Towards a Generalized, Fully-anisotropic Transposition Model

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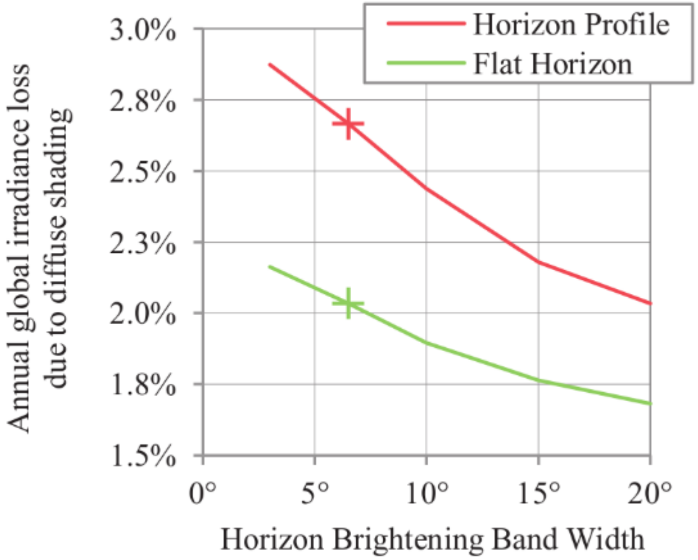
Motivation

Empirical transposition models are limited:

- Fitted on shade-free conditions
- No room for arbitrary distributions (clouds!)
- Diffuse shading is difficult to *localize*
- Rigid in their inputs
  - GTI sensors?
  - Shaded sensors?

Applications:

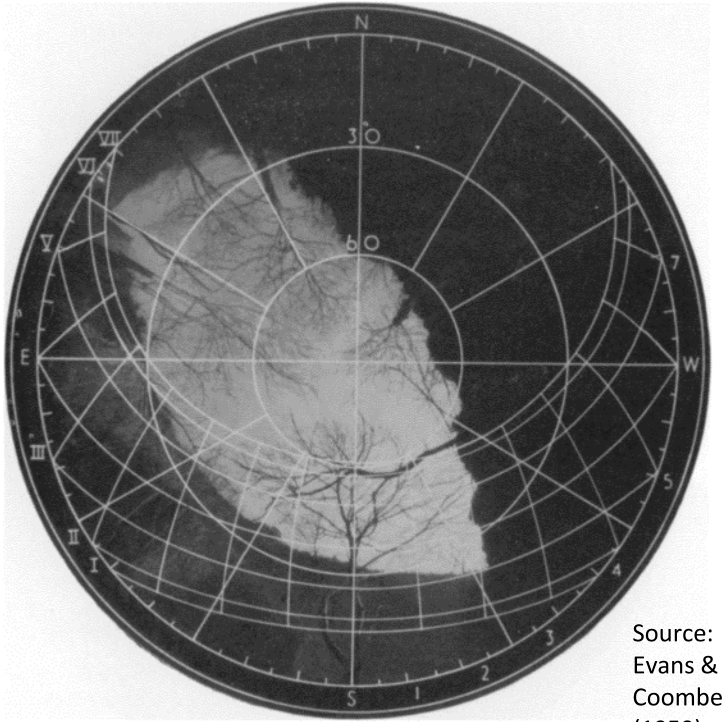
- Nowcasting (O&M)
- Short-term forecasting
- Site assessment
- Bi-Facial modeling?
- ...



Source: Capdevila, Herrerías & Marola (2014)

Prior art

- View factors
  - Evans & Coombe (1959) / Anderson (1964)
- Continuous Distribution Models (CDM's) for Sky Luminance
  - Hooper & Brunger (1980)
  - Nakamura (1985)
  - Perez et al (1993)
  - Kittler & Darula (2002)
- Masks on CDM's
  - [Forest Ecology / Building Simulation]
  - Bosch et al. (2010)
  - Ivanova (2013)
- Discretized CDM's
  - Satel-Light Project (1996)
  - Goss et al. (2014)



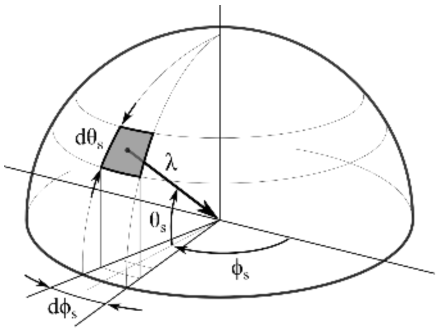
Source: Evans & Coombe (1959)

Irradiance Transposition

The *global effective irradiance* incident on a point on a PV surface is the integral (over the complete unit sphere) of the incoming spectral radiance $L_{e,\nu}(\theta, \phi, \nu)$ [W/(m^2 sr Hz)], from each particular direction $\boldsymbol{p}(\theta, \phi)$ weighted by the spectral response of the PV material $S_R(\nu)$, and by a function $g(\gamma)$ of the incidence angle between the surface normal $\boldsymbol{u}$ and the light source $\boldsymbol{p}$:

$$I_u = \int_0^{2\pi} \int_{-\pi/2}^{\pi/2} \int_{-\infty}^{\infty} L_{e,v}(\theta, \phi, \nu)\, S_R(\nu)\, g(\gamma) \cos\theta \, d\nu d\theta d\phi$$

$$g(\gamma) = |\cos\gamma|\, f_{IAM}(\gamma) \ , \ \gamma = \cos^{-1}\left(\boldsymbol{p}^T \boldsymbol{u}\right)$$



Transposition by View Factors

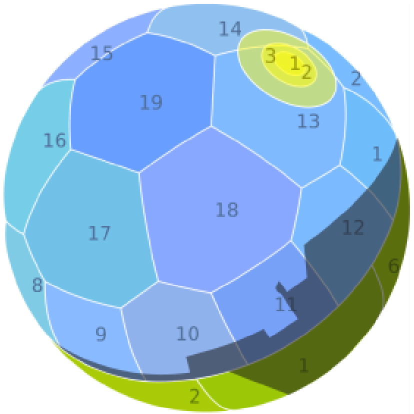
If we assume that all light comes from an underlying *far field* radiance distribution, and that we can divide the unit sphere into a set of *patches* $\{s_1, s_2, \ldots, s_n\}$ with approximately uniform effective radiance $\{\widetilde{L}_1, \widetilde{L}_2, \ldots, \widetilde{L}_n\}$, we can write:

$$I_u \approx \sum_{j=1}^{n} \int_{-\infty}^{\infty} L_{e,v}(j,\nu)\, S_R(\nu) \iint_{s_j} f_{u,j}(\phi,\theta)\, g(\gamma)\, dA$$

$$I_u \approx \sum_{j=1}^{n} \widetilde{L}_j F_j = \boldsymbol{F_u^T L_t}$$

Where $f_{u,j}$ is the fraction of $\widetilde{L}_j$ that is visible from $\boldsymbol{u}$.

We call $\boldsymbol{F_u} = \{F_1, F_2, \ldots, F_n\}_u$ the *view factors* for regions 1 to n at point $\boldsymbol{u}$, and $\boldsymbol{L_t} = \{\widetilde{L}_1, \widetilde{L}_2, \ldots, \widetilde{L}_n\}_t$ the n *irradiance components* at time t.



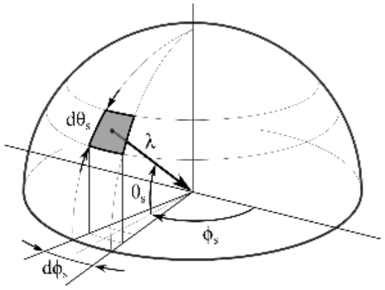
View Factors by Custom Projection

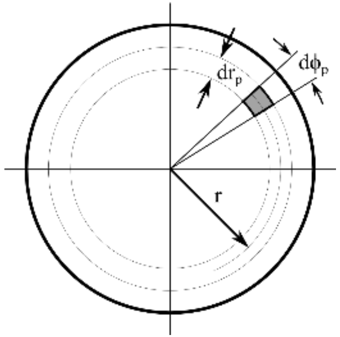
Typically we set $f_{u,j} = 1$ for all points A_u of the far-field directly visible from $\boldsymbol{u}$, and zero otherwise (no reflections*). Then the view-factors become a function of geometry only:

$$F_j = \iint_{s_j \cap A_u} g(\gamma)\, dA$$

And it is easy to find a projection function $r_p(\gamma)$ that turns this integral into an area over a plane:

$$\begin{aligned} A_{j,p} = \iint_{s_{j,p} \cap A_{u,p}} dA_p &= \iint_{s_j \cap A_u} g(\gamma)\, dA \\ dA_p = r_p(\gamma)\, dr_p d\phi &= |\cos\gamma|\, f_{IAM}(\gamma) \sin\gamma\, d\gamma d\phi \\ r_p^2(\gamma) &= \int_0^{\gamma} f_{IAM}(\gamma) \sin 2\gamma\, d\gamma \,,\ 0 \leq \gamma \leq \pi/2 \end{aligned}$$





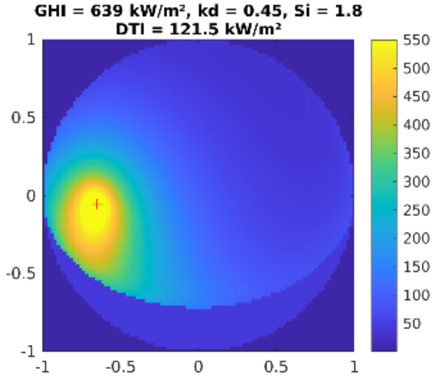
CDM's as Transposition Model

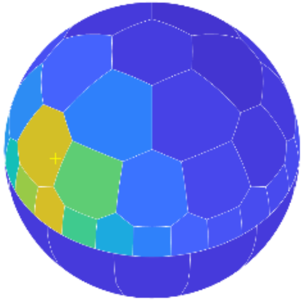
Empirical Continuous Radiance Distribution Models can be used as a drop-in replacement for transposition models:

- Igawa, Koga, Matsuza & Nakamura (2004)
  - Parametrization of std. (gradation x scattering) function in terms of a single „Sky-index“
  - Fitted to radiance [W/m²sr], not luminance [cd/m²sr]

- Discretizing the model seems like extra-steps, but can reduce computational effort and memory requirements:

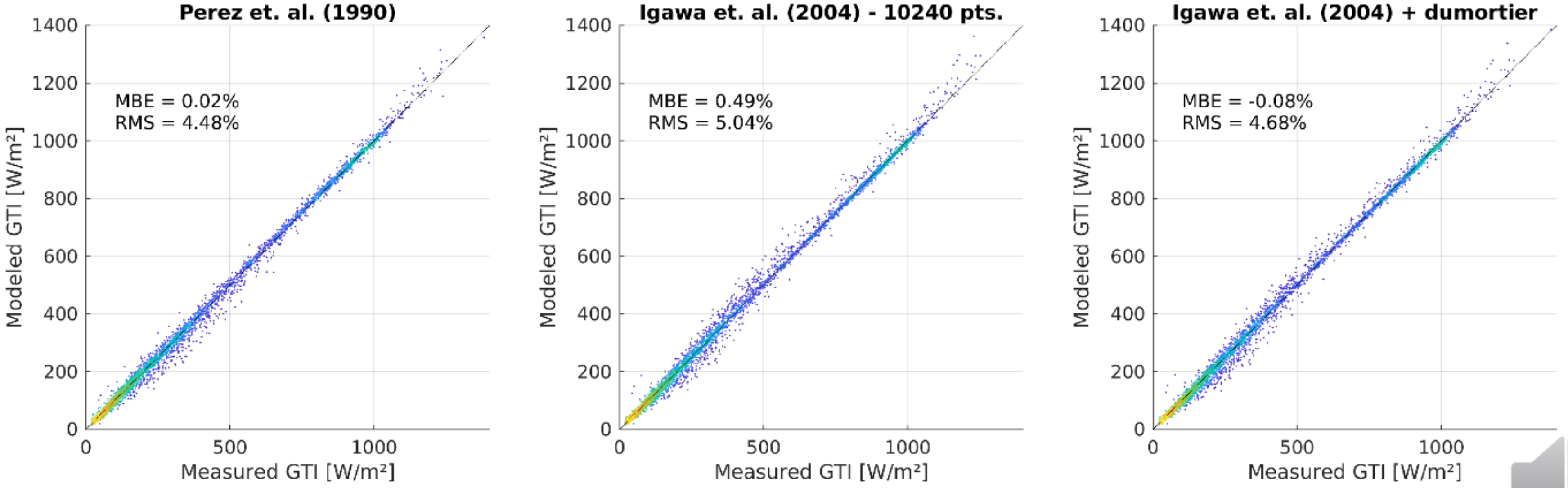
$$\text{Quadrature points} : \mathcal{O}\left(u \times q^2\right)$$
$$\text{View} - \text{Factors} : \mathcal{O}\left(u \times n^2 + q\right)$$





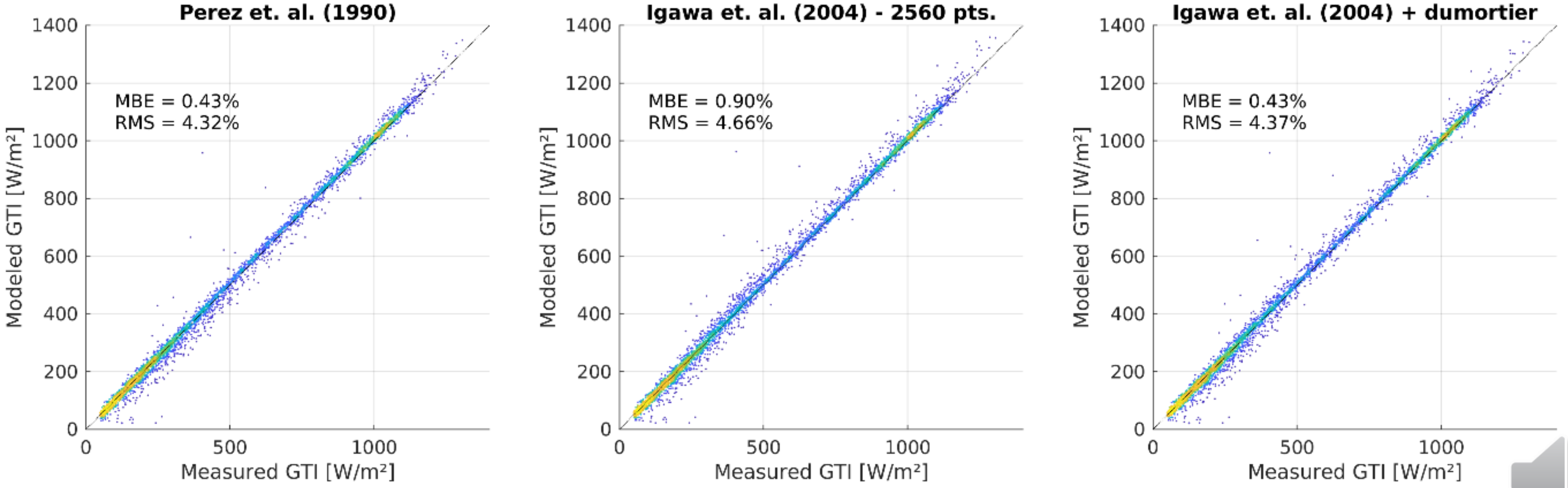
CDM's as Transposition Model

- NREL's Data for Validating Models - Marion et al. (2014)
  - Eugene, Oregon (44°N, 123°W, 145 mASL, 44° tilt)



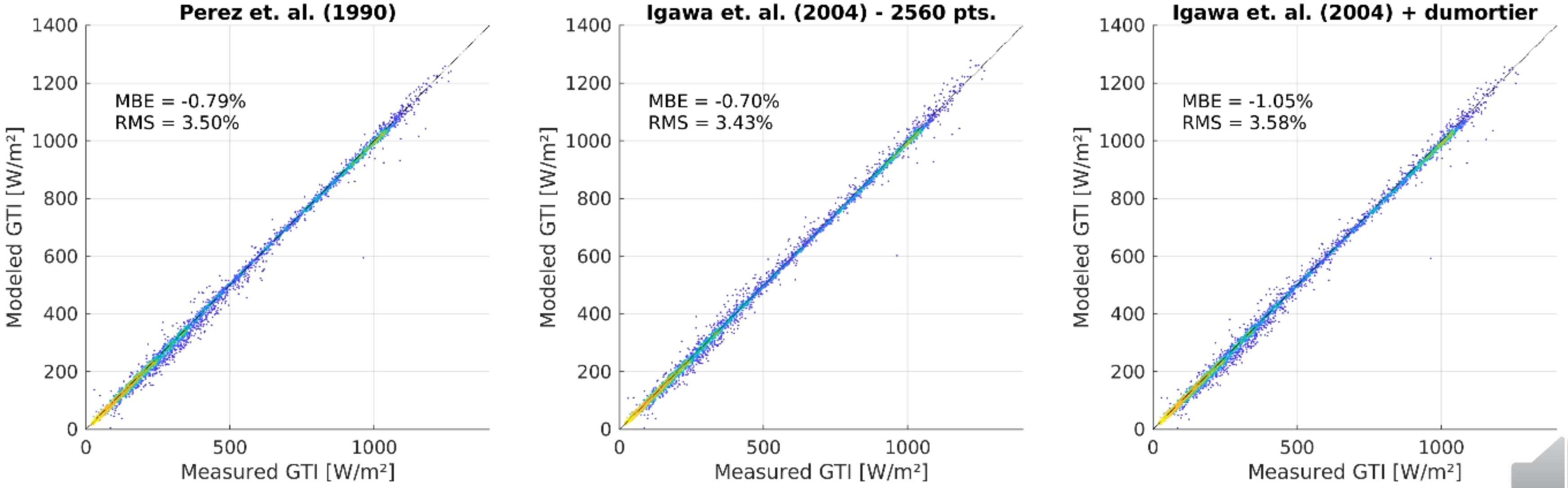
CDM's as Transposition Model

- NREL's Data for Validating Models - Marion et al. (2014)
  - Golden, Colorado (39.7°N, 105.2°W, 1798 mASL, 40° tilt)



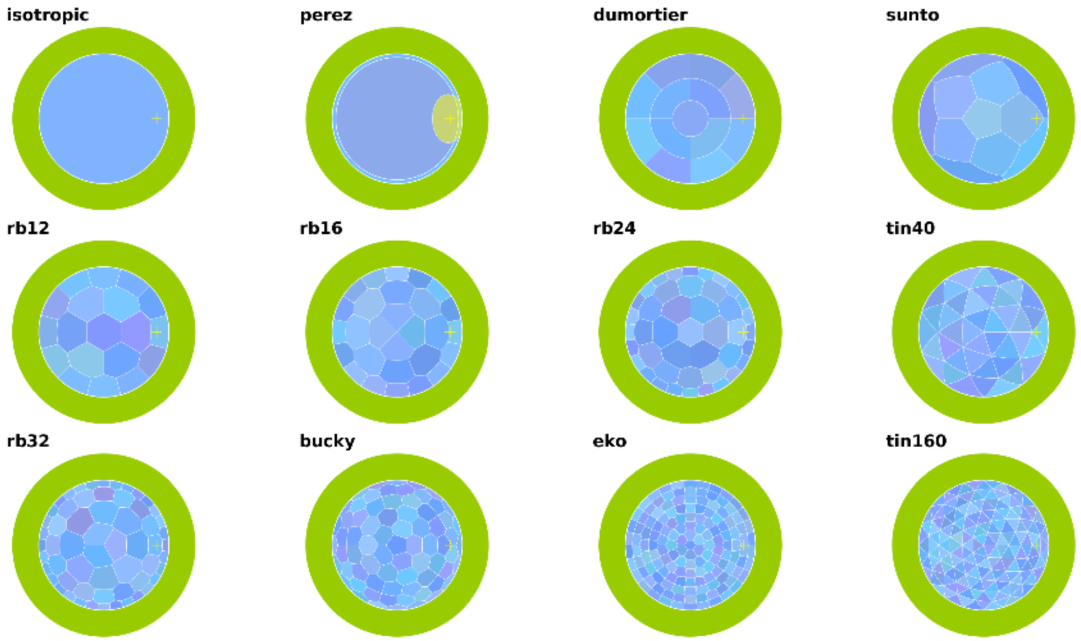
CDM's as Transposition Model

- NREL's Data for Validating Models - Marion et al. (2014)
  - Cocoa, Florida (28.4°N, 80.5°W, 12 mASL, 28.5° tilt)

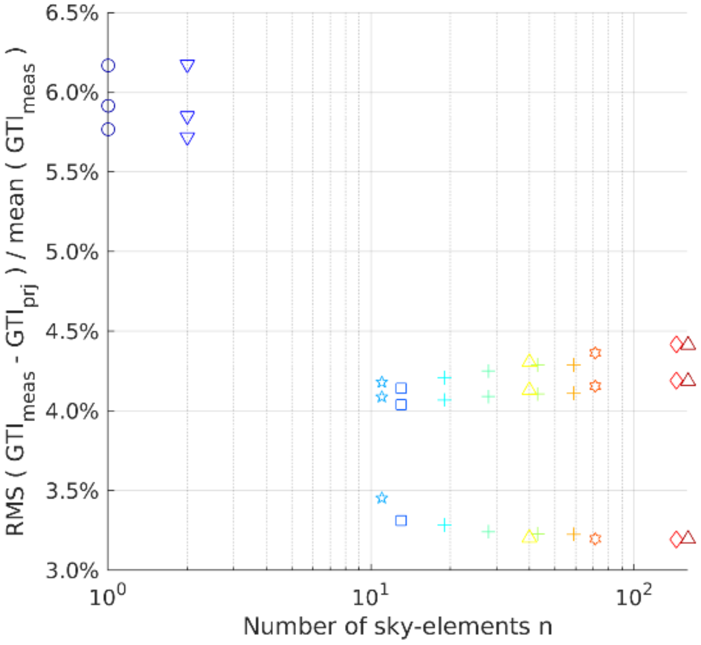


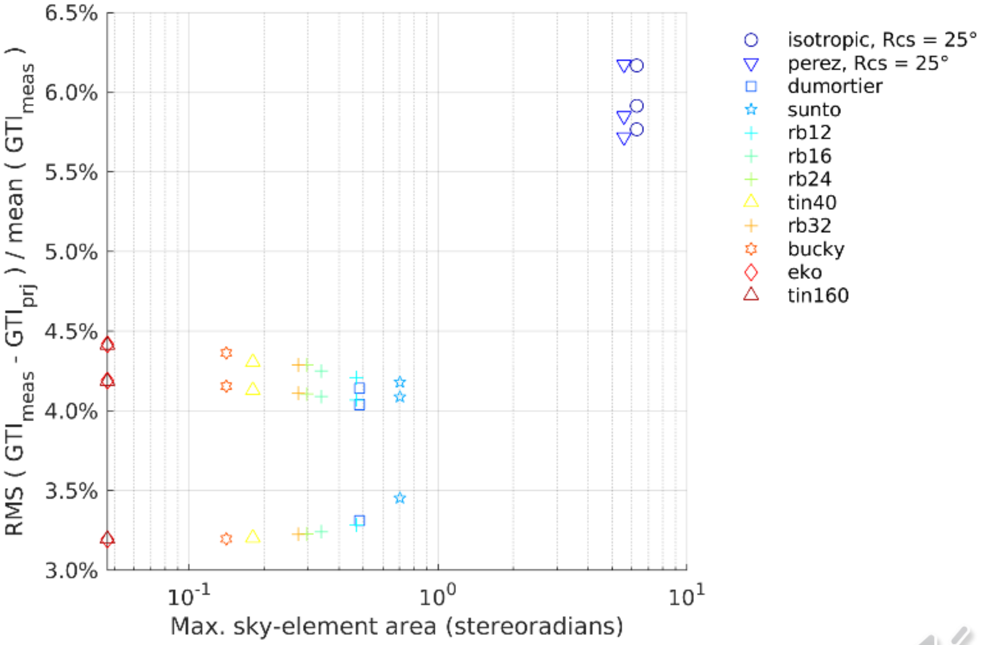
Effect of discretization?

- Integration errors increase with patch size and steeper gradients
- Sign of bias ~ gradation
- Final transposition error (no shading!) rather insensitive to anything above ~10 sky regions.
- Moving circumsolar regions don't seem to reduce error, except in simplest cases



Effect of discretization (cont.)



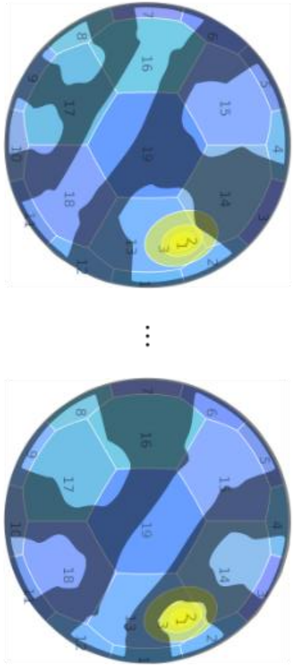


Estimating Radiance using View Factors

Given a set of sensors $\{1 \dots m\}$ (pyranometers, reference & calibrated cells, faceted-sensors, etc.), we can calculate their view-factor matrix $\boldsymbol{F_M} = [\boldsymbol{F_1}, \dots, \boldsymbol{F_m}]^T$ based only on their geometrical configuration (position, orientation, shade-masks, etc.), and use it as a set of constraints for the unknown $\hat{\boldsymbol{L}}_t$ based on measurements $\boldsymbol{I_{M,t}} = \left[I_{m,1} \dots I_{m,n_m}\right]^T$:

$$\boldsymbol{F_M} \cdot \hat{\boldsymbol{L}}_t = \boldsymbol{I_{M,t}}$$

Sadly, in most cases, we'll have less sensors than regions, and the problem will be underdetermined ($\boldsymbol{F_M^T F_M}$ will not be invertible).



Least-Norm Solution

One possibility is to start with a "reasonable assumption" L_o (derived from empirical models) and use sparse-regression to find a solution for the problem:

$$\begin{aligned} F_M \cdot (L_o + \varepsilon) &= I_{M,t} \\ F_M \cdot \varepsilon &= I_{M,t} - F_M L_o \end{aligned}$$

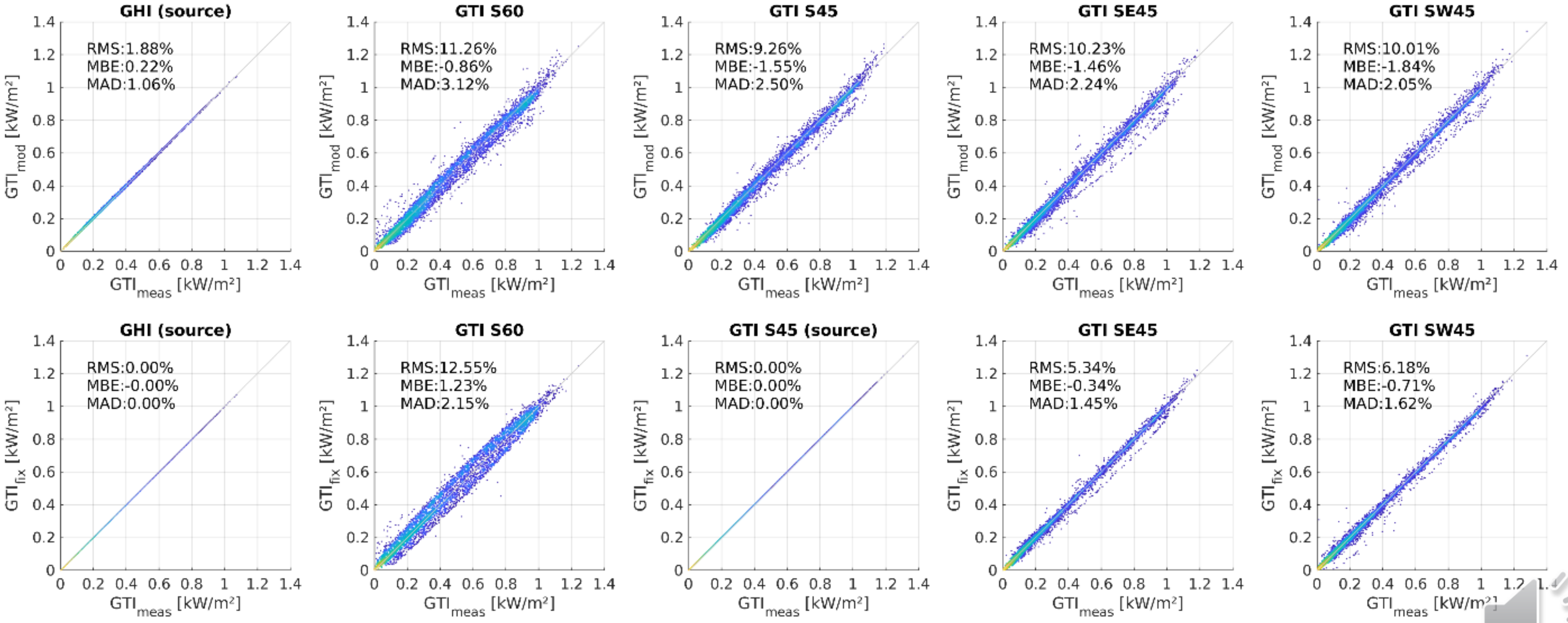
that minimizes a given norm $|\varepsilon|_p$ of the vector of differences ε with the empirical model.

Test case: Least L_2 norm (Ridge Regression)

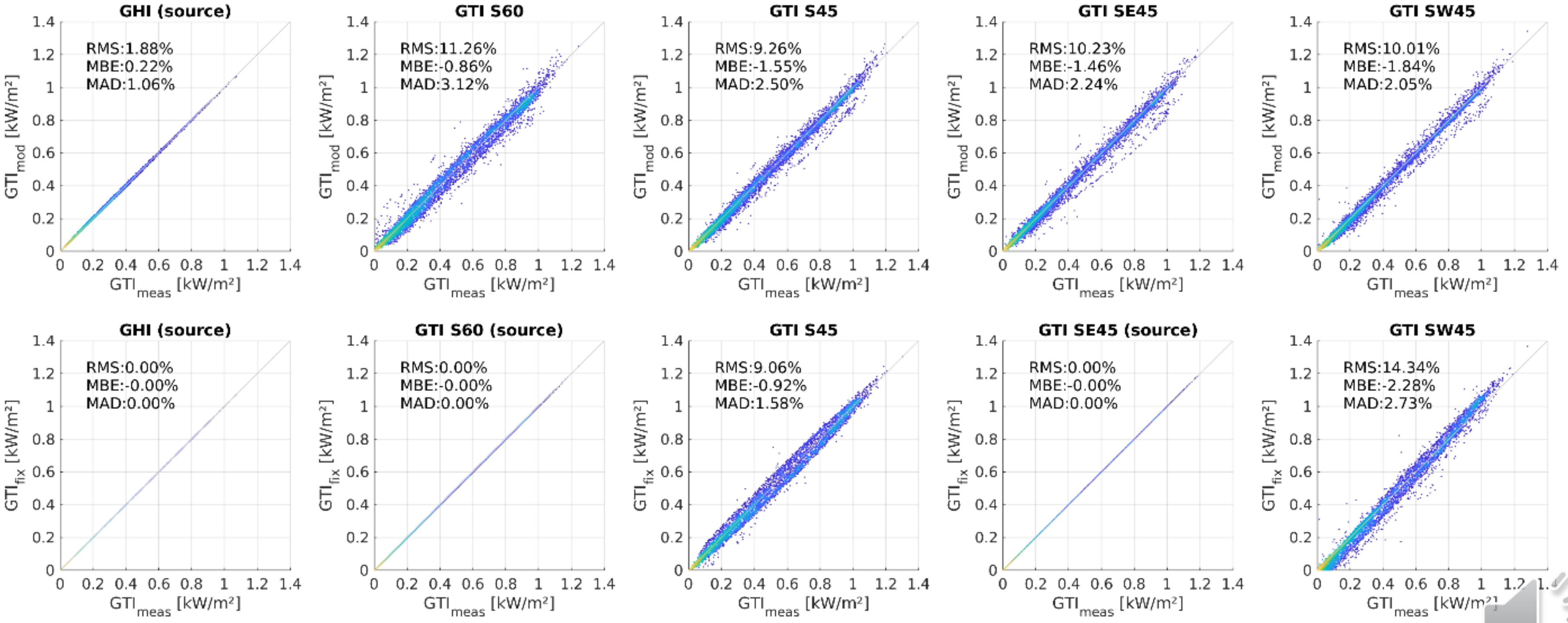
Data from the Karl von Ossietzky University of Oldenburg

- Secondary Standard Pyranometers for:
  - GHI, DHI
  - South 45°
  - South 60°
  - South-East 45°
  - South-West 45°
- 10000 points at random, from 1 year of 1-minute data

Least-Norm Solution: GHI + S 45° (Uni. Oldenburg)



Least-Norm Solution: GHI + S 60° + SE 45° (Uni. Oldenburg)



Future Work

- Decomposition Problem: hard & soft constraints, uncertainty and smoothness priors to reduce overfitting
- Estimating diffuse fraction
- Testing & Validation, new data sets and sensor configurations
- Spectral content correction for individual components
- Obstacle & terrain (self) shadows, non-Lambertian albedo
- Performance Optimization

Thanks

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References

- Anderson, M.C., 1964. Studies of the Woodland Light Climate: I. The Photographic Computation of Light Conditions. Journal of Ecology 52, 27–41. https://doi.org/10.2307/2257780
- Bosch, J.L., Batlles, F.J., Zarzalejo, L.F., López, G., 2010. Solar resources estimation combining digital terrain models and satellite images techniques. Renewable Energy 35, 2853–2861. https://doi.org/10.1016/j.renene.2010.05.011
- Capdevila, H., Herrerías, M., Marola, A., 2014. Anisotropic Diffuse Shading Model for Sun-tracking Photovoltaic Systems. Energy Procedia, 2013 ISES Solar World Congress 57, 144–151. https://doi.org/10.1016/j.egypro.2014.10.018
- Darula, S., Kittler, R., 2002. CIE general sky standard defining luminance distributions, in: Proc. Conf. ESim 2002. Presented at the Canadian conference on building energy simulation, Montreal, Canada, p. 9.
- Evans, G.C., Coombe, D.E., 1959. Hemisperical and Woodland Canopy Photography and the Light Climate. Journal of Ecology 47, 103–113. https://doi.org/10.2307/2257250
- Goss, B., Cole, I., Betts, T., Gottschalg, R., 2014. Irradiance modelling for individual cells of shaded solar photovoltaic arrays. Solar Energy 110, 410–419. https://doi.org/10.1016/j.solener.2014.09.037
- Hooper, F.C., Brunger, A.P., 1980. A Model for the Angular Distribution of Sky Radiance. Journal of Solar Energy Engineering 102, 196. https://doi.org/10.1115/1.3266154

References (cont.)

- Igawa, N., Koga, Y., Matsuzawa, T., Nakamura, H., 2004. Models of sky radiance distribution and sky luminance distribution. Solar Energy 77, 137–157. https://doi.org/10.1016/j.solener.2004.04.016
- Ineichen, P., 1996. Use of Meteosat data to produce sky luminance maps. Satellight, Commision of the European Communities, Bergen.
- Ivanova, S.M., 2013. Estimation of background diffuse irradiance on orthogonal surfaces under partially obstructed anisotropic sky. Part I – Vertical surfaces. Solar Energy 95, 376–391. https://doi.org/10.1016/j.solener.2013.01.021
- Marion, B., Anderberg, A., Deline, C., Cueto, J. del, Muller, M., Perrin, G., Rodriguez, J., Rummel, S., Silverman, T.J., Vignola, F., Kessler, R., Peterson, J., Barkaszi, S., Jacobs, M., Riedel, N., Pratt, L., King, B., 2014. New data set for validating PV module performance models, in: 2014 IEEE 40th Photovoltaic Specialist Conference (PVSC). Presented at the 2014 IEEE 40th Photovoltaic Specialist Conference (PVSC), pp. 1362–1366. https://doi.org/10.1109/PVSC.2014.6925171
- Nakamura, H., Oki, M., Hayashi, Y., 1985. Luminance distribution of Intermediate Sky. Journal of Light & Visual Environment 9, 1_6-1_13. https://doi.org/10.2150/jlve.9.1_6
- Perez, R., Seals, R., Michalsky, J., 1993. All-weather model for sky luminance distribution—Preliminary configuration and validation. Solar Energy 50, 235–245. https://doi.org/10.1016/0038-092X(93)90017-I