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Huge spread in CMIP6 diffuse radiation impairs carbon budget estimates

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Abstract

Diffuse solar radiation ($K_{\downarrow,d}$) modulates canopy photosynthesis, thereby mechanistically linking atmospheric aerosol and cloud scattering, and their associated uncertainties, to the terrestrial carbon sink. Here we show that across 16 CMIP6 models, historical $K_{\downarrow,d}$ estimates diverge by 2.8-fold (~3-fold over land), with severe growing-season underestimations against observations. This divergence could introduce multi-petagram uncertainties for gross primary productivity and its projections, highlighting the importance of constraining $K_{\downarrow,d}$ in Earth system models.

Solar radiation reaching Earth's surface ($K_{\downarrow}$) comprises direct-beam radiation ($K_{\downarrow,b}$) and multidirectional diffuse radiation ($K_{\downarrow,d}$), sunlight scattered forward by atmospheric gases, clouds, and aerosols. Unlike $K_{\downarrow,b}$, $K_{\downarrow,d}$ penetrates deeper into plant canopies to illuminate shaded leaves while reducing light saturation in sunlit leaves¹. This “diffuse radiation fertilization effect” (Fig. S1) enhances terrestrial gross primary productivity (GPP), alters transpiration, and cools the land surface^{1–3}.

In Earth system models (ESMs), diffuse-direct partitioning is estimated via atmospheric radiative transfer calculations, which are heavily influenced by uncertain cloud and aerosol parameterizations^{4,5}. $K_{\downarrow,d}$ is thus an additional mechanistic coupling pathway between the terrestrial carbon budget and atmospheric processes largely independent of the overall $K_{\downarrow}$. Yet, despite its strong biospheric impacts and known observational uncertainties⁶, the accuracy of $K_{\downarrow,d}$ in ESMs remains largely unbenchmarked. It is rarely archived as a standard Coupled Model Intercomparison Project version 6 (CMIP6)⁷ output and is sometimes assumed to be a fixed fraction of simulated $K_{\downarrow}$ ³. Similarly, only 8 of 23 dynamic global vegetation models (DGVMs) considered in the latest Global Carbon Budget assessment⁸ treat $K_{\downarrow,d}$ and $K_{\downarrow,b}$ forcings separately.

Here, we evaluate historical $K_{\downarrow,d}$ across 21 CMIP6 model configurations from 16 modeling centers against each other and Global Energy Balance Archive (GEBA) ground observations⁹. For 2000–2014, the global mean $K_{\downarrow,d}$ showed an extraordinary 2.8-fold divergence (full range = 66.2 W m⁻²; multi-model mean = 64.9 W m⁻²; Fig. 1a). Even closely affiliated model frameworks, such as those sharing the UK Met Office Unified Model atmospheric core, exhibit wide discrepancies (e.g., KACE-1-0-G at 103.1 W m⁻² versus UKESM1-0-LL at 63.1 W m⁻²; see Tables S1, S2 for model details). The multi-model mean $K_{\downarrow,d}$ peaks over equatorial rainforests and heavy aerosol corridors (Fig. S2a). Importantly, inter-model spread peaked (>80 W m⁻²) directly over highly productive tropical carbon sinks like the Amazon, Congo Basin, and Asian monsoon region (Fig. S2d). Point-to-grid evaluation against 16,590 collocated GEBA monthly records demonstrates substantial biases against observations (Figs 1b, S3, S4). While the multi-model mean correlates moderately with observations ($R^2 = 0.77$; RMSE = 19 W m⁻²), it exhibits a persistent negative bias (mean percentage error = -11.6%).

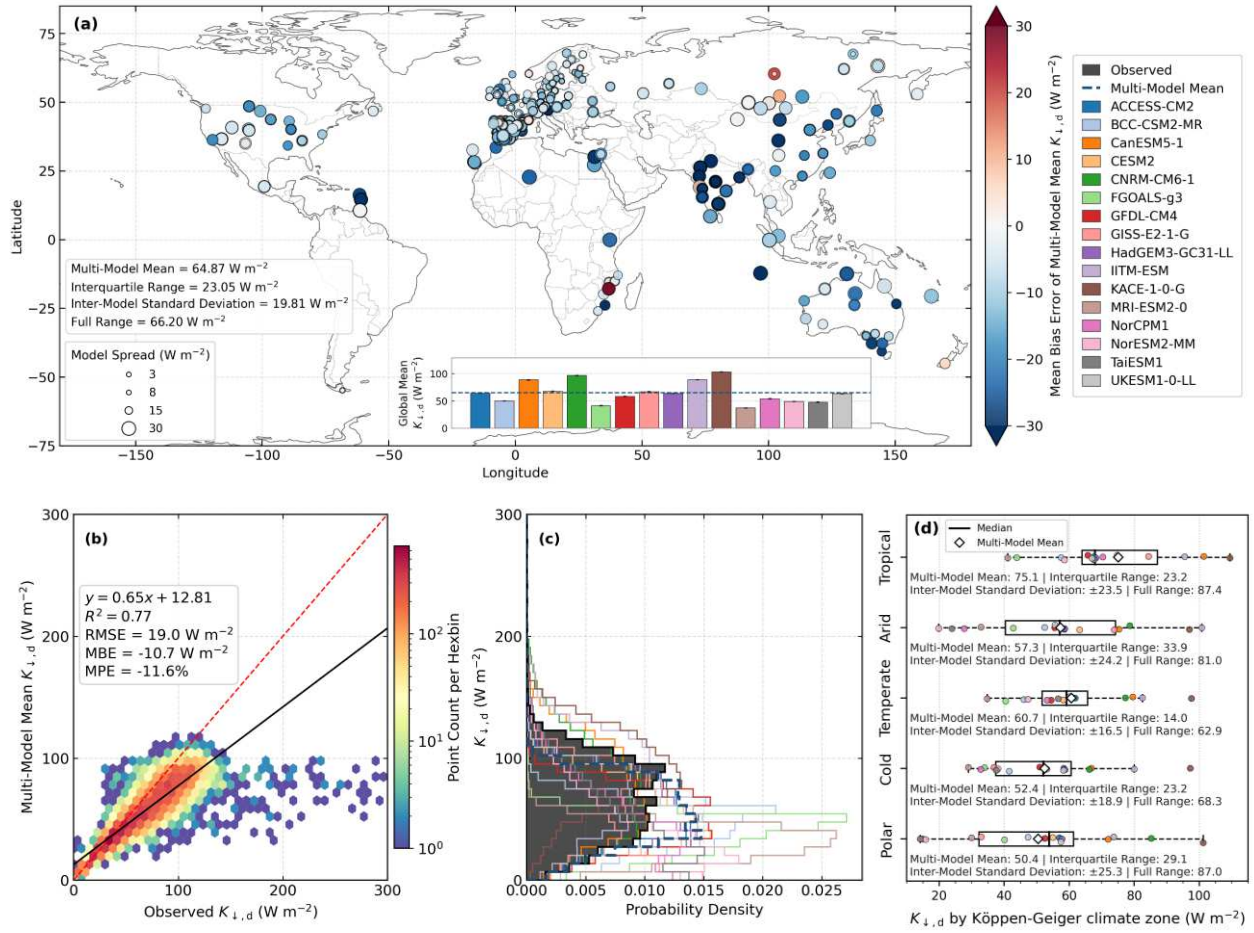


Figure 1 | Distributions of CMIP6 diffuse shortwave radiation ($K_{↓,d}$) | **a**, Multi-model mean bias error (MBE, $W m^{-2}$) at GEBA stations (color) and inter-model spread (bubble size). Insets show global mean ensemble statistics (left) and individual model global means (dashed line denotes multi-model mean). **b**, Hexbin comparison of monthly multi-model mean versus collocated GEBA observations ($n = 16,590$). The solid black line denotes ordinary least-squares regression and the dashed red line indicates 1:1 identity. **c**, Probability density distribution of monthly $K_{↓,d}$ across all station records for observations (gray shading; using $5 W m^{-2}$ bin widths), the multi-model mean (dashed blue line), and 16 individual CMIP6 models (colored lines). **d**, Boxplots of annual mean $K_{↓,d}$ across the 16 models by Köppen-Geiger climate zone. Boxes indicate the interquartile range; whiskers denote the full range; vertical black lines indicate the median; white diamonds indicate the multi-model mean; colored dots represent individual models, with summary statistics annotated below each box.

This model divergence spans every major Köppen-Geiger climate zone (Figs 1d, S5). Multi-model mean $K_{↓,d}$ predictably decreases from the Tropics through Temperate, Arid, Cold, and Polar regions. However, large inter-model spreads persist in all zones, with the inter-model full range spanning between $62.9 W m^{-2}$ in temperate zones to $87.4 W m^{-2}$ in the tropics. In nearly every zone, inter-model spread exceeds the multi-model mean itself. Notably, GEBA stations are

sparse across tropical forests where model divergence is highest (Fig. S2), underscoring the need to expand $K_{\downarrow,d}$ observation networks to these regions.

Discrepancies peak during summer in both hemispheres: reaching an inter-model interquartile spread of 44.5 W m^{-2} in May (Northern Hemisphere; Fig. 2a) and 34.7 W m^{-2} in November (Southern Hemisphere; Fig. 2b). Station benchmarking shows that CMIP6 models systematically underestimate seasonal amplitude of $K_{\downarrow,d}$ (Fig. 2). Across Northern Hemisphere GEBA stations, observed $K_{\downarrow,d}$ peaks in June at 101 W m^{-2} , whereas the multi-model mean peaks at only 84 W m^{-2} (Fig. 2c). This produces a multi-model mean growing-season bias of -15 to -18 W m^{-2} from May through August (Fig. 2d). Individual model biases span nearly 95 W m^{-2} , from $+40.5 \text{ W m}^{-2}$ in KACE-1-0-G to -54 W m^{-2} in FGOALS-g3 (Fig. 2d). Across Southern Hemisphere stations, observed $K_{\downarrow,d}$ peaks in January at 99.1 W m^{-2} versus a multi-model mean of 79.8 W m^{-2} (Fig. 2e). The multi-model mean bias is persistently negative, reaching -20 W m^{-2} during the peak growing-season (Fig. 2f).

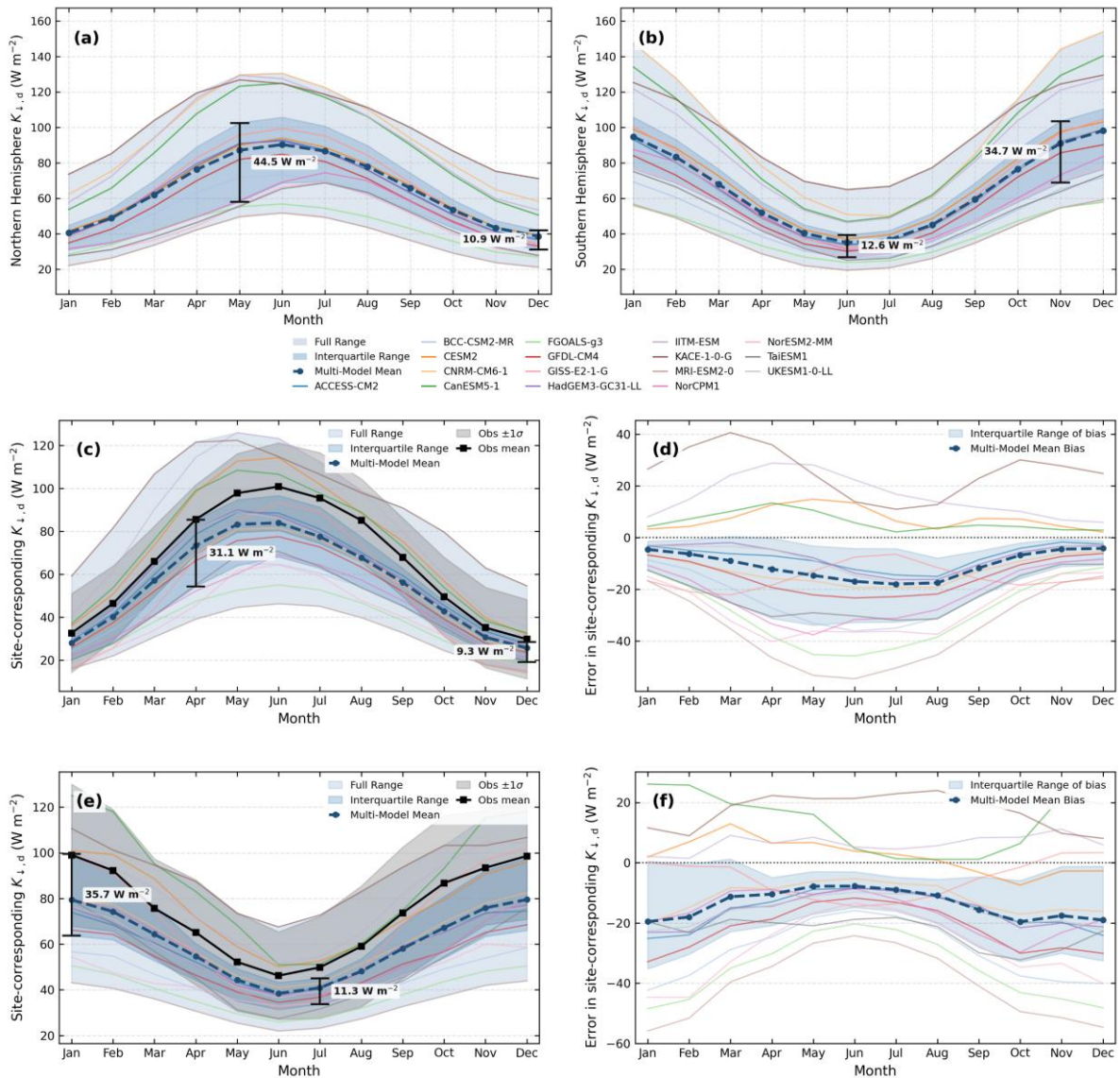


Figure 2 | Hemispheric seasonal cycles and growing-season biases in CMIP6 diffuse shortwave radiation ($K_{\downarrow,d}$) | **a,b**, Climatological monthly spatial mean $K_{\downarrow,d}$ across the Northern (**a**) and Southern (**b**) Hemispheres for 16 CMIP6 models (colored lines), multi-model mean (dashed line), interquartile range (dark blue shading), and full model range (light blue shading), with maximum and minimum interquartile spreads annotated. **c,e**, Climatological monthly $K_{\downarrow,d}$ collocated at Northern (**c**) and Southern (**e**) Hemisphere GEBA stations for observations (black line $\pm 1\sigma$ gray shading) and models (colors as in **a**). **d,f**, Monthly model bias across Northern (**d**) and Southern (**f**) Hemisphere stations, showing multi-model mean bias (dashed line) and interquartile range (blue shading).

The model divergence documented here parallels the widespread spread across global gridded reanalyses and satellite products⁶, but is far larger. Observational constraints have been shown to exhibit a 1.9-fold spread (52.8–102.6 W m⁻²)⁶, whereas the CMIP6 global spread of 2.8-fold (Table S3) widens over land to 3-fold (33.9–100.9 W m⁻²), with major implications for surface climate and the carbon and water budgets. Applying a previously estimated linear GPP-diffuse fraction sensitivity for the Community Land Model (CLM)¹⁰ yields a GPP uncertainty of ~13 Pg C yr⁻¹ (or around 11% of the global terrestrial GPP). This first-order sensitivity assumes that uncertainty in total $K_{\downarrow}$ (20.8 W m⁻²; see Wild *et al.*⁵) remains far smaller than the ~50 W m⁻² spread in $K_{\downarrow,d}$ found here. For tropical climate, with higher range in $K_{\downarrow,d}$ and sensitivity of GPP, these models would yield an uncertainty of ~8 Pg C yr⁻¹ (or over 13% of tropical GPP). Though canopy saturation and moisture limitations modulate local responses, these first-order uncertainties are several times higher than the global land and forest carbon sinks^{11,12}.

Although some version of CLM is used in many of the models (4 of 16; 8 of 21) considered here, there are no comparable comprehensive sensitivity analyses of GPP to $K_{\downarrow,d}$. Applying the CMIP6 spread to the sensitivity of GPP to $K_{\downarrow,d}$ (0.08% increase per 0.2% rise in $K_{\downarrow,d}$) for the Joint UK Land Environment Simulator (JULES) land-surface model, as noted by Rap *et al.*¹³, yields unrealistically inflated values. In contrast, a 3.11% increase in GPP was found for the Yale Institute for Biospheric Studies (YIBS) DGVM model when moving from a reanalysis forcing (diffuse fraction of 0.43) to a machine-learning derived one (0.56)¹⁴; yielding a sensitivity 41% smaller than that in CLM¹⁰. Neither framework fully accounts for non-linear canopy saturation or negative biospheric feedbacks¹⁵, underscoring the need for coordinated, coupled sensitivity benchmarks in the future. Furthermore, no study has evaluated the seasonal sensitivity of GPP to $K_{\downarrow,d}$. Given the systematic underestimation of growing-season $K_{\downarrow,d}$ in the Northern Hemisphere (Fig. 2d), ESMs likely underestimate diffuse fertilization in temperate and boreal forests during peak carbon uptake.

Unrealistic $K_{\downarrow,d}$ values compromise historical estimates and future projections of forest carbon uptake¹², agricultural productivity¹⁶, and terrestrial hydrology¹⁰. Moreover, constraining $K_{\downarrow,d}$ is equally vital for assessing solar radiation management (SRM) risks, benefits, and trade-offs^{17,18}. Just as air-quality improvements have decreased $K_{\downarrow,d}$, potentially weakening the terrestrial sink and reducing crop yields¹⁴, stratospheric aerosol injection could enhance land carbon uptake¹⁸. Accurately evaluating these trade-offs requires reliable baseline representations of $K_{\downarrow,d}$ in ESMs.

The poor representation of the impacts of $K_{\downarrow,d}$ on the Earth system is not limited to the $K_{\downarrow,d}$ forcing differences in atmospheric models, but also stems from the oversimplified canopy radiative transfer¹⁹ and upscaling schemes²⁰ in land surface models, including common use of "one-big-

leaf" schemes that do not resolve $K_{\downarrow,d}$ fertilization^{3,8}. Current CMIP6 Model Intercomparison Projects (MIPs) systematically overlook $K_{\downarrow,d}$. For instance, the Radiative Forcing MIP (RFMIP)⁴ assesses total radiative forcing but ignores diffuse-direct partitioning; the Land Surface, Snow and Soil Moisture MIP (LS3MIP)²¹ and the Coupled Climate–Carbon Cycle MIP (C4MIP)²² do not prescribe or evaluate $K_{\downarrow,d}$; and the Land-Use MIP (LUMIP)²³ forcing data contain only total $K_{\downarrow}$, leaving the diffuse-direct partitioning to unbenchmarked internal algorithms.

Constraining $K_{\downarrow,d}$ across both atmospheric and land surface components is thus critical for reducing multi-petagram uncertainties in the global carbon budget, accurately projecting future carbon sinks, and establishing trustworthy baselines for climate policy. With CMIP7 design underway, standardizing the archival, evaluation, and process-based representation of diffuse radiation, ideally through a dedicated MIP, will address a critical blind spot in 21st-century climate projections.

Methods

Surface Radiation Observations from GEBA

Monthly surface diffuse shortwave radiation ($K_{\downarrow,d}$) records were obtained from the Global Energy Balance Archive (GEBA), which compiles quality-controlled pyranometer measurements from meteorological networks worldwide⁹. Stations with valid, non-zero diffuse shortwave records during 2000–2014, for which the bulk of the $K_{\downarrow,d}$ observations are available, were matched against model outputs⁷. For seasonal cycle comparisons, station records were separated into Northern Hemisphere (latitude $> 0^\circ$) and Southern Hemisphere (latitude $< 0^\circ$) coordinates with continuous data coverage. Station-month data pairs with missing or zero GEBA observations were excluded.

CMIP6 Model Extractions and Statistical Analysis

Incoming $K_{\downarrow,d}$ (rsdsdiff) fields from historical simulations of 21 CMIP6 model configurations were extracted from the Earth System Grid Federation (ESGF)²⁴. To keep the analysis tractable, we only consider simulations with first realization, first initialization, parametrization 1, and forcing 1 (r1i1p1f1) across all available models, apart from UKESM1-0-LL, for which only forcing 2 (r1i1p1f2) was available. Since GEBA is available at monthly scales, monthly averaged model outputs were considered or aggregated from 3-hourly outputs (Tables S1, S2). Global area-weighted climatological means were computed by weighing by the cosine of the grid latitude. Finally, Kish's effective sample size (n_{eff}):

$$n_{\text{eff}} = \frac{(\sum_{i=1}^n w_i)^2}{\sum_{i=1}^n w_i^2} \quad (1)$$

was used to calculate spatial weighted standard errors, where w is the weight of each sample. In addition to global estimates, stratified estimates are provided over land and for present-day Köppen-Geiger climate zones²⁵.

For station benchmarking, simulated monthly $K_{\downarrow,d}$ were collocated (or aggregated from finer time scales) with individual GEBA station coordinates using nearest-neighbor indexing. Evaluation metrics included Ordinary Least Squares (OLS) regression parameters (slope, intercept, R^2), root-mean-square error (RMSE), mean bias error (MBE), and mean percentage error (MPE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_i - O_i)^2} \quad (2)$$

$$\text{MBE} = \frac{1}{N} \sum_{i=1}^N (M_i - O_i) \quad (3)$$

$$\text{MPE} = \frac{1}{N} \sum_{i=1}^N \left(\frac{M_i - O_i}{O_i} \right) \times 100\% \quad (4)$$

where M_i and O_i represent modeled and observed monthly diffuse irradiances, respectively. Probability density functions were estimated using normalized histograms with 5 W m^{-2} bin widths.

167 Our primary focus is on the 16 unique models for which $K_{\downarrow,d}$ fields were available. However,
168 some of these models have alternative configurations for the same realizations. Those results are
169 noted in the Supplementary Information (Figs S6, S7).

170

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Author Contributions

T.C. conceptualized the study, analyzed the CMIP6 and GEBA datasets, and drafted the manuscript.

Competing Interests

The authors declare no competing interests.

Additional Information

Supplementary Information is available for this paper.

Correspondence and requests for materials should be addressed to T.C.

Data Availability

CMIP6 model outputs are openly available via the Earth System Grid Federation portal (<https://esgf-node.llnl.gov/>). GEBA ground measurements are accessible through the ETH Zurich GEBA database (<https://geba.ethz.ch/>).

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