Solar Performance and Energy Prediction Modeling

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First Solar | LEADING THE WORLD'S SUSTAINABLE ENERGY FUTURE

ChatGPT Answer for PV Performance and Prediction Engineer

Performance Analysis

- Monitoring and analyzing the performance of solar PV systems.
- Using data from sensors and monitoring systems to assess how well the solar panels are converting sunlight into electricity.
- Identifying and diagnosing issues impacting performance, such as shading, equipment malfunctions, or degradation of the PV modules.

Prediction and Modeling

- Developing and implementing models to predict the energy generation from solar power plants.
- Using meteorological data, historical performance data, and advanced algorithms to forecast future performance.
- Assessing the impact of various factors such as weather, soiling, and aging on the performance of the solar systems.

Reporting

- Preparing detailed reports on the performance of solar PV systems for stakeholders.
- Communicating findings, performance metrics, and recommendations to project managers, investors, and other relevant parties.

Research and Development

- Staying updated with the latest advancements in PV technology and performance prediction methodologies.
- Conducting research to improve existing models and develop new techniques for better performance estimation and optimization.

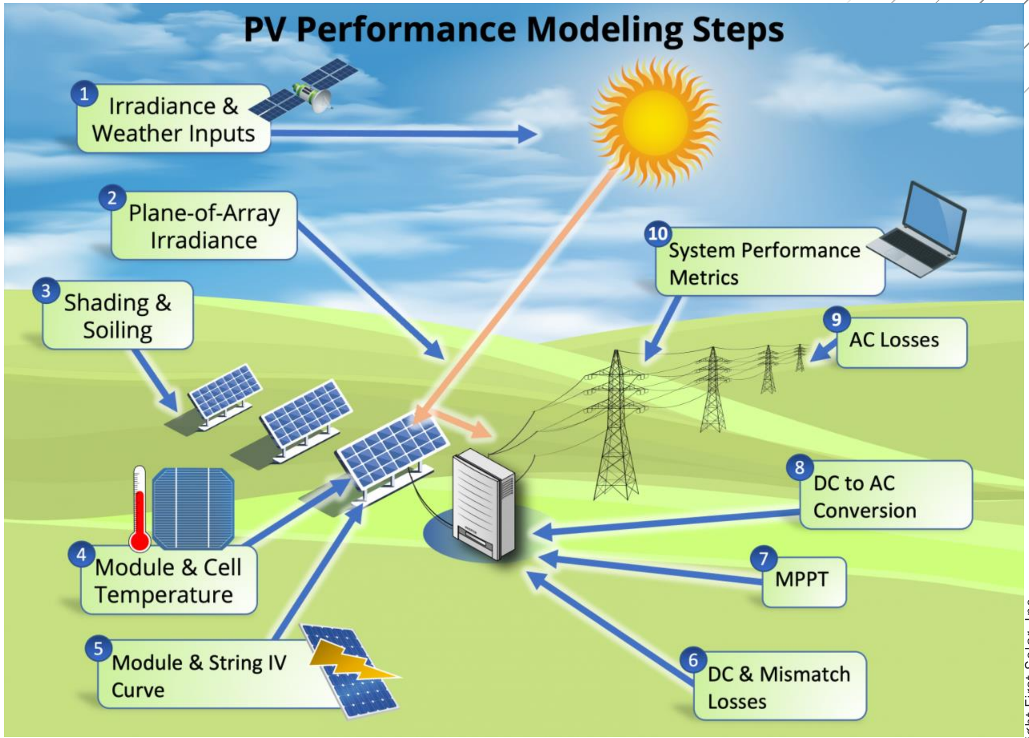
Overall, a PV Performance and Prediction Engineer ensures that solar power installations operate efficiently and reliably, and uses advanced analytics to predict and enhance future performance.

PV Performance Modeling Workflow

- Understanding the expected performance of a solar power plant or solar energy technology crosses several scientific disciplines including mathematics, statistics, data science, physics-based modeling, meteorology and electrical engineering.

- It is a discipline that places a premium on both accuracy and precision in order to properly value, and de-risk, a solar development asset or solar energy technology.

- In order to achieve this goal, engineers interact with a set of physics-based or data-driven models.



https://pvpmc.sandia.gov/

Prediction of Module Performance

Solar panels have expected performance based on nameplate values

- Nameplate defines the STC metrics of a module (1000 1.5G irradiance, 25C)
- Example – 470W, -0.28%/C Pmax Tco, 800 irradiance, 50C module temp

$$Power_{Actual} = 470 \times \frac{800}{1000} \times \left(1 - 0.0028(50 - 25)\right) = 349.7W$$

Congratulations! Being a Performance Engineer is super easy!

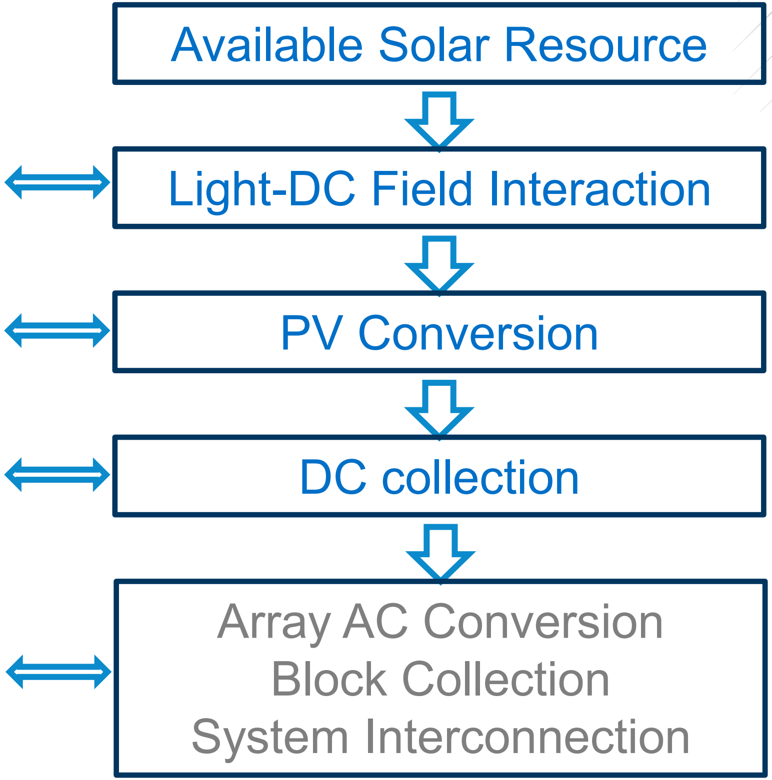
- Not so fast, lots of <u>enormous</u> factors influence performance as well
- A must read from an industry expert: https://kurt-rhee.gitbook.io/blog/writings/pv/so-you-want-to-be-a-pv-performance-engineer

Energy Prediction Flowchart

Loss Factors

PV System

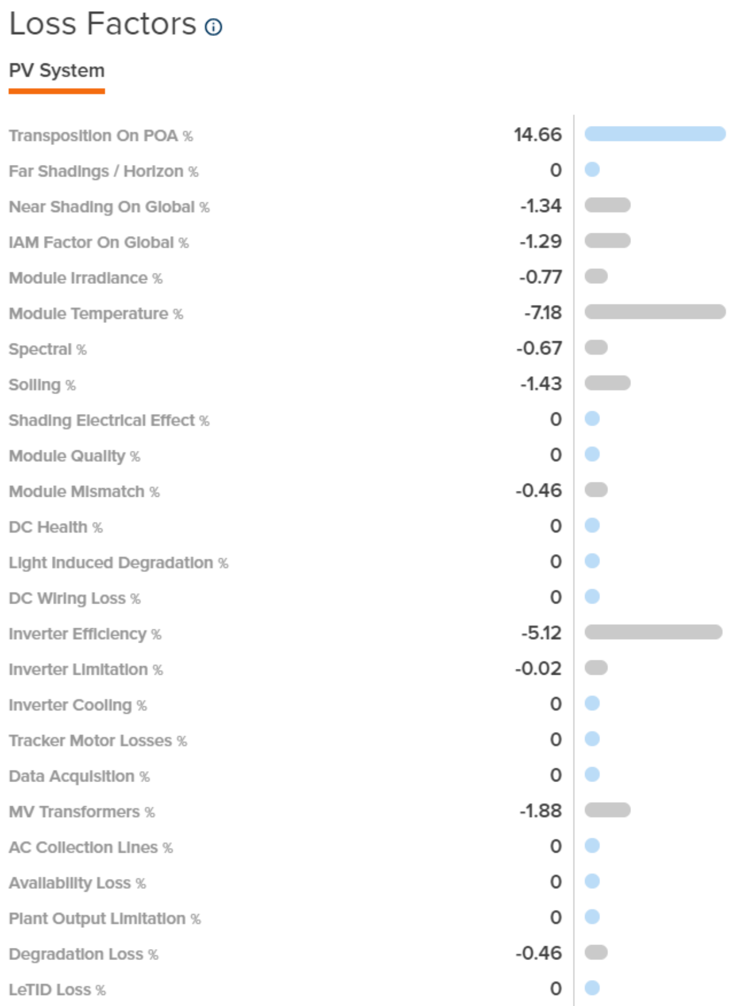
Transposition On POA %	46.25
Far Shadings / Horizon %	0
Near Shading On Global %	-1.2
IAM Factor On Global %	-1.01
Soiling %	-0.59
Module Irradiance %	-1.23
Module Temperature %	-1.78
Spectral %	-1.26
Shading Electrical Effect %	0
Module Quality %	0
Module Mismatch %	-0.48
DC Health %	0
Light Induced Degradation %	0
DC Wiring Loss %	0
Inverter Efficiency %	-6.33
Inverter Limitation %	-0.03
Inverter Cooling %	0
Tracker Motor Losses %	0
Data Acquisition %	0
MV Transformers %	-2.42
AC Collection Lines %	0
Availability Loss %	0
Plant Output Limitation %	0
Degradation Loss %	-0.22
LeTID Loss %	0



Loss (or Gain) Factors

Every performance model is an assumption!

- <u>All models are wrong, but some are useful</u>
  - George Box, statistician
- Individual influences on module performance are combined based on measured or TMY weather data & orientation information
  - Effects are typically independent
  - To yield a net energy performance of the system
    - These predictions are invaluable in determining the value or health of a system



2024 18th PV Performance Modeling Collaborative (PVPMC)

Salt Lake City, Utah, USA

May 9, 2024

Presentation downloadable from

https://www.sandia.gov/app/uploads/sites/243/dlm_uploads/2024/05/Curran_PVPMC_24_slides.pdf

Simple Photovoltaic Spectral Correction Model Based on FARMS-NIT Modeled Spectra

Alan Curran, Boris Lin
First Solar

First Solar

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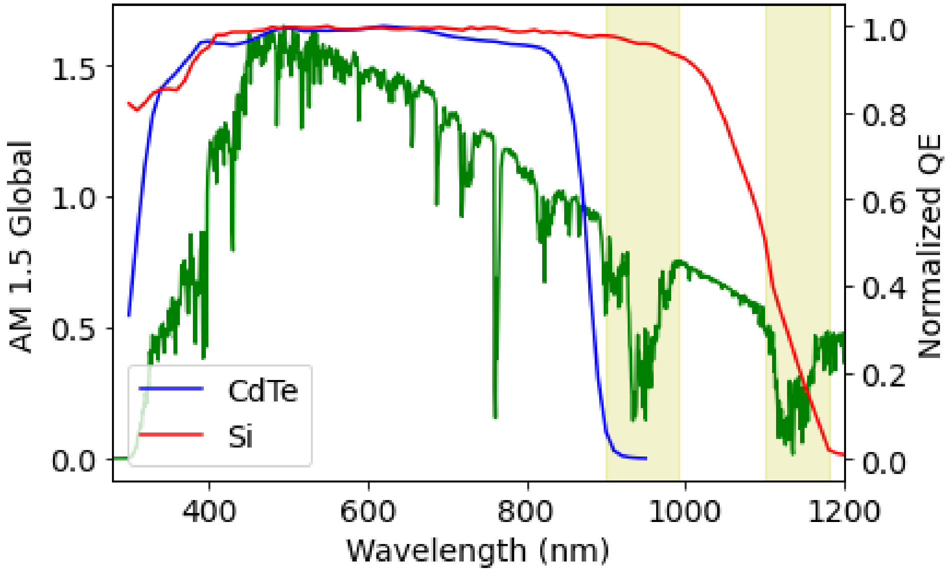
Spectral Modeling for CdTe

Spectral correction is an irradiance adjustment based on pyranometers

- Thermopile pyranometers observe the full spectrum, solar cells do not
- Certain weather effects target specific wavelengths which may change the performance of the devices differently



CdTe narrower QE gives it a larger spectral response

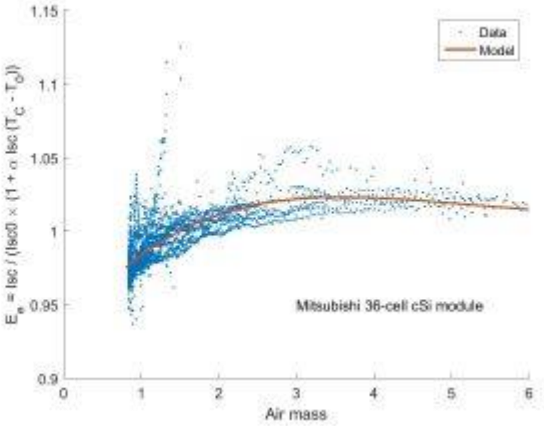
Spectral Modeling For Silicon

For Silicon PVsyst references a Sandia Air Mass model

- “The Sandia model defines a spectral correction, as a function of the Air mass only (no dependence of the Kt)”
- Which is a 4th order polynomial (red flag for me)

In the SAPM, a 4th degree polynomial $f_1(AM_a)$ is fit to data and the coefficients are normalized so that $f_1(AM_a = 1.5) = 1$:

$$f_1(AM_a) = \alpha_0 + \alpha_1 \times AM_a + \alpha_2 \times AM_a^2 + \alpha_3 \times AM_a^3 + \alpha_4 \times AM_a^4$$



General assumption is Si spectral correction is Dependent on Air Mass

2-Parameter Spectral Model

$$M = a + b \cdot AM + c \cdot p_{wat} + d \cdot \sqrt{AM} + e \cdot \sqrt{p_{wat}} + f \cdot \frac{AM}{\sqrt{p_{wat}}}$$

Available with coefficients for both CdTe and Si

- Primary guidance for CdTe modules

Developed using the SMARTS model to predict a range of spectral correction

- Based on provided range of precipitable water and absolute air mass
  - 37-tilt angle
- Assumes clear-sky conditions for results
  - Pessimistic due to cloud cover benefits

Lee, Mitchell, and Panchula, Alex.
Spectral Correction for Photovoltaic Module Performance Based on Air Mass and Precipitable Water.
IEEE Photovoltaic Specialists Conference, Portland, 2016

SMARTS Model

Series of equations (first principles and empirical) for atmospheric corrections

- Precipitable water and air mass input to fit the 2-parameter model
  - 37-degree tilt
  - No TMY data used
- Assumes clear sky conditions

https://www.nrel.gov/docs/gen/fy04/36320.pdf

Table 1. Transmission expressions developed for SMARTS model (versions 2.9 and later).

Extinction Process	Transmittance Expression	Source
Rayleigh scattering	$Tr(\lambda)=\exp\{(P/P_0)/[a_0(\lambda/\lambda_1)^4+a_1(\lambda/\lambda_1)+a_2+a_3(\lambda/\lambda_1)^{-2}]\}$	Gueymard[20, 22]
Ozone absorption	$To(\lambda) = \exp[-m_o u_o Ao(\lambda)]$	Daumont et al. (1992)[26], Bogumil et al. (2003)[27], Burrows et al. (1999)[28], Anderson et al. (1993)[29]
Mixed Gases absorption (j=1–7)	$Tmg_j(\lambda) = \exp[-m_j u_j A_j(T,\lambda)]$.	Various laboratory spectroscopic data for CH_4 CO_2, CO, N_2, N_2O, O_2, and O_4
Trace Gases absorption (k=1–10)	$Ttg_k(\lambda) = \exp[-(m_k u_k A_k(T,\lambda))]$.	Mixed: Various laboratory spectroscopic data for BrO, CH_2O, $ClNO_3$, HNO_2, HNO_3, NH_3, NO, NO_2, NO_3, and SO_2
Water Vapor absorption	$Tw(\lambda) = \exp[-(m_w u_w)^n B_w(u_w,\lambda) B_m(m_w,\lambda) B_p(P,\lambda) B_{mw}(m,u_w,\lambda) A_w(\lambda)]$	Gueymard fits to MODTRAN4 Water vapor band models.
Aerosol extinction	$Ta(\lambda) = \exp[-m_a \beta_i (\lambda/\lambda_1)^{-\alpha i}]$	General Ångström relation, visibility or meteorological range based on Koschmeider[30]

Table 1 expression parameters are; P: station pressure; P_0: standard pressure; T: temperature; a_i: fitting coefficients; m_x: optical mass correction for extinction process x; u_x: abundance for absorber x, A_x: absorption coefficient for absorber x, B: water vapor band function or scaling factor; α_i and βi,: Ångström parameters, i= 1 for $\lambda<500$ nm, i=2 for $\lambda\geq500$ nm[⊕], λ_1: reference wavelength (1000 nm or 1 µm)

Goals for Modeling Advancement

1. Assess and capture cloud cover influence on spectral performance

2. Easy to integrate into existing pipelines/software
   - No significant additional data or infrastructure

3. Coefficients for different orientations
   - 1-axis, fixed tilt

4. Works well for silicon modules as well

Spectral 3.0 Model

New proposed Spectral 3.0 model (current iteration):

- M = SCF = Spectral correction factor

$$\boxed{M = \beta_0 CSI + \beta_1 P_{Wat} + \beta_2 AM + \beta_3}$$

Captures cloud based spectral benefit using clear sky index as a simple quantitative value for cloud cover

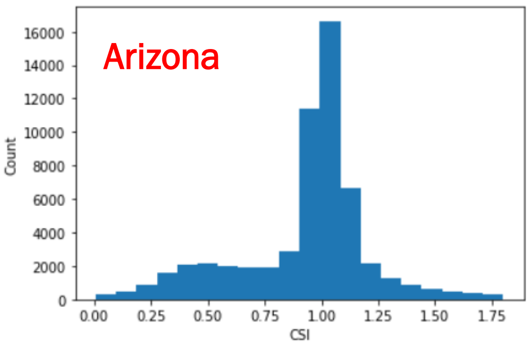
- 2-parameter model was fit to SMARTS which is a clear sky assumption
- Irradiance weighted regression used to bias fit towards higher production periods

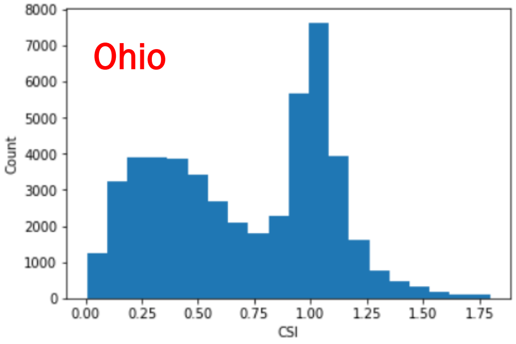
Clear Sky Index: Quantifying Cloud Cover

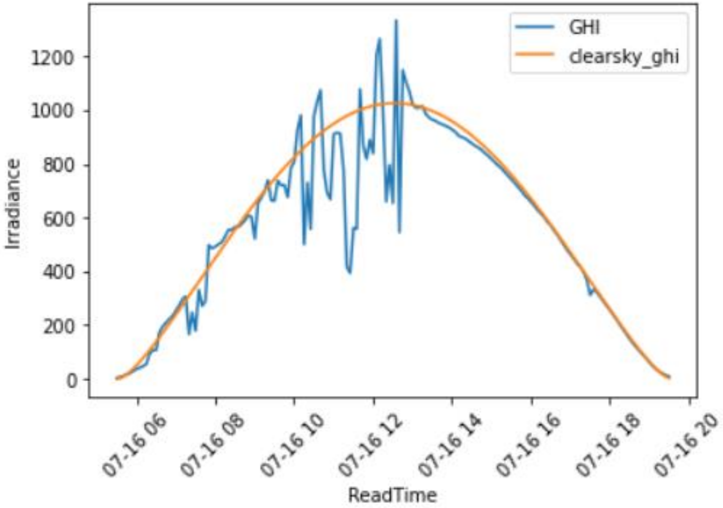
Clear sky index (CSI)

- Ratio of measured irradiance and clear sky irradiance
  - Lower CSI = more clouds (inverse)
- Clearness index also being assessed

$$CSI = \frac{TMY\ Irradiance}{Modeled\ Clearsky\ Irradiance}$$







FARMS-NIT Model

The FARMS-NIT model is an expansion on the SMARTS model to add cloud impact predictions

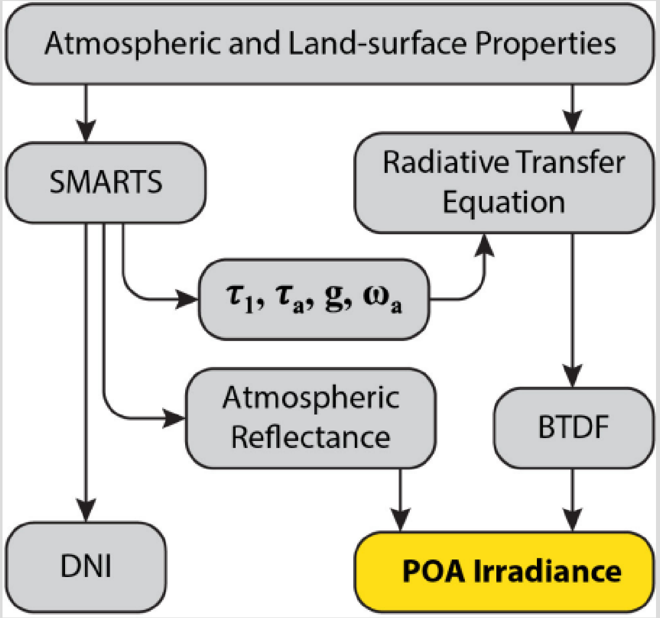
- Satellite data is used for cloud estimations
- bidirectional transmittance distribution function (BTDF)

Multi-year, orientation tunable spectra

- Across all of US
- Drawbacks: cannot be used for instantaneous measurements (up to 2023)

https://www.nrel.gov/docs/fy21osti/71722.pdf

SMARTS is used to compute atmospheric properties, combined with the solution of radiative transfer equation and BTDF of cloud/aerosol, and compute atmospheric radiances.



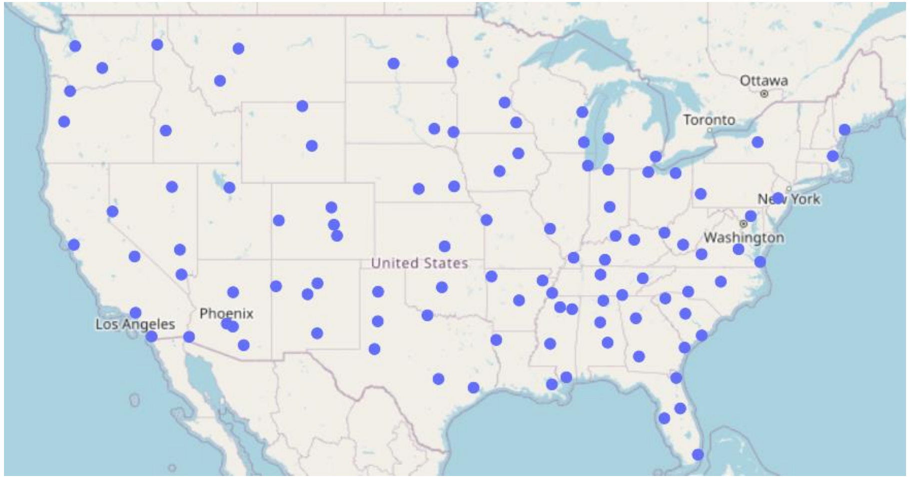
FARMS-NIT Data Set

104 locations across the US selected for fitting/validation

- 2 years at each location, 1-axis orientation (fixed tilt also being modeled)

Modeling was done on a subset of locations

- Found to be a better fit to field measured data
- All sites still used for validation



<u>Note: this presentation will not cover magnitude impacts due to unfinished nature of model</u>

1-Axis Fitting Results: 104 FARMS-NIT Systems

Spectral 3.0 shows the best fitting in all cases for both technologies (G > 100)

- Silicon 2-parameter model shows minor improvements to no correction
- Silicon has overall lower error than CdTe
  - Lower magnitude of spectral impact

Model	CdTe RMSE	CdTe Weighted RMSE	CdTe MAE	CdTe Weighted MAE	Si RMSE	Si Weighted RMSE	Si MAE	Si Weighted MAE
Spectral 3.0	0.038	13.820	0.021	8.706	0.026	8.317	0.013	5.274
2-parameter	0.055	17.514	0.034	12.441	0.035	11.292	0.020	7.693
SAPM AM	-	-	-	-	0.035	12.044	0.021	8.656
No Correction	0.064	24.607	0.044	19.219	0.036	12.703	0.024	9.929

RMSE – Root Mean Square Error
MAE – Mean Absolute Error
Weighted terms are irradiance weighted to bias towards higher irradiance predictions, (Predicted – Actual) * Irradiance

22^o Tilt Fitting Results: 104 FARMS-NIT Systems

Spectral 3.0 maintains best fit compared to other models

- CdTe error increases vs. 1-axis, Si error decreases compared to 1-axis
- CdTe spectral correction increases with greater diffuse light
  - GHI best case for CdTe, 2-axis best case for Si

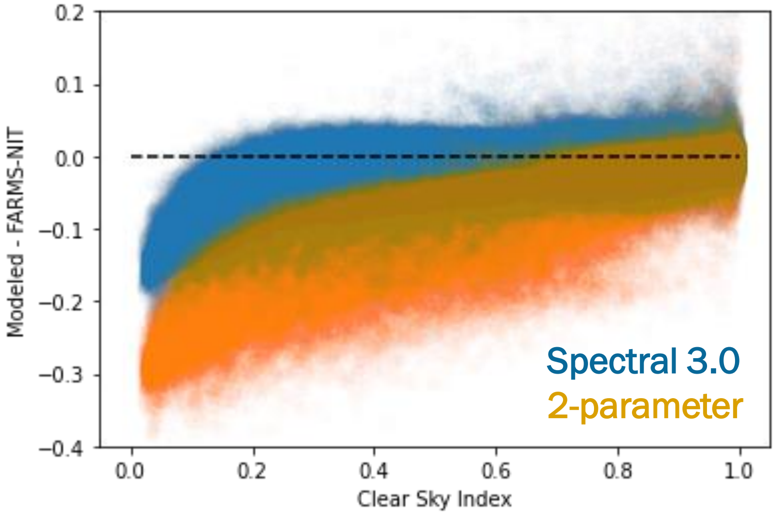
	CdTe				Si			
Model	RMSE	Weighted RMSE	MAE	Weighted MAE	RMSE	Weighted RMSE	MAE	Weighted MAE
Spectral 3.0	0.044	14.506	0.022	7.810	0.025	7.862	0.012	4.202
2-parameter	0.063	18.323	0.037	11.878	0.036	11.149	0.021	7.181
SAPM AM	-	-	-	-	0.036	11.917	0.021	8.120
No Correction	0.069	23.562	0.045	17.100	0.036	11.603	0.022	8.067

RMSE – Root Mean Square Error
MAE – Mean Absolute Error
Weighted terms are irradiance weighted to bias towards higher irradiance predictions, (Predicted – Actual) * Irradiance

FARMS-NIT Trend with Cloud Cover

2-parameter underprediction to FARMS-NIT increases with decreasing CSI

- Spectral 3.0 also beings to underpredict at very low CSI
  - partial result of weighted irradiance
- Models converge at clear sky periods, predictions are similar



* CSI = 1 excluded from plot for clarity

Field Study: 1-Axis Tripod Spectrometers

SolarSIM-Gs & ST-5 tracker systems sent to partner sites

- Arizona, Ohio, Florida (UCF), Louisiana (ULL), Northern California (RETC)
  - Installations Aug-Sept 2023, nearing full year of data
- 1-axis tracking orientation spectral measurements
  - 5-minute interval, precipitable water collection as well
  - 280-4000nm range, irradiance calculated from spectra to avoid potential offsets to pyranometers
- CSI evaluated from GHI data at each location
  - 1-axis data more difficult to align to clear sky model

Fitting Results: Fielded 1-Axis Data

Spectral 3.0 continues to show the best performance

- One exception of better irradiance weighted RMSE
- ~8 months of available spectral data

	CdTe				Si			
Model	RMSE	Weighted RMSE	MAE	Weighted MAE	RMSE	Weighted RMSE	MAE	Weighted MAE
Spectral 3.0	0.034	16.221	0.024	11.957	0.026	10.047	0.016	7.183
2-parameter	0.048	16.103	0.032	12.784	0.034	10.782	0.021	8.218
SAPM AM	-	-	-	-	0.034	11.770	0.022	9.250
No Correction	0.054	19.766	0.038	16.128	0.036	12.341	0.024	10.037

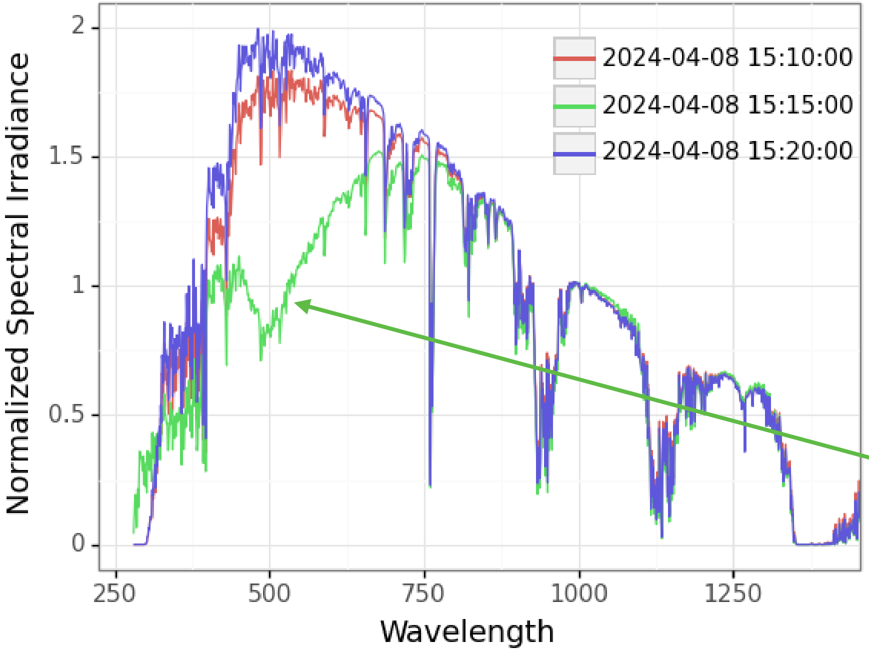
Conclusions

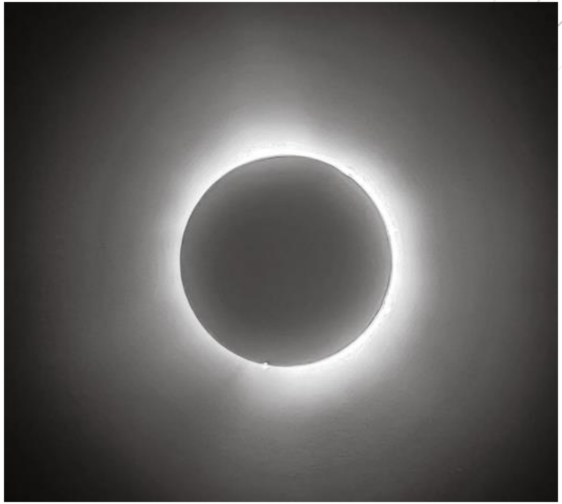
Spectral 3.0 model using Clear Sky Index shows improved prediction of spectral performance

- Both against FARMS-NIT and measured spectral data
  - For both Si and CdTe modules
- Successful fitting improvement for 1-axis and fixed tilt scenarios
- Can be integrated into existing workflows, no new data to chase

Bonus: Totality Spectral Correction

Significant visible region losses during totality





CdTe spectral correction during totality = -11%

Thank You

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