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Quantifying the Effects of Averaging and Sampling Rates on PV System and Weather Data

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Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

Why do we model PV output based on weather inputs?

1. Compare expected system performance for multiple systems prior to purchase of components
2. Monitoring of existing PV system health
3. Determine expected energy output in a “typical” year

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Collecting weather data

- Typically collected at low rates (every 15 minutes)
  - Handling a lot of data is cumbersome
  - Older equipment has limited memory

- Methods of data reduction
  - Reducing the sample rate below the maximum sample rate of the device (under-sampling)
  - Averaging a number of samples together and holding only the averaged value

What effect does the data reduction process have on modeled output?

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Procedure

1. Collect high resolution weather data (3 second)
2. Model weather data using Sandia PV Array Performance Model
   - This is now “real-time” modeled data
3. Under-sample or average the weather data at many intervals
4. Model the under-sampled or averaged weather data using the same model
5. Compare the model output from under-sampled/averaged data to the “real-time” model output

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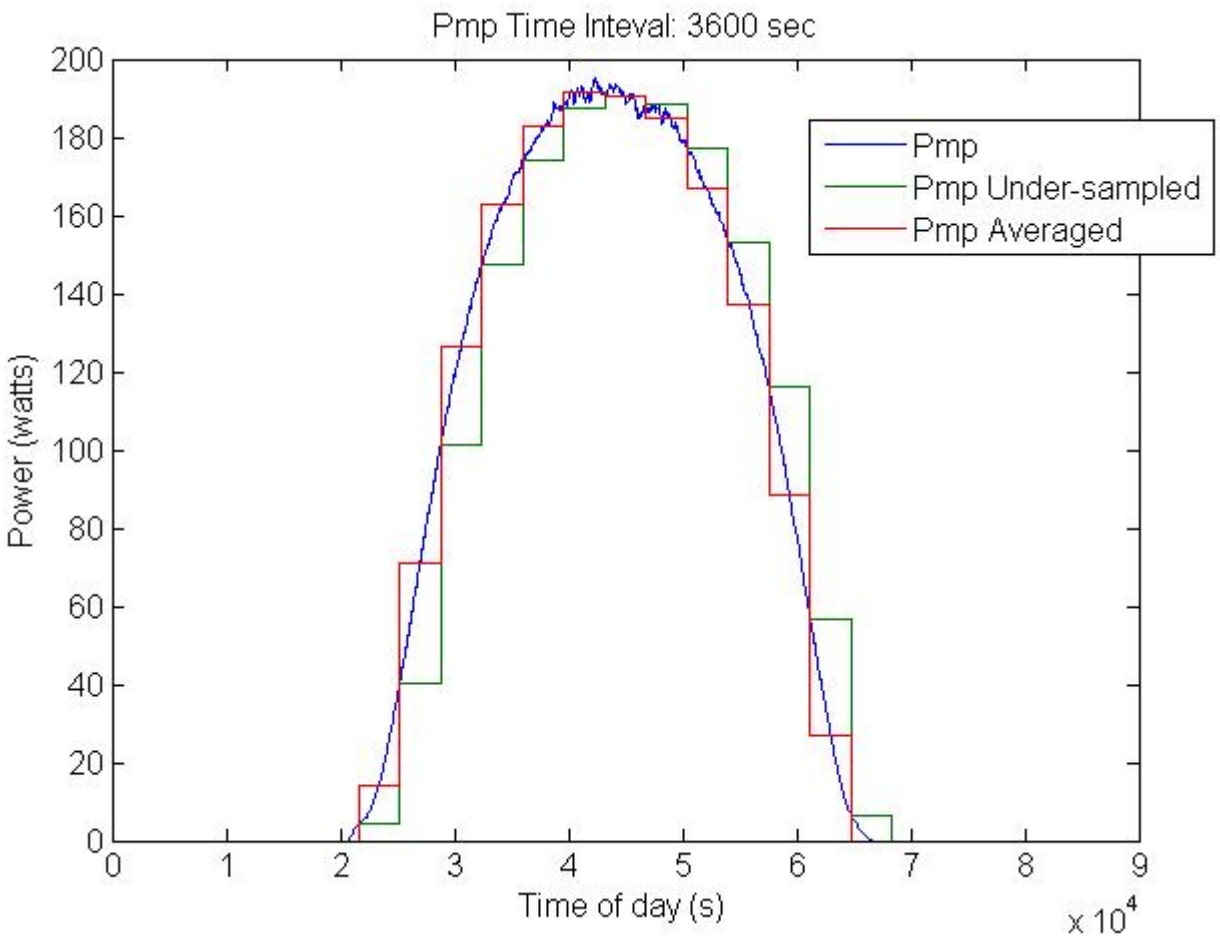
Procedure Graphically



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Primary comparison statistics

- **Root Mean Squared Deviation**

$$\mathrm{RMSD} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(y_i - x_i \right)^2 \right]^{0.5}$$

- **Mean Absolute Error**

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - x_i \right|$$

- **Daily Energy Deviation**

$$\mathrm{DED} = \sum_{i=1}^{n} \left[\left(y_i - x_i \right) * \left(t_{i+1} - t_i \right) \right]$$

All statistics were divided by module W_P to allow for comparison between modules and scaling from module to array size

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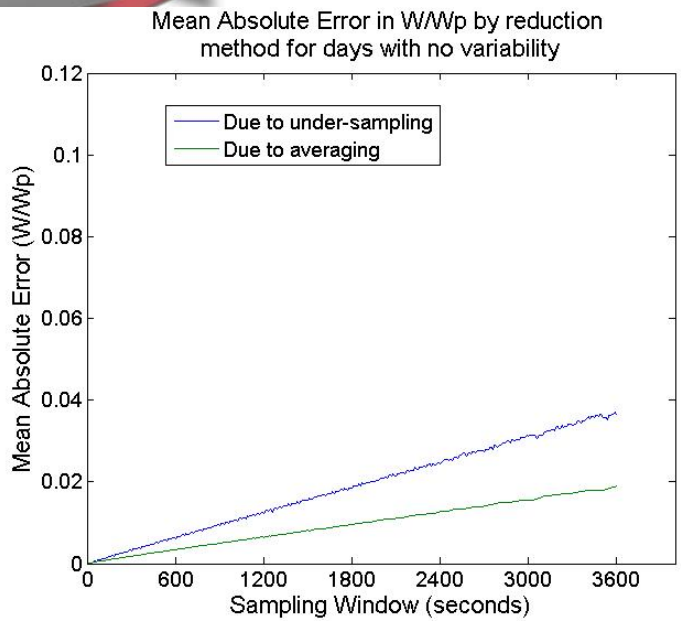
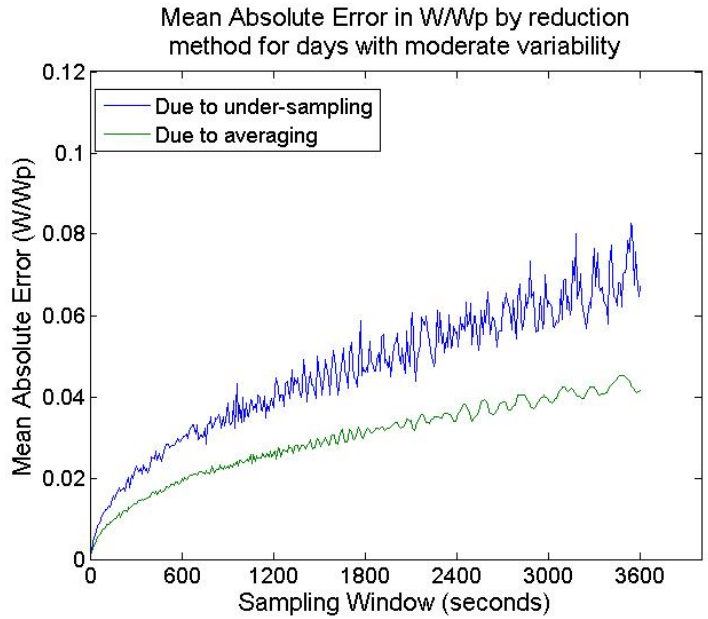
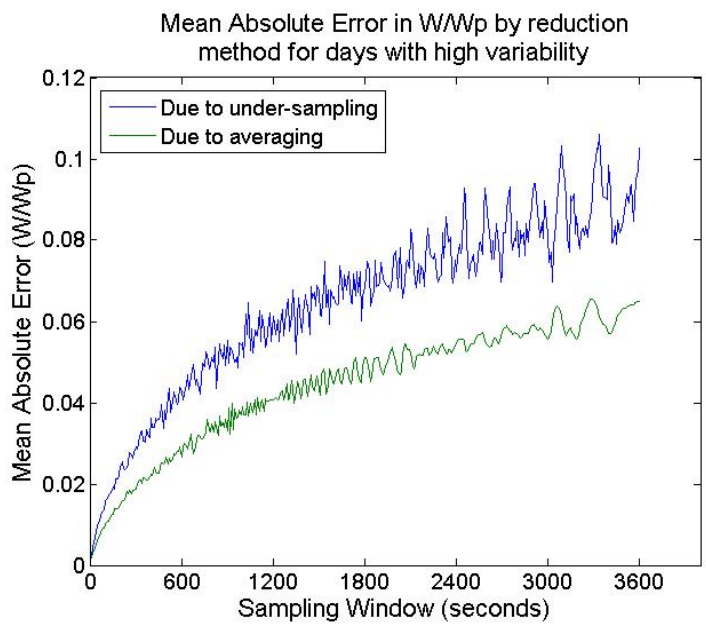
Under-Sampling vs. Averaging





- **Regardless of the day, under-sampling always produced more errors as shown by the MAE**



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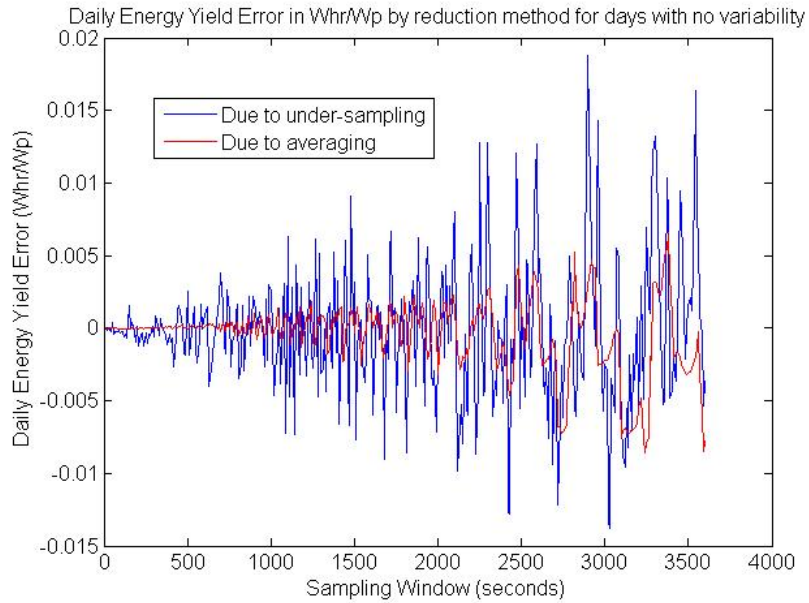
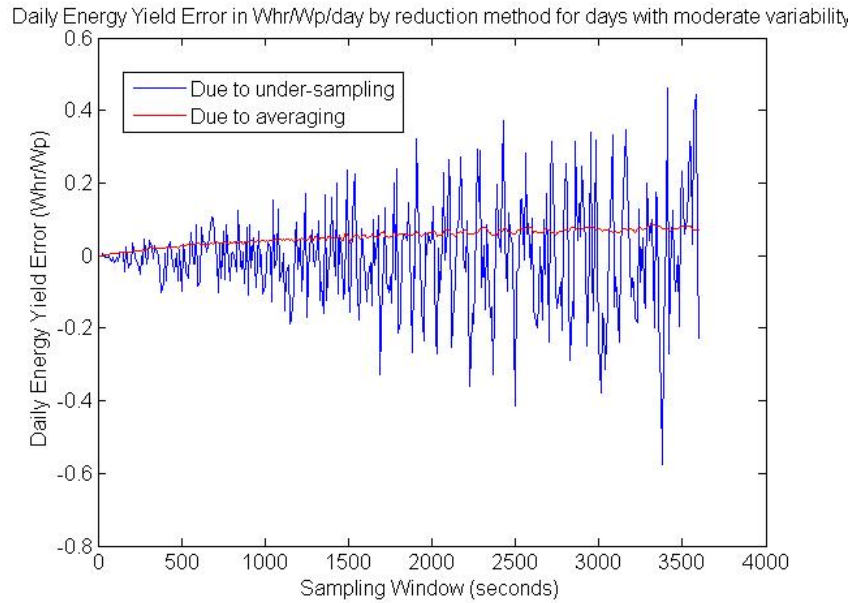
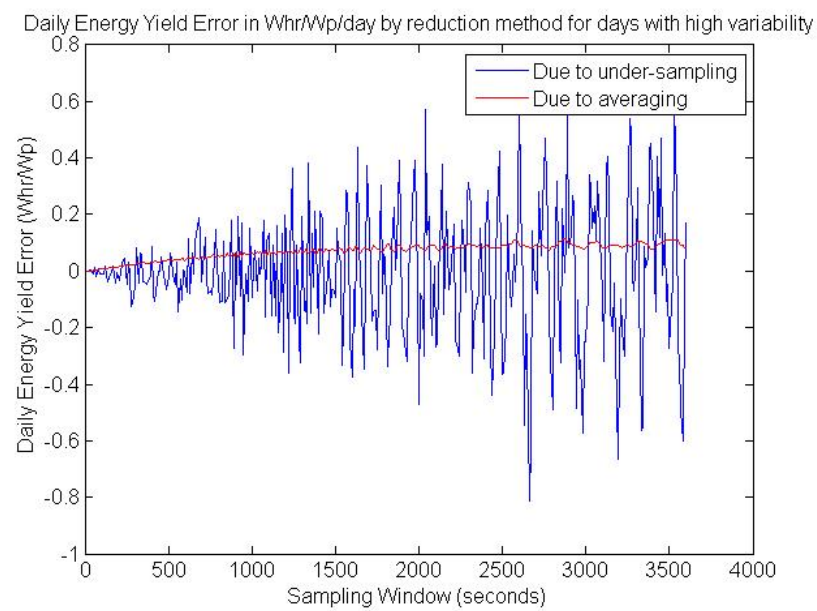
Under-Sampling vs. Averaging

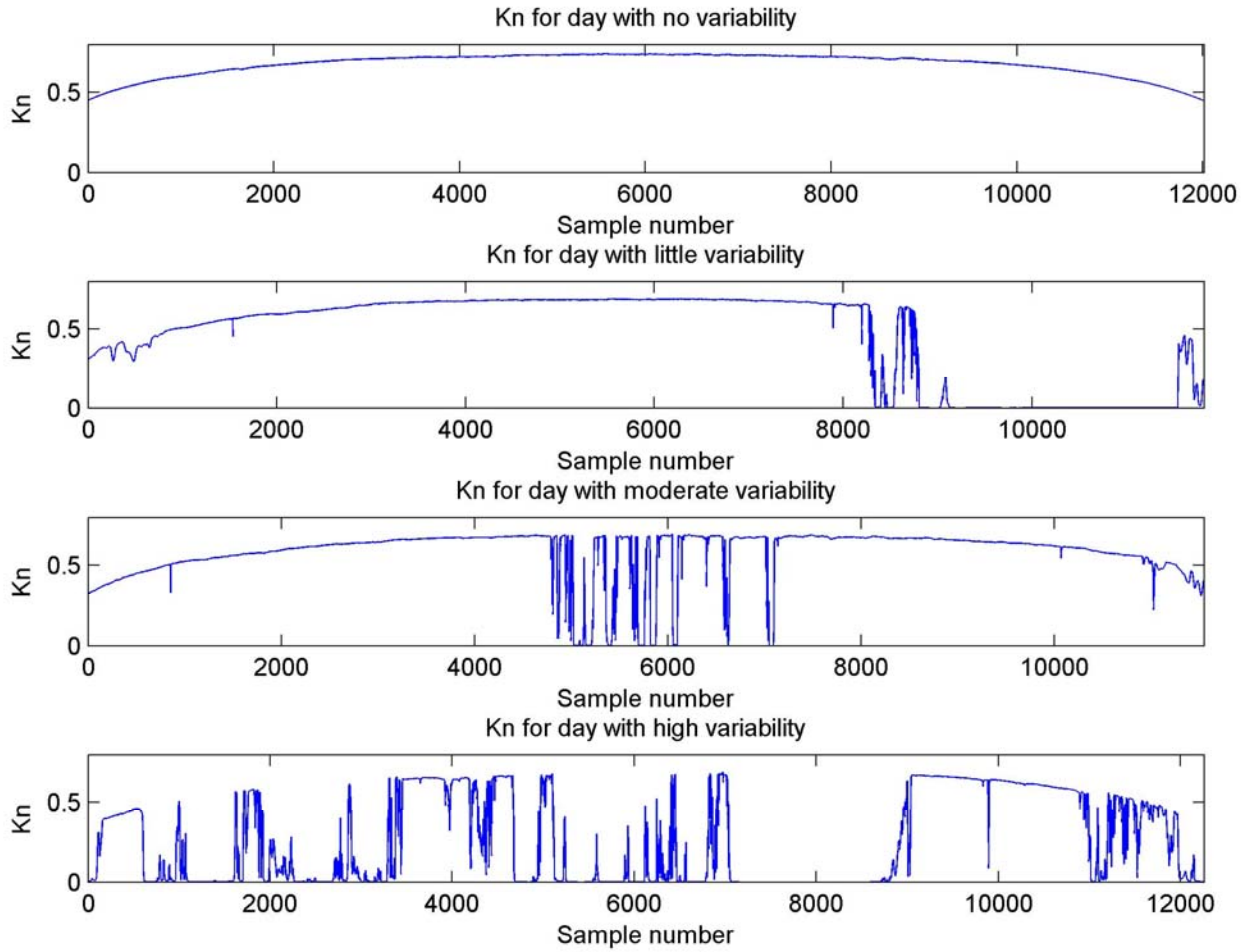




- **Energy yield errors show a larger discrepancy between under-sampling and averaging than the MAE might indicate**
- **Energy yield errors obtained by under-sampling are an order of magnitude smaller for days with no variability**



Daily variability binning



- **Days were binned by variability based on variance of direct beam transmittance, Kn**
  - **4 bins, “No variability”, “Little variability”, “Moderate variability”, and “High variability”**
  - **3 days per bin**

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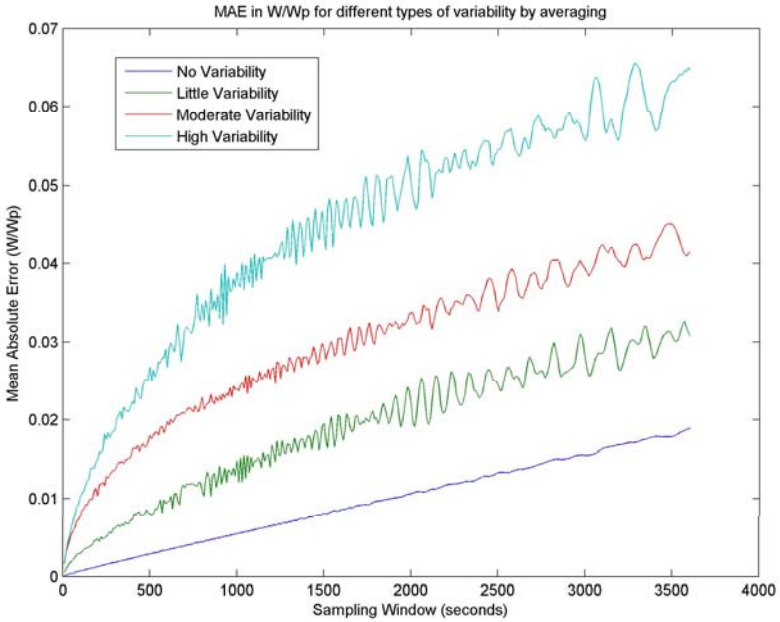
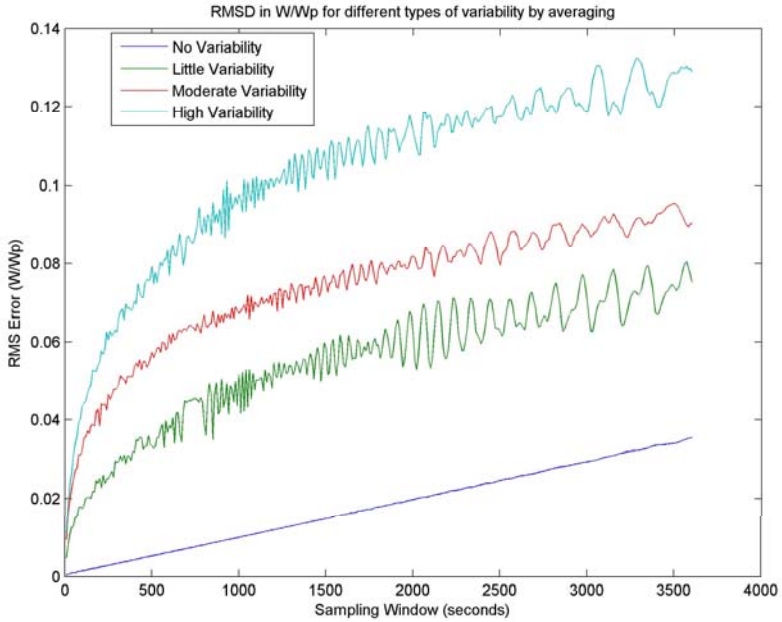
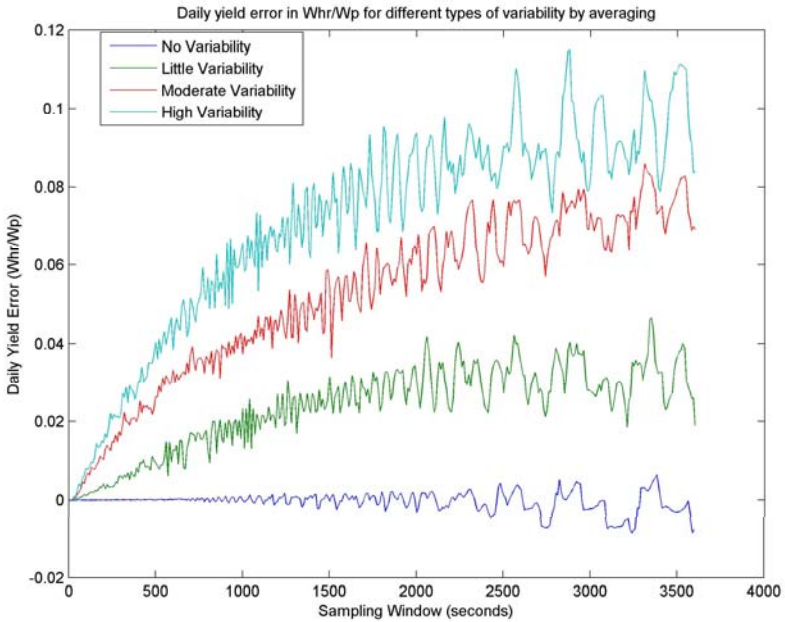
Daily variability results







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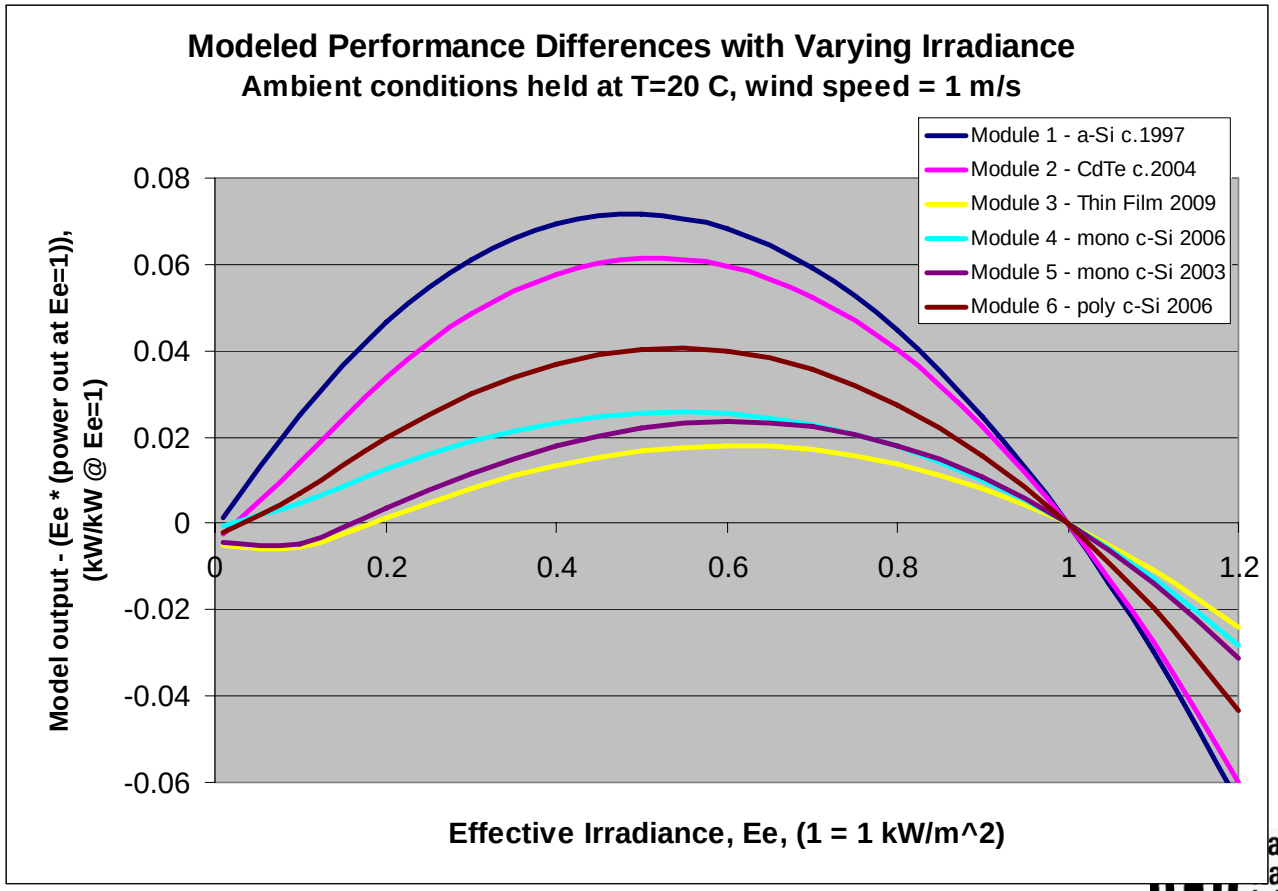
Error differences increased for some modules

- **Modules respond non-linearly to changes in irradiance**
- **Averaging of irradiance data shifts a portion of annual insolation from high and low irradiances to some medium irradiance**



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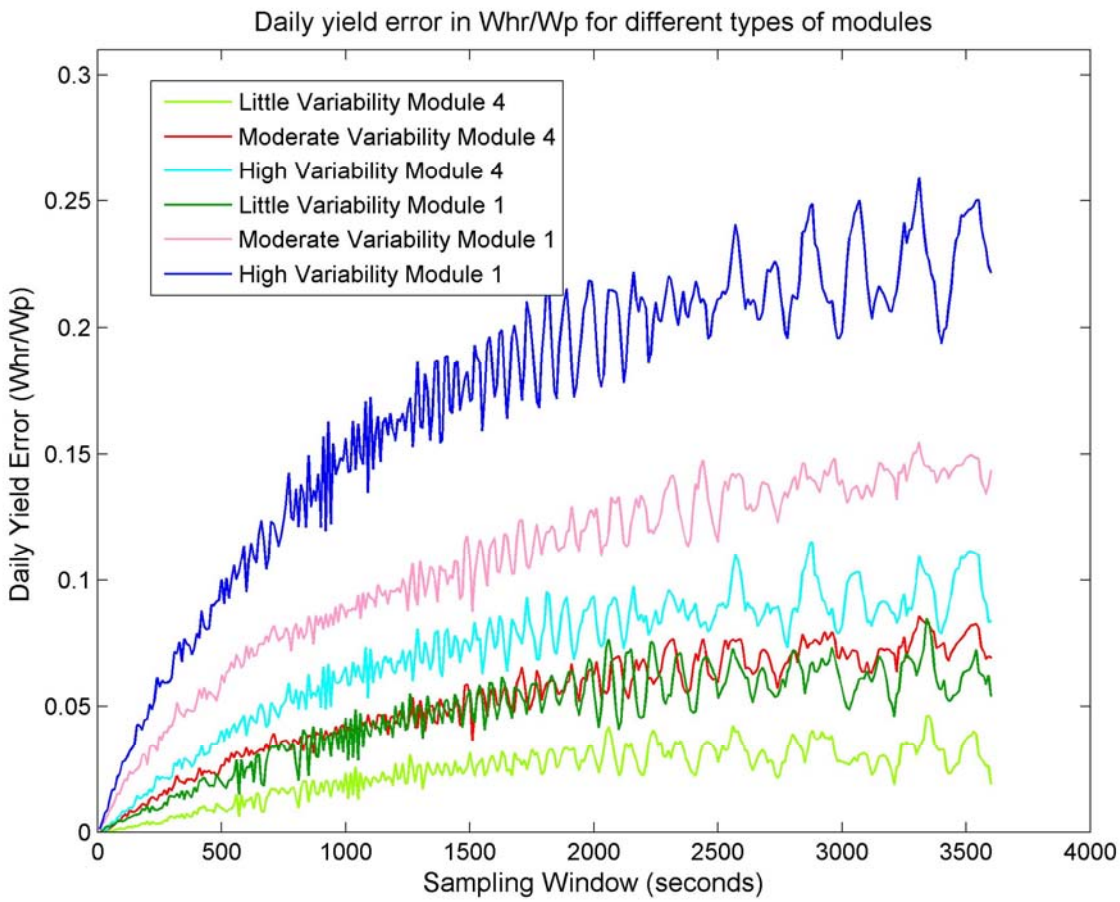
Energy errors vary by module type

- **Modeling modules which increase in efficiency with falling light level will artificially increase energy predictions if averaged irradiances are used**



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What is the best sampling rate and method?

- Depends on your tolerance to error, application, equipment capability, location, and other factors
- A modeler should be aware of the errors which may be induced by sampling and adjust accordingly
  - Sampling faster to achieve less error
  - Attaching larger error bars to output predictions

Conclusions

- When possible, taking many samples and averaging to reduce data produces smaller errors than simply sampling less frequently
- As daily variability increases, errors induced due to sample rate also increase
- Averaging of irradiance data compounds with module nonlinear response to irradiance to over predict energy generation for many module types
  - Since the nonlinearities differ based on module, the amount of over prediction varies by module, making comparisons more difficult

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References

- S. Ransome, and P. Funtan, “Why Hourly Averaged Measurement Data is Insufficient to Model PV System Performance Accurately”, Twentieth European PVSEC, 2005
- D.King et al., “Photovoltaic Array Performance Model”, SAND 2004-3535, 2004

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Thank You !

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