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Chapter 7: Solar Irradiance Uncertainty and Data Quality Assessment

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Overview

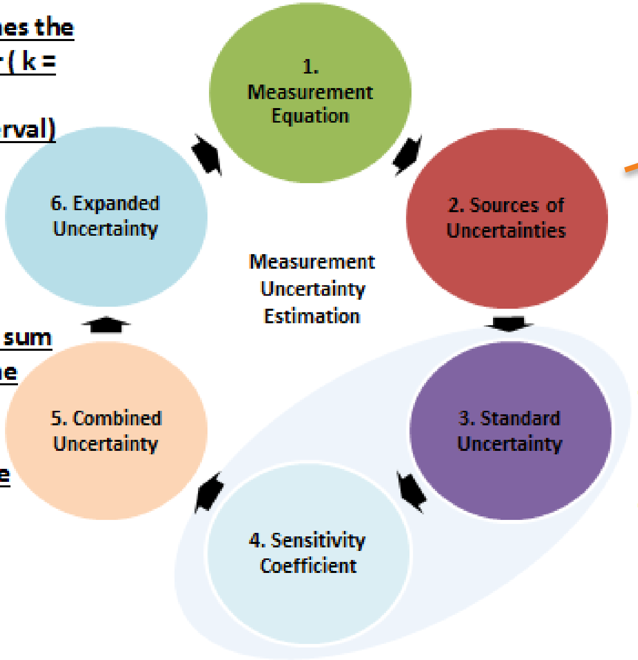
This chapter discusses the uncertainties associated with measured or modeled solar resource data along with data quality assessment. These are important because:

- they provide a basis to assess confidence in the predicted output of a planned PV system and is thus a key factor when determining the bankability of the project.

Solar Resource Measurement Uncertainty

Estimation of Calibration and Field Measurement Uncertainty

The combined uncertainty times the coverage factor (k = 1.96 for a 95% confidence interval)



The root of the sum of squares of the standard uncertainty (3) weighted by the sensitivity coefficient (4)

Expanded Uncertainty from given sources of uncertainties [Type B]]

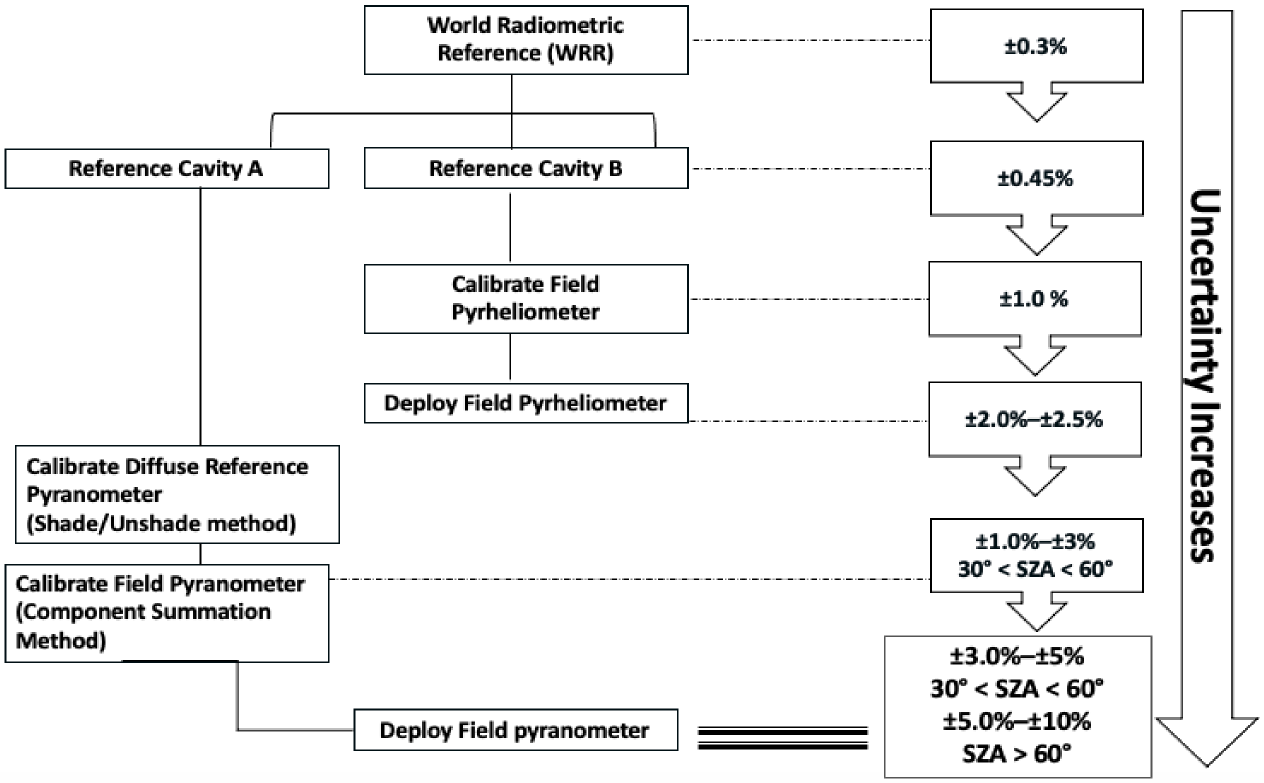
Uncertainties derived from statistical analysis of measurements [Type A]

Partial derivative for each variable in the measurement equation

- Calibration
- Spectral response
- Directional response
- Data logger uncertainty
- Temperature dependence
- Non-linearity

Calibration and Field Measurement Uncertainty

Calibration traceability and accumulation of measurement uncertainty for pyrheliometers and pyranometers



Solar Resource Measurement Uncertainty

Example of Estimated Expanded Uncertainties of Responsivities of Field Pyranometers and Pyrheliometers. *Modified from Reda (2011)*

Type B Uncertainty Source	Thermopile Pyranometer (%)	Photodiode Pyranometer (%)	Thermopile Pyrheliometer (%)	Photodiode Pyrheliometer (%)
Calibration[a]	3	5	2	3
Zenith response[b]	2	2	0.5	1
Azimuth response	1	1	0	0
Spectral response	1	5	1.5	8
Tilt[c]	0.2	0.2	0	0
Nonlinearity	0.5	1	0.5	1
Temperature response	1	1	1	1
Aging per year	0.2	0.5	0.1	0.5
U_{95}	**4.1**	**8.0**	**2.7**	**8.9**

Some uncertainties have higher impact on the overall uncertainty

Quantification of Model Uncertainty

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Quantification of Model Uncertainty

- An important distinction between measurements and model estimates is that the latter actually include two separate sources of uncertainty, which in principle would need to be decoupled.
  - The intrinsic model's uncertainty [caused by inadequacies in the model's functions, which do not perfectly describe the physical radiation transport processes in the atmosphere]; and
  - The error propagation uncertainty [caused by unavoidable imperfections in the model's inputs, which make their way to the model's outputs].

How do we quantify the uncertainty of these errors?

Quantification of Irradiance Model Uncertainty

- The error propagation effects can be evaluated by analyzing the model's sensitivity to variations in its inputs (of supposedly known uncertainty), however this approach is not easy and in practice, the quality of modeled irradiance is evaluated against ground measurements.
  - Ground measurement uncertainty needs to be included in the estimation of overall uncertainty.

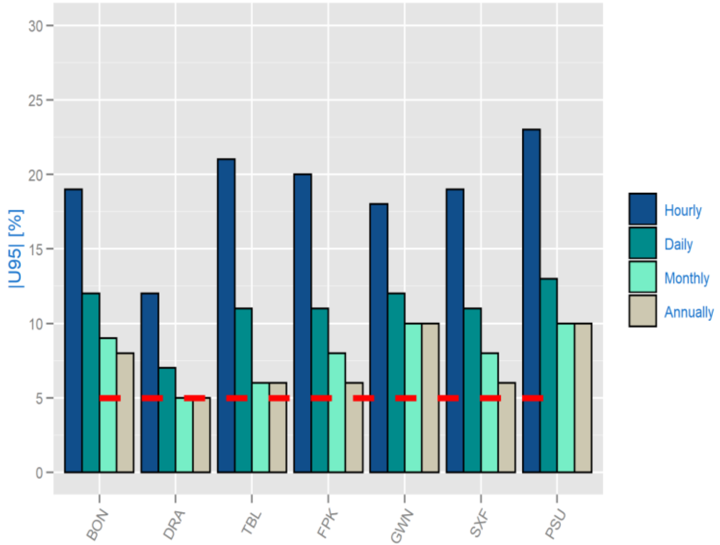
Approaches to quantify overall model uncertainty

Example of Irradiance Model Uncertainty

- In the absence of a specific standard for the evaluation of model uncertainty, the National Renewable Energy Laboratory (NREL) developed a way to include these sources and derive the uncertainty estimate for a 95% confidence interval representing two standard deviations (coverage factor of ≈2):

$$U_{95} = k * \sqrt{\left(\frac{U_{meas}}{k}\right)^2 + \left(\frac{bias}{k}\right)^2 + \left(\frac{\mathrm{RMSE}}{k}\right)^2}$$

  - **Issue:** this is a conservative approach, the resulting U_{95} may be pessimistic because RMSE includes the bias error, which is thus counted twice. Therefore, authors of this handbook are investigating to find statistical metrics that assist in quantifying the overall uncertainty.



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Example of Irradiance Model Uncertainty

- *Solargis* implemented a slightly different approach to determine uncertainty in their satellite-derived data sets by incorporating the model uncertainty, the uncertainty of the ground-based irradiance measurements, and the interannual irradiance variability:

$$u_{\text{combined}} = \pm\sqrt{(U_{meas})^2 + (U_{model})^2 + \left(\boldsymbol{U_{interannual\,variability}}\right)^2}$$

Automated Data Quality Evaluation Methods

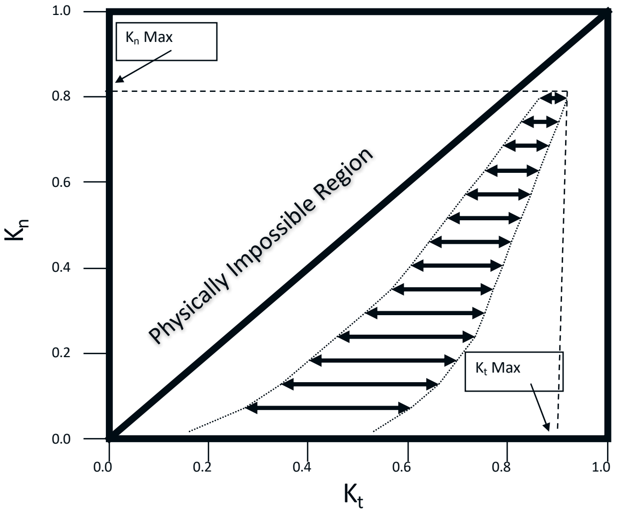
Automated Data Quality Evaluation Methods

Data Quality Assessment Using NREL's SERI-QC

Depending on the available data, SERI-QC performs one-element, two-element, or three-element tests, each with a progressively narrow filter for acceptability:

Maximum K_t and K_n

Gompertz curve used to create an envelope that fits multiyear ground measurements.



Air Mass / Zenith Angle Ranges

Range	Air Mass	Zenith Angle
Low	1.00–1.25	0.00–36.96
Medium	1.25–2.50	36.96–66.57
High	2.50–5.76	66.57–80.00

SERI-QC flags encode the magnitude of discrepancy to facilitate error analysis.

SERI-QC publication: https://www.nrel.gov/docs/legosti/old/5608.pdf

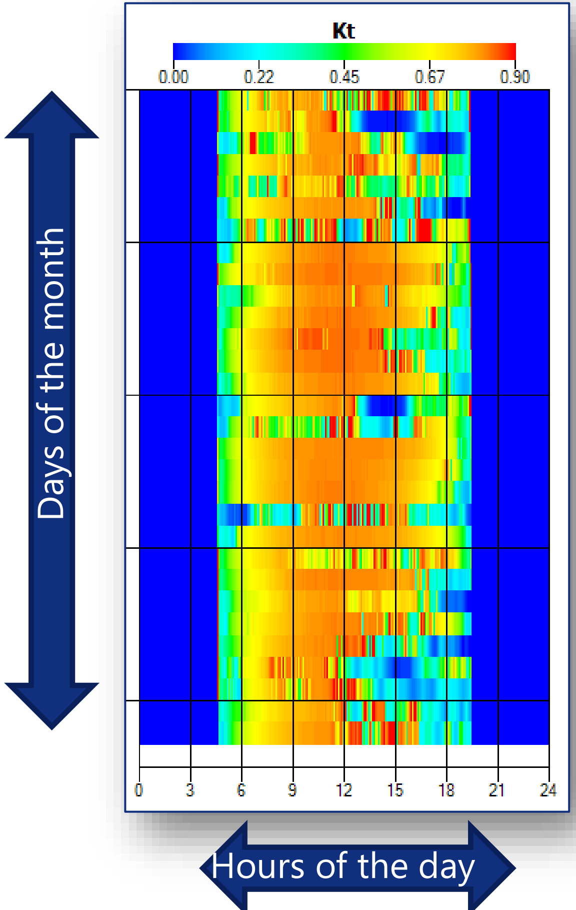
Methods of Automated Data Quality Evaluation

Data Quality Assessment Using NREL's SERI-QC

Daily Quality Checks

SERI-QC cylinder plots:

- A full month of data and quality flags can be seen at a glance
- Shows data for each of the three solar components
- Errors become instantly evident
- Flags can be correlated with irradiance values
- The three components can be viewed in context with each other.



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