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.

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