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From GHI to POA: Validation of Decomposition and Transposition Models Using Field Measurements

Abstract

Accurate plane-of-array (POA) irradiance estimation is fundamental to PV performance analysis. Converting widely available global horizontal irradiance (GHI) to POA irradiance requires two sequential modeling steps — each introducing uncertainty that propagates into modeled energy yield:

- Decomposition: GHI → DNI + DHI
- Transposition: Horizontal Irradiance → POA Irradiance of Modules

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- **Decomposition:** GHI → DNI + DHI
- **Transposition:** Horizontal irradiance → POA irradiance of modules

Models Evaluated: **9** decomposition × **7** transposition = **70 combined** model configurations — *63 fully modeled (GHI-only) + 7 using measured DHI* paired with each transposition model. All models limited to those natively available in pvlib.

Methodology: Modeled DHI and POA irradiance are compared against co-located measurements using two metrics normalized to mean measured irradiance:

- **rRMSD** — *captures spread* (magnitude of timestep-by-timestep differences; sensitive to large instantaneous errors)
- **rMBD** — *captures bias* (systematic over- or under-estimation tendency across the full period)

"*Difference*" replaces "*Error*" throughout — measurement uncertainty in the reference sensor means true error cannot be established.

Analysis Spans: Multiple utility-scale sites, distinct climate regimes, 1-minute to 60-minute granularities and all seasons

Benchmarks: PVsyst default (ERBS + Perez) · PlantPredict default (DIRINT + Perez)

Decomposition Models — From GHI to DNI & DHI

All decomposition models take **GHI** as input and estimate **DNI** and **DHI**. They differ fundamentally in *what they estimate first* and *how they get there*.

Model	Year	Origin	Family	Physics- informed	Inputs beyond GHI & zenith	DOY	Primary est.	Climate of development
DISC	1987	NREL, USA	Kn	Yes	Pressure	Yes	DNI	Desert (USA)
DIRINT	1992	NREL/SUNY, USA	Kn	Yes	Pressure, ΔKt' (req.), Tdew (opt.)	Yes	DNI	Desert (USA)
DIRINDEX	2002	SUNY, USA	Kn	Yes	Pressure, ΔKt' (req.), Tdew (opt.), CS GHI/DNI	Yes	DNI	Multi-climate
ERBS	1982	U. Wisconsin, USA	Kt	No	No	Yes	DHI	USA + Europe
ERBS-Driesse	2022	Fraunhofer ISE, DE	Kt	No	DNI_extra (TOA)	Yes	DHI	USA + Europe
Orgill-Hollands	1977	U. Waterloo, CA	Kt	No	No	Yes	DHI	Temperate (CA)
Boland	2001	Univ. South Australia	Kt	No	No	Yes	DHI	Australia
Campbell-Norman	1998	Textbook, USA	CS-based	Yes	Pressure, CS GHI/DNI	No	DNI	General
Louche	1991	U. Corsica, FR	Kn	No	No	Yes	DNI	Mediterranean

Three Model Families:

1. **Kt family** (ERBS, ERBS-Driesse, Orgill-Hollands, Boland) — estimate the diffuse fraction k_d directly from the clearness index K_t:

$$k_t = \frac{\mathrm{GHI}}{\mathrm{E_a} \times \cos Z} \qquad \mathrm{E_a}(\mathrm{DNI}_{extra}) = \mathrm{E}_{sc} \times \left(\frac{\mathrm{R_0}}{\mathrm{R}}\right)^2$$

E_{sc}: Solar constant ≈ 1361 W/m² | $\left(\frac{\mathrm{R_0}}{\mathrm{R}}\right)^2$: Orbital eccentricity correction: varies ±3.3% through the year

$$k_d = f(K_t)$$

2. **Kn family** (DISC, DIRINT, DIRINDEX, Louche) — estimate the direct normal clearness index K_n directly:

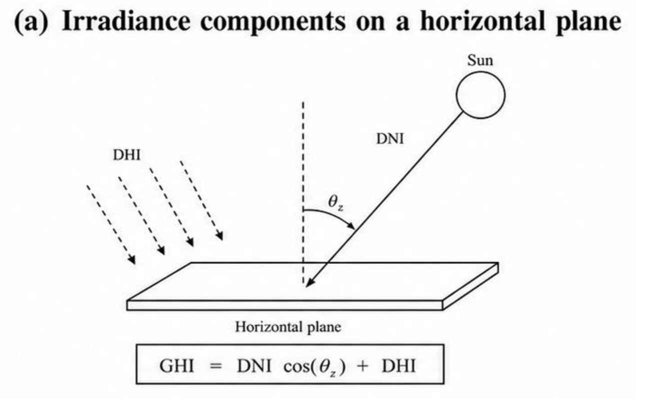
3. **CS-based** (Campbell-Norman):derives DNI from atmospheric transmittance τ using a calibrated clear sky reference, then blends DHI from an energy balance. Physically motivated but requires clear sky GHI and DNI as inputs.

Model	Approach	Kt ≤ 0.22 (overcast)	0.22 < Kt ≤ 0.80 (partly cloudy)	Kt > 0.80 (clear)	Full-range equation	Discontinuities	Extra inputs beyond Kt	Primary output
ERBS	Piecewise bins on Kt	kd = 1 − 0.09·Kt	kd = 0.9511 − 0.1604·Kt + 4.388·Kt² − 16.638·Kt³ + 12.336·Kt⁴	kd = 0.165	—	Yes	—	kd → DHI
ERBS-Driesse	Piecewise bins on Kt	kd = 1 − 0.09·Kt (same as ERBS)	Refitted polynomial (improved high-Kt segment)	Refitted constant (reduced bias vs ERBS)	—	Yes	DNI_extra (TOA)	kd → DHI
Orgill-Hollands	Piecewise bins on Kt	kd = 1 − 0.249·Kt	kd = 1.557 − 1.84·Kt	kd = 0.177	—	Yes	—	kd → DHI
Boland	Single logistic curve	—	—	—	kd = 1 / (1 + exp(a·(Kt − b))) a=8.645, b=0.613	No	—	kd → DHI
Louche	Polynomial Kt→Kn	—	—	—	Kn = 0.9751 − 0.2149·Kt² − 0.5452·Kt + 0.0213·Kt³ (polynomial, 5th order in pvlib)	No	—	Kn → DNI
Campbell-Norman	Transmittance (τ) + clearsky	—	—	—	DNI via atmospheric τ; DHI blended from energy balance + clearsky reference	No	Pressure, CS GHI/DNI/DHI	DNI → DHI
DISC	Lookup table on Kn	—	—	—	Kn = f(Kt, SunEl) via lookup table	No	SunEl, Pressure	Kn → DNI
DIRINT	Lookup table on Kn	—	—	—	Kn = f(Kt, SunEl, ΔKt') via lookup table	No	SunEl, Pressure, ΔKt', Tdew	Kn → DNI
DIRINDEX	Lookup table on Kn	—	—	—	Kn = f(Kt, SunEl, ΔKt') normalised to clearsky	No	SunEl, Pressure, ΔKt', Tdew, CS DNI	Kn → DNI

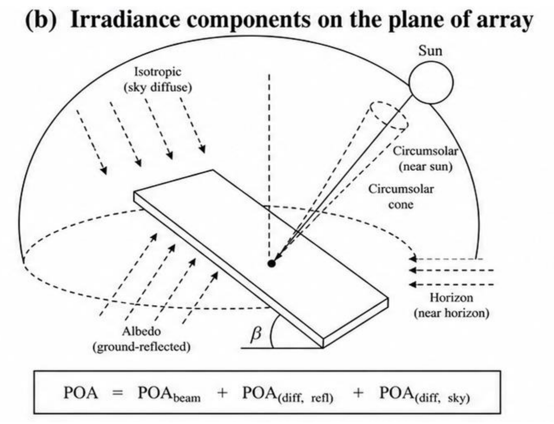
ΔKt' = temporal rate-of-change of Kt (stability index)
CS DNI/GHI/DHI = calibrated clear-sky model required

*Note: **Campbell–Norman & DIRINDEX Excluded**:* Both models rely on a clear-sky reference for normalization. Under cloudy or highly variable conditions—when measured GHI deviates significantly from the clear-sky estimate—this dependency can lead to increased uncertainty and instability in the derived DHI values. While their performance is generally strong under clear-sky conditions, they tend to be less reliable in overcast or rapidly changing skies. As a result, both models are excluded from most of the plots and results presented in this study.

(a) Irradiance components on a horizontal plane



(b) Irradiance components on the plane of array



Transposition Models — From GHI, DNI & DHI to POAI

All transposition models compute total POA irradiance as the **sum of three components**:

$$POA = \mathrm{POA}_{beam} + \mathrm{POA}_{diff,refl} + \mathrm{POA}_{diff,sky}$$

Beam and **ground-reflected** components are **identical across all models**:

$$\mathrm{POA}_{beam} = DNI \times \cos(\theta)$$

$$\mathrm{POA}_{diff,refl} = GHI \times \rho \times \frac{1-\cos\beta}{2}$$

β = surface tilt | ρ= ground albedo*

*constant = 0.2 in this study for all models except King, which computes albedo internally as

$$\rho = 0.012 \times \theta_Z - 0.04$$

The only difference between models is how they treat sky-diffuse irradiance. **Specifically, how much of the diffuse sky radiation is assumed to come from different parts of the sky dome.**

Model	Year	Origin	Inputs beyond DNI, DHI, tilt	Sky diffuse treatment
Isotropic	1960	Liu & Jordan, USA	Albedo	Isotropic only
Klucher	1979	Klucher, USA	Albedo	Isotropic + cloudiness factor
Hay-Davies	1980	Hay & Davies, CA	Albedo, DNI_extra, SunAz	Circumsolar + isotropic
Reindl	1990	Reindl et al., USA	Albedo, DNI_extra, SunAz	Circumsolar + horizon + isotropic
King (Sandia)	2004	Sandia NL, USA	SunZen (albedo computed internally)	Isotropic + empirical albedo
Perez	1990	Perez et al., SUNY	Albedo, DNI_extra, SunAz, AM	Circumsolar + horizon + isotropic
Perez-Driesse	2023	Driesse et al., USA	Albedo, DNI_extra, SunAz, AM	Circumsolar + horizon + isotropic

Note: These models use combinations of DNI, DHI, and/or GHI (depending on formulation), along with surface tilt (β), surface azimuth (ψ), and solar zenith angle (Z).

Model	Sky diffuse components	POA_diff,sky equation	Anisotropy index	Circumsolar	Horizon bright.	Coeff. source
Isotropic	Isotropic only	DHI · (1 + cos β) / 2	—	No	No	—
Klucher	Isotropic + cloudiness factor	DHI · (1 + cos β) / 2 · (1 + F · sin³(β/2)) F = 1 − (DHI/GHI)²	F = 1 − (DHI/GHI)²	No	No	Fitted (USA)
Hay-Davies	Circumsolar + isotropic	DHI · [(Ai · cos θ / cos Z) + (1 − Ai) · (1 + cos β) / 2] Ai = DNI / DNI_extra	Ai = DNI / DNI_extra	Yes	No	Physical (DNI_extra)
Reindl	Circumsolar + isotropic + horizon brightening	DHI · [(Ai · cos θ / cos Z) + (1 − Ai) · (1 + cos β) / 2 · (1 + f · sin³(β/2))] f = √(DNI/GHI), Ai = DNI / DNI_extra	Ai = DNI / DNI_extra f = √(DNI/GHI)	Yes	Yes	Fitted + physical
King (Sandia)	Isotropic + empirical albedo	DHI · (1 + cos β) / 2 (albedo computed internally: ρ = 0.012·SunZen − 0.04)	—	No	No	Fitted (Albuquerque)
Perez	Circumsolar + horizon + isotropic background	DHI · [F1 · (a/b) + (1 − F1) · (1 + cos β) / 2 + F2 · sin β] a = max(0, cos θ), b = max(cos 85°, cos Z) F1, F2 from empirical lookup table (ε, Δ)	F1 (circumsolar) F2 (horizon)	Yes	Yes	Lookup table (multi-site)
Perez-Driesse	Circumsolar + horizon + isotropic background	DHI · [F1 · (a/b) + (1 − F1) · (1 + cos β) / 2 + F2 · sin β] Same structure as Perez; F1, F2 from refitted coefficients (Driesse 2023)	F1 (circumsolar) F2 (horizon)	Yes	Yes	Refitted lookup table (Driesse 2023)

θ= angle of incidence ·θ_Z $(or\ Z)$= solar zenith angle · β= surface tilt angle·$\mathrm{E}_a(or\ DNI_{extra})$ =top-of-atmosphere DNI (computed from DOY, not measured) · AM = airmass (Perez and Perez-Driesse only)

Evaluation & Findings

Evaluation Framework

Performance is evaluated at two stages of the GHI→POA pipeline:

- **Stage 1 — Decomposition:** Modeled DHI vs. measured DHI
- **Stage 2 — Transposition:** Modeled POA vs. measured POA

Two metrics, both normalized to mean measured irradiance:

rRMSD (relative Mean Bias Difference) — captures *scatter*: how much the model deviates from measurements on a timestep-by-timestep basis. Sensitive to large instantaneous errors.

$$rRMSD\% = \frac{\sqrt{\frac{1}{N}\sum(M_i - O_i)^2}}{O_{ref}} \times 100$$

rMBD (relative Mean Bias Difference) — captures *bias*: systematic over- or under-estimation over the full period. Positive = overestimate · Negative = underestimate.

$$rMBD\% = \frac{\frac{1}{N}\sum(M_i - O_i)}{O_{ref}} \times 100$$

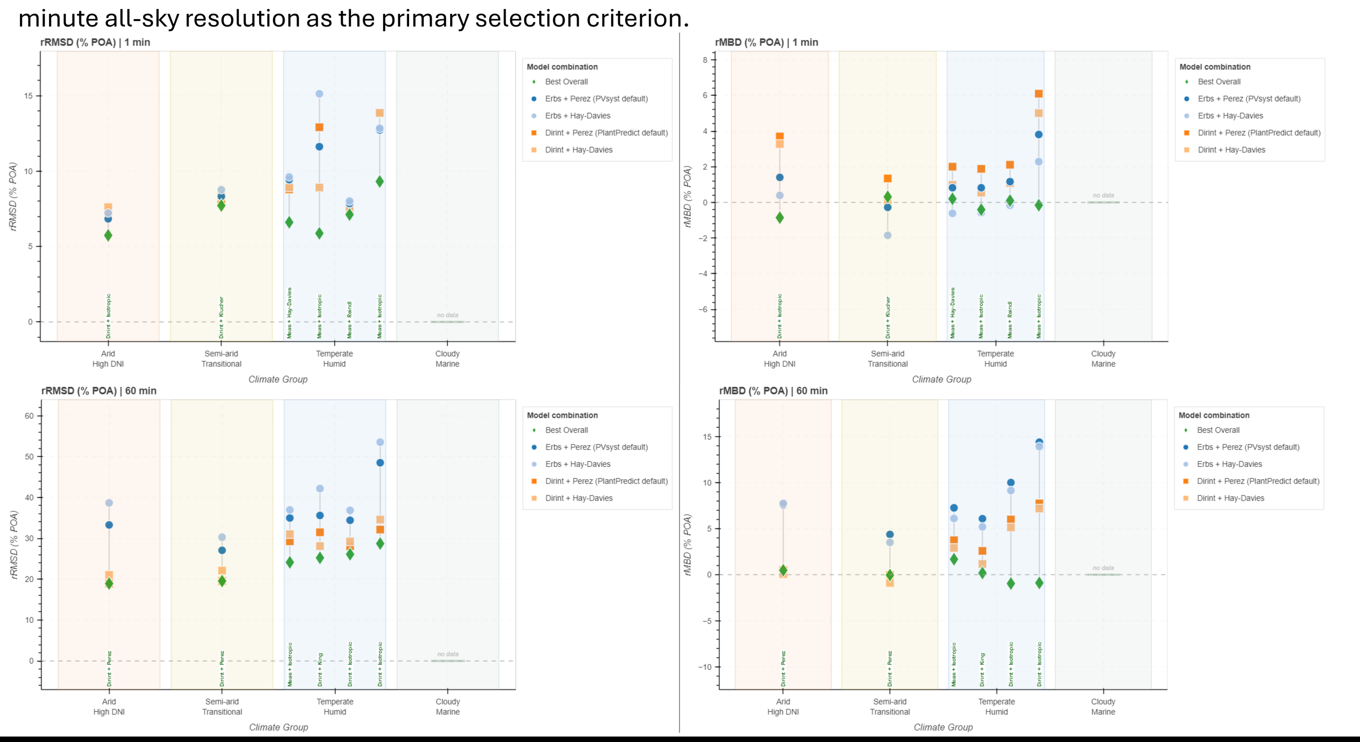
O_{ref} =mean GHI (Decomposition stage) and mean POA (Transposition stage)

Model Ranking

Models are ranked using a composite score — the sum of individual ranks on RMSD and absolute MBD:

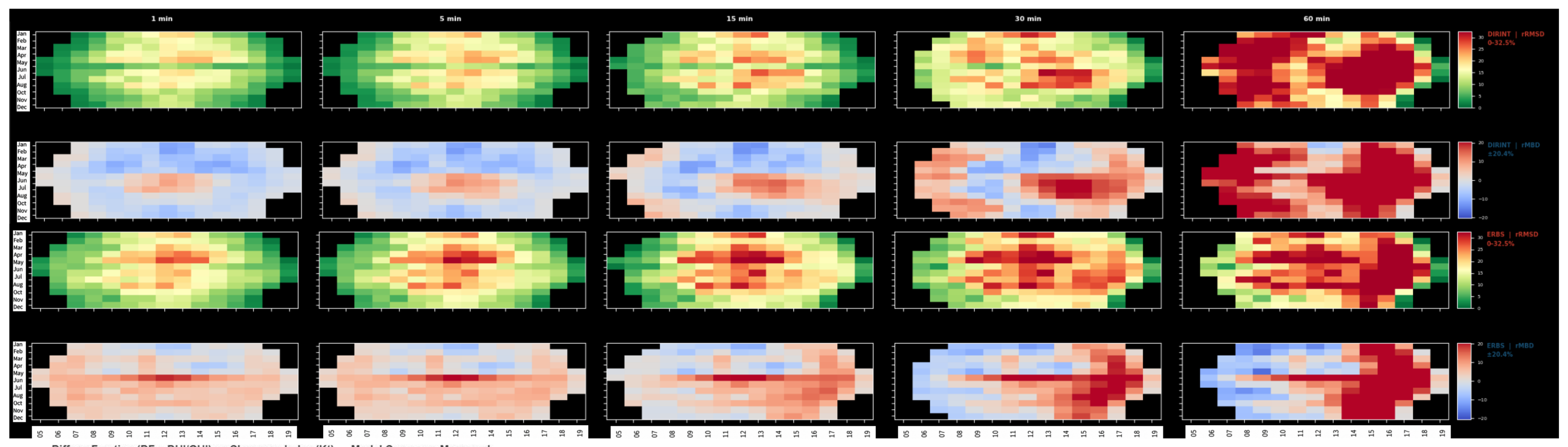
$$Score = rank(RMSD) + rank(MBD)$$

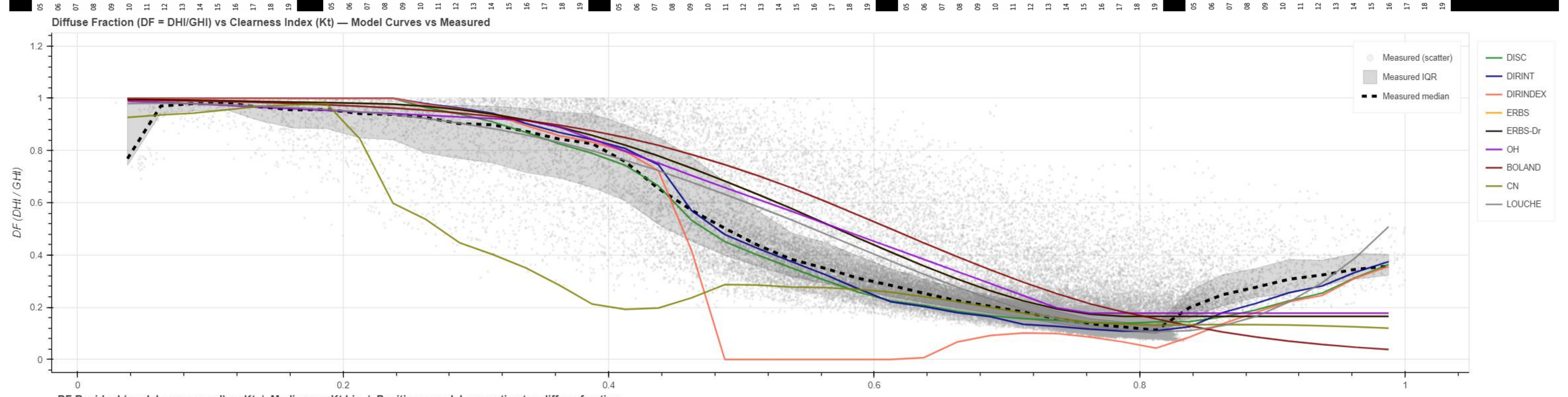
Both metrics contribute equally. The model with the lowest score — best combined scatter and bias performance — is selected as the top performer. Rankings are computed across all 70 POA combinations at 1-minute and 60-minute all-sky resolution as the primary selection criterion.

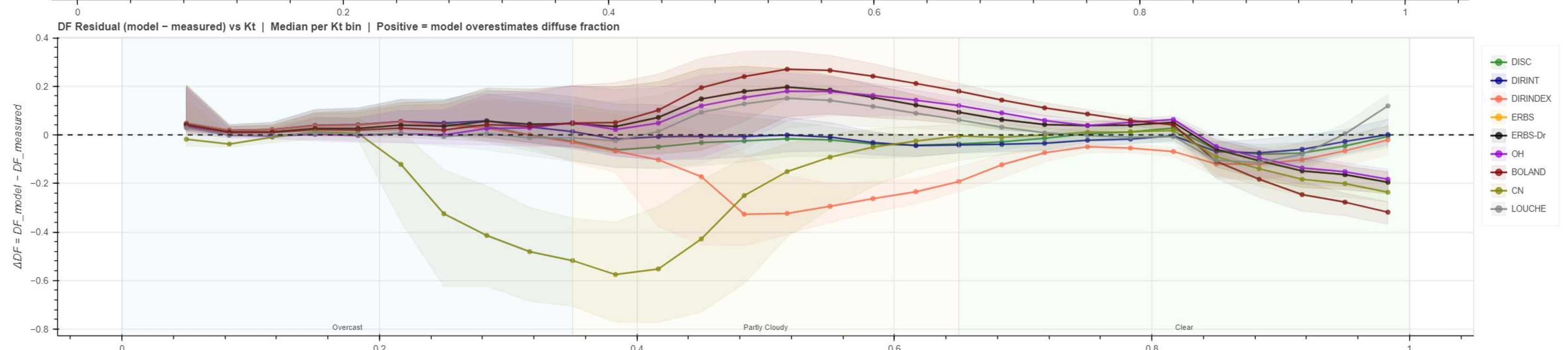


Results & Visual Summary – Part A – Decomposition Models

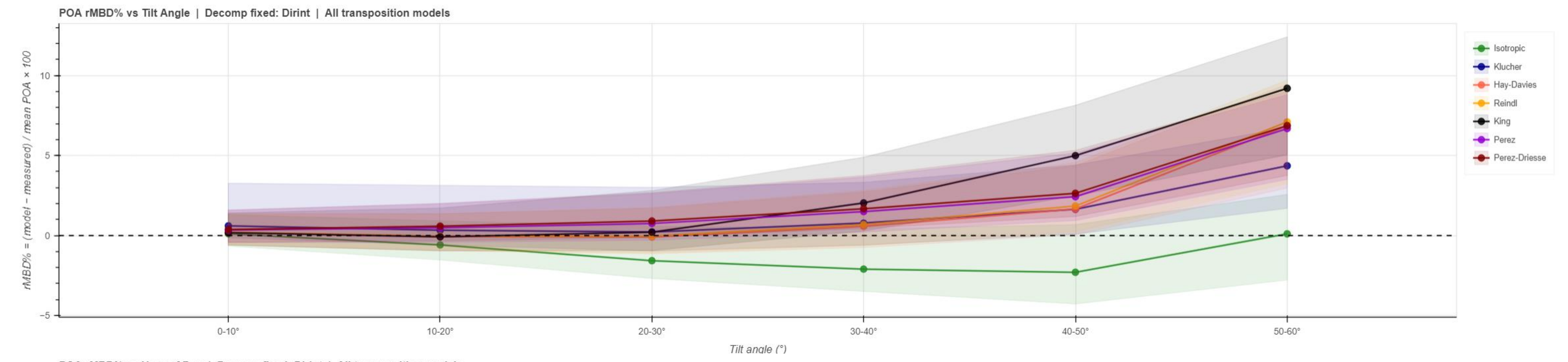
Month × Hour heatmaps of rRMSD and rMBD for DIRINT and ERBS models across temporal resolutions (1–60 min)

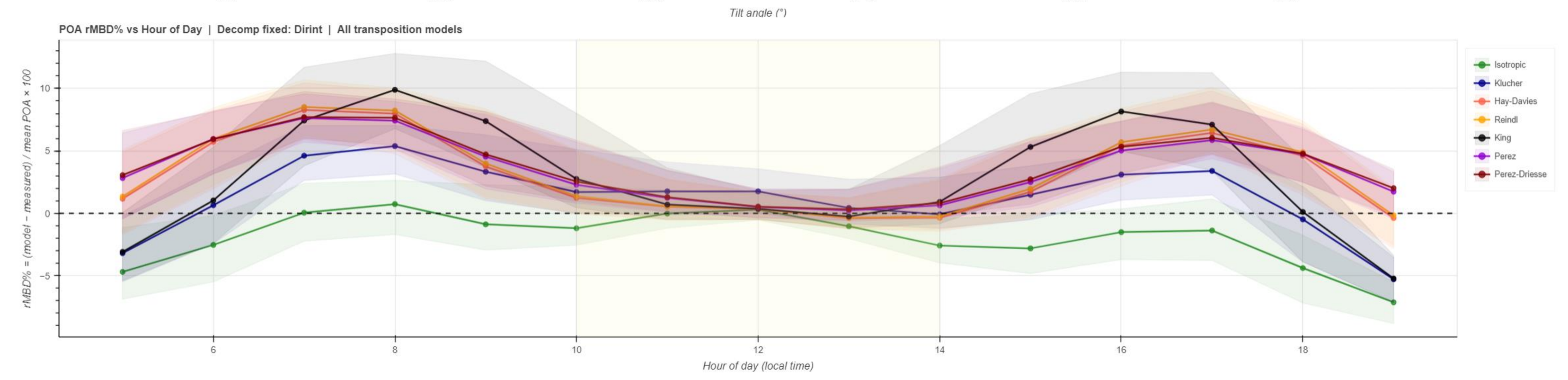




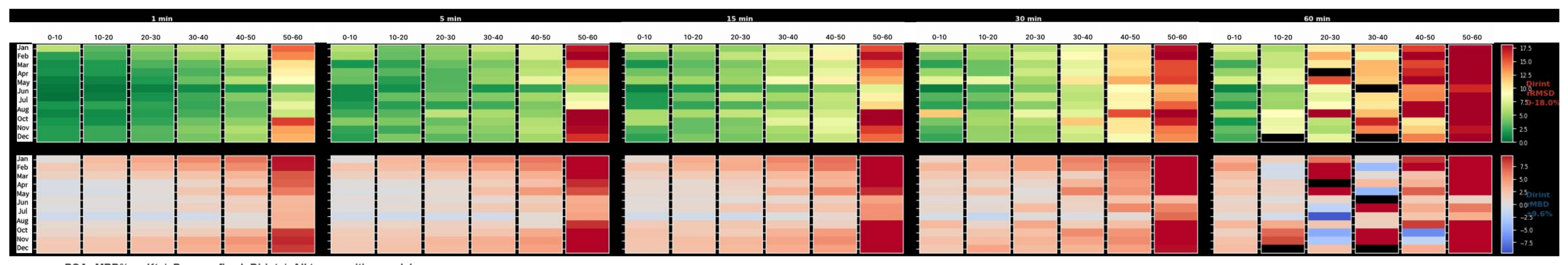


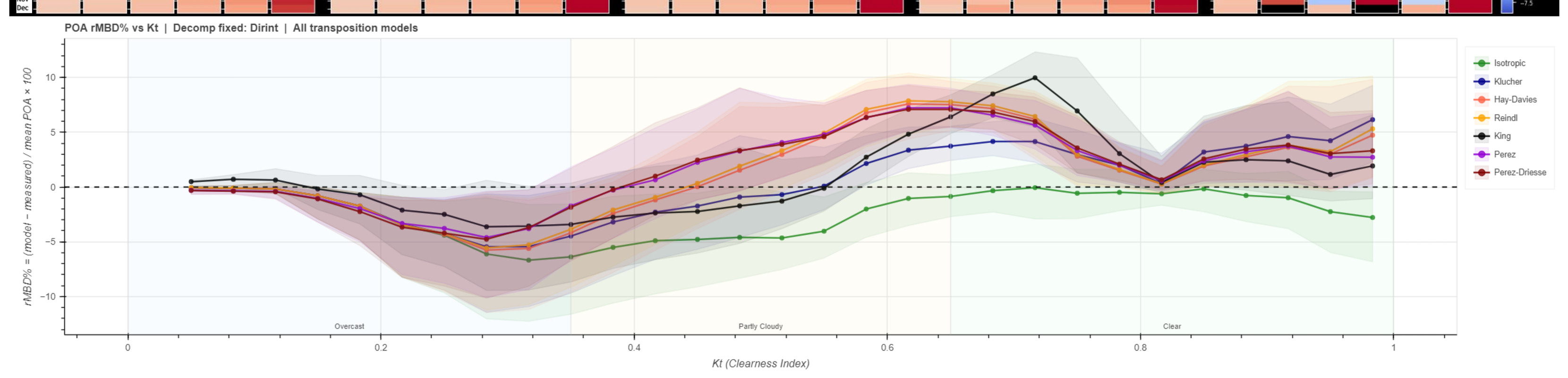
Results & Visual Summary – Part B – Transposition Models



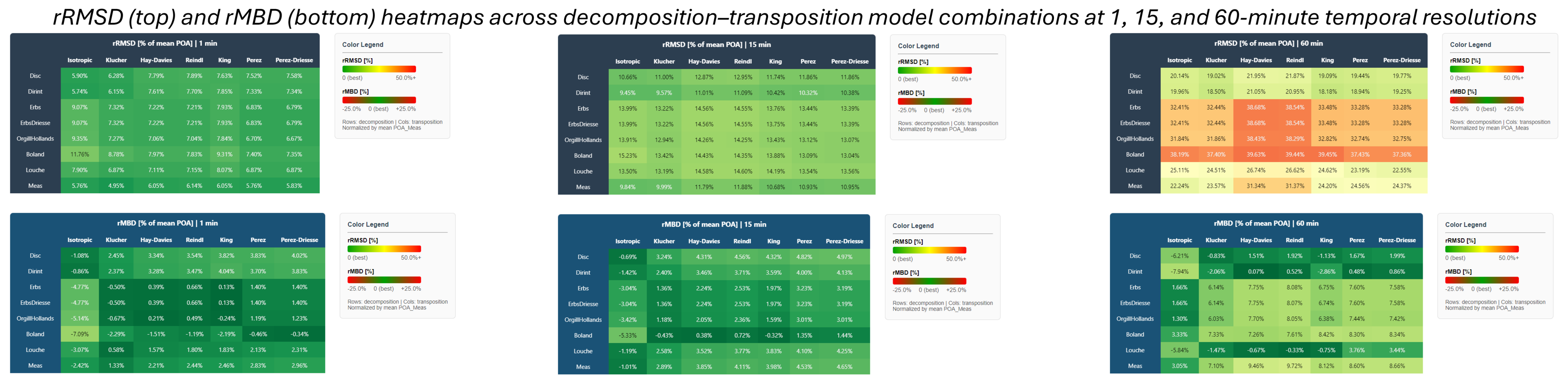


Month × Hour heatmaps of rRMSD (top) and rMBD (bottom) for DIRINT + Perez across varying tilt angles and temporal resolutions (1–60 min)



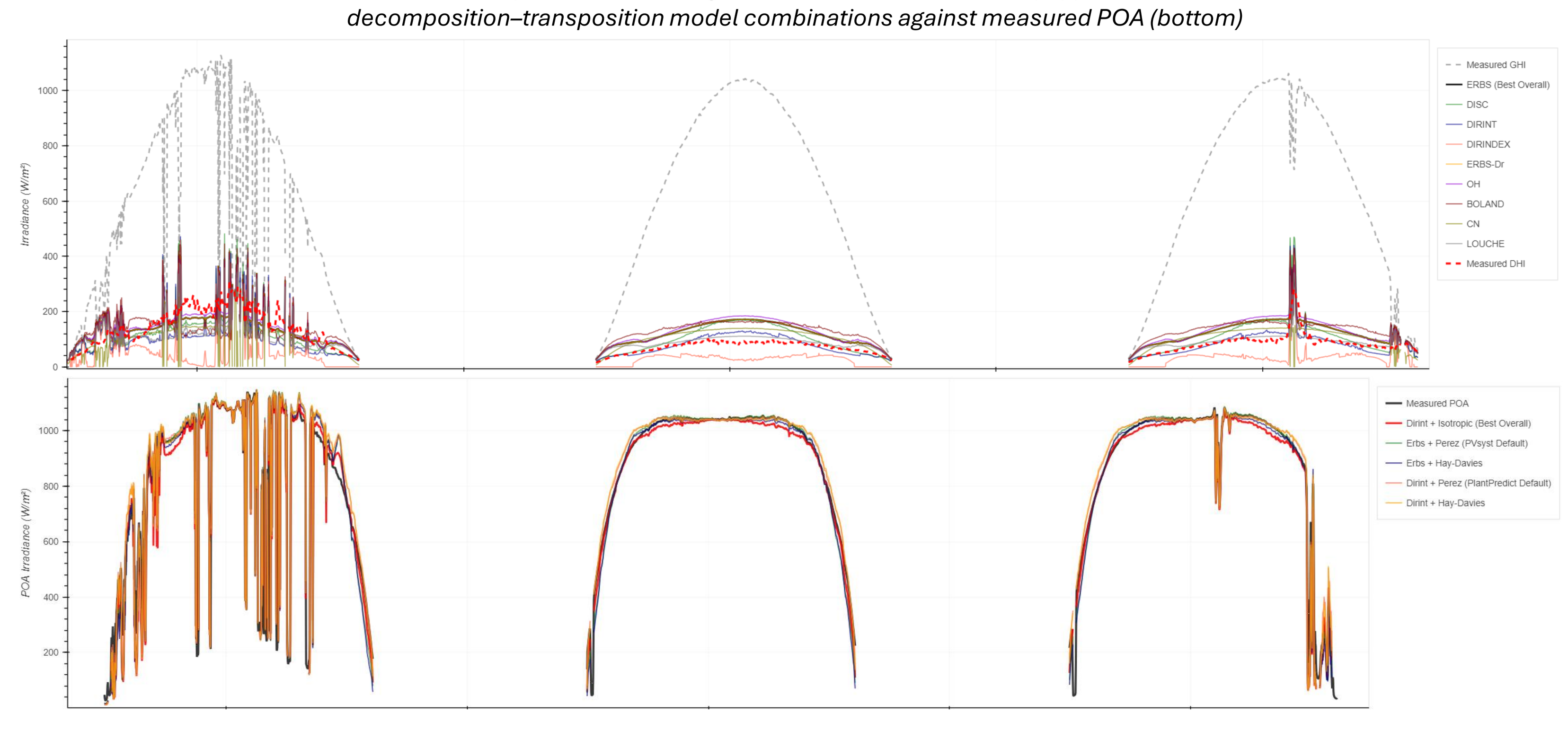


rRMSD (top) and rMBD (bottom) heatmaps across decomposition–transposition model combinations at 1, 15, and 60-minute temporal resolutions



Results & Visual Summary – Part C – Sample Irradiance Time Series

Time series of modeled DHI from nine decomposition models against measured GHI and DHI (top), and modeled POA irradiance from selected decomposition–transposition model combinations against measured POA (bottom)



Conclusions

- No universally optimal decomposition or transposition model exists — **the best-performing combination is site-specific** and should be selected based on locally available measured data.
- Among decomposition models, the **Kn-family** — and **DIRINT** in particular — consistently outperformed all others evaluated.
- **Perez** and **Hay-Davies** showed similar trends across climate groups, with Perez generally yielding higher POA irradiance bias. The gap narrowed at coarser resolution in several climate groups, with Arid High DNI being a notable exception where Perez produced a marginally lower estimate at 60-minute granularity.
- Coarser temporal resolution consistently increased both scatter (**RMSD**) and bias (**MBD**), underscoring the value of high-resolution data in performance analysis.
- At higher tilt angles, transposition models generally exhibited elevated scatter and bias, indicating sensitivity to array geometry that may not generalize across tilt configurations.

Recommendations

- POA irradiance model selection directly affects performance analysis results and should be explicitly accounted for in any monitoring or analysis workflow.
- A site-specific evaluation of decomposition and transposition model combinations is strongly recommended, particularly for projects involving production modeling from measured weather data such as PR testing, where model-induced differences increase test uncertainty.
- Neglecting model selection introduces avoidable uncertainty — both in benchmarking modeled production against typical weather files for financing, and in comparing measured system performance against modeled expectations.
- Routine cleaning and leveling of pyranometers and shaded pyranometer sensors is a mandatory maintenance activity, with periodic calibration as required. Dirt accumulation or misalignment undermines irradiance data quality and, by extension, model selection and performance analysis reliability.
- Performance modeling and monitoring software developers are encouraged to expand available decomposition and transposition model libraries, giving owners, developers, and other stakeholders the flexibility to select the most appropriate model combination for their site.

References

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