest Science, 75*, 50-50

de Wit, C.T. (1965). Photosynthesis of leaf canopies. In: Pudoc

Dong, T., Liu, J., Shang, J., Qian, B., Ma, B., Kovacs, J.M., Walters, D., Jiao, X., Geng, X., & Shi, Y. (2019). Assessment of red-edge vegetation indices for crop leaf area index estimation. *Remote Sensing of Environment, 222*, 133-143

Goel, N.S., & Thompson, R.L. (1984). Inversion of vegetation canopy reflectance models for estimating agronomic variables. V. Estimation of leaf area index and average leaf angle using measured canopy reflectances. *Remote Sensing of Environment, 16*, 69-85

Jacquemoud, S., Flasse, S., Verdebout, J., & Schmuck, G. (1994). Comparison of Several Optimization Methods To Extract Canopy Biophysical Parameters - Application To Caesar Data, 291-298

Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P.J., Asner, G.P., François, C., & Ustin, S.L. (2009). PROSPECT+SAIL models: A review of use for vegetation characterization. *Remote Sensing of Environment, 113*, S56-S66

King, D.A. (1997). The Functional Significance of Leaf Angle in Eucalyptus. *Australian Journal of Botany, 45*, 619-639

Lawrence, D.M., Fisher, R.A., Koven, C.D., Oleson, K.W., Swenson, S.C., Bonan, G., Collier, N., Ghimire, B., Van Kampenhout, L., & Kennedy, D. (2019). The Community Land Model version 5: Description of new features, benchmarking, and impact of forcing uncertainty. *Journal of Advances in Modeling Earth Systems, 11*, 4245-4287

le Maire, G., Marsden, C., Verhoef, W., Ponzoni, F.J., Lo Seen, D., Bégué, A., Stape, J.-L., & Nouvellon, Y. (2011). Leaf area index estimation with MODIS reflectance time series and model inversion during full rotations of Eucalyptus plantations. *Remote Sensing of Environment, 115*, 586-599

Li, S., Fang, H., & Zhang, Y. (2023). Determination of the Leaf Inclination Angle (LIA) through Field and Remote Sensing Methods: Current Status and Future Prospects. *Remote Sensing, 15*, 946

Liang, S. (2005). *Quantitative remote sensing of land surfaces*. John Wiley & Sons

Liu, J., Pattey, E., & Jégo, G. (2012). Assessment of vegetation indices for regional crop green LAI estimation from Landsat images over multiple growing seasons. *Remote Sensing of Environment, 123*, 347-358

Liu, J., Skidmore, A.K., Wang, T., Zhu, X., Premier, J., Heurich, M., Beudert, B., & Jones, S. (2019). Variation of leaf angle distribution quantified by terrestrial LiDAR in natural European beech forest. *ISPRS Journal of Photogrammetry and Remote Sensing, 148*, 208-220

Majasalmi, T., & Bright, R.M. (2019). Evaluation of leaf-level optical properties employed in land surface models – example with CLM 5.0. *Geoscientific Model Development Discussions*, 1-24

Myneni, R.B., Hoffman, S., Knyazikhin, Y., Privette, J.L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G.R., Lotsch, A., Friedl, M., Morisette, J.T., Votava, P., Nemani, R.R., & Running, S.W. (2002). Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data. *Remote Sensing of Environment, 83*, 214-231

Pisek, J., & Adamson, K. (2020). Dataset of leaf inclination angles for 71 different Eucalyptus species. *Data Brief, 33*, 106391

Pisek, J., Diaz-Pines, E., Matteucci, G., Noe, S., & Rebmann, C. (2022). On the leaf inclination angle distribution as a plant trait for the most abundant broadleaf tree species in Europe. *Agricultural and Forest Meteorology, 323*

Raabe, K., Pisek, J., Sonnentag, O., & Annuk, K. (2015). Variations of leaf inclination angle distribution with height over the growing season and light exposure for eight broadleaf tree species. *Agricultural and Forest Meteorology, 214-215*, 2-11

Ross, J. (1981). *The radiation regime and architecture of plant stands*. Springer Science & Business

Media

Tang, H., Ganguly, S., Zhang, G., Hofton, M.A., Nelson, R.F., & Dubayah, R. (2016). Characterizing leaf area index (LAI) and vertical foliage profile (VFP) over the United States. *Biogeosciences, 13*, 239-252

Toda, M., Ishihara, M.I., Doi, K., & Hara, T. (2022). Determination of species-specific leaf angle distribution and plant area index in a cool-temperate mixed forest from UAV and upward-pointing digital photography. *Agricultural and Forest Meteorology, 325*

van Zanten, M., Pons, T.L., Janssen, J.A.M., Voesenek, L.A.C.J., & Peeters, A.J.M. (2010). On the Relevance and Control of Leaf Angle. *Critical Reviews in Plant Sciences, 29*, 300-316

Verhoef, W. (1984). Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model. *Remote Sensing of Environment, 16*, 125-141

Zhang, Y., Tang, L., Liu, X., Liu, L., Cao, W., & Zhu, Y. (2017). Modeling the leaf angle dynamics in rice plant. *PLoS ONE, 12*, 1-13

Zhao, J., Li, J., Liu, Q., Xu, B., Yu, W., Lin, S., & Hu, Z. (2020). Estimating fractional vegetation cover from leaf area index and clumping index based on the gap probability theory. *International Journal of Applied Earth Observation and Geoinformation, 90*, 102-112

Zou, X., & Mõttus, M. (2015). Retrieving crop leaf tilt angle from imaging spectroscopy data. *Agricultural and Forest Meteorology, 205*, 73-82

Zou, X., Mõttus, M., Tammeorg, P., Torres, C.L., Takala, T., Pisek, J., Mäkelä, P., Stoddard, F.L., & Pellikka, P. (2014). Photographic measurement of leaf angles in field crops. *Agricultural and Forest Meteorology, 184*, 137-146