Fusing Satellite-Derived Irradiance and Point Measurements through Optimal Interpolation GC51C-1170

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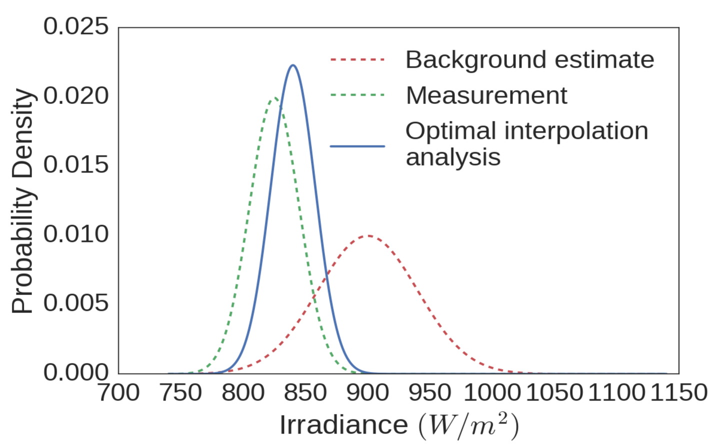
Summary

- **Motivation:** Accurate irradiance estimates are needed for resource assessment, real-time estimates of PV power generation, and forecasts of PV power generation.
- **Idea:** Combine satellite derived irradiance estimates over a large area with sparse, accurate irradiance measurements though optimal interpolation.
- **Results:** Optimal interpolation reduces root mean square error (RMSE) by up to 50% and nearly eliminates mean bias error (MBE).

Essentials of optimal interpolation

Suppose a model suggests that irradiance outside is ~900 W/m² and a sensor measures the irradiance to be ~850 W/m². How can you optimally combine these two pieces of information?

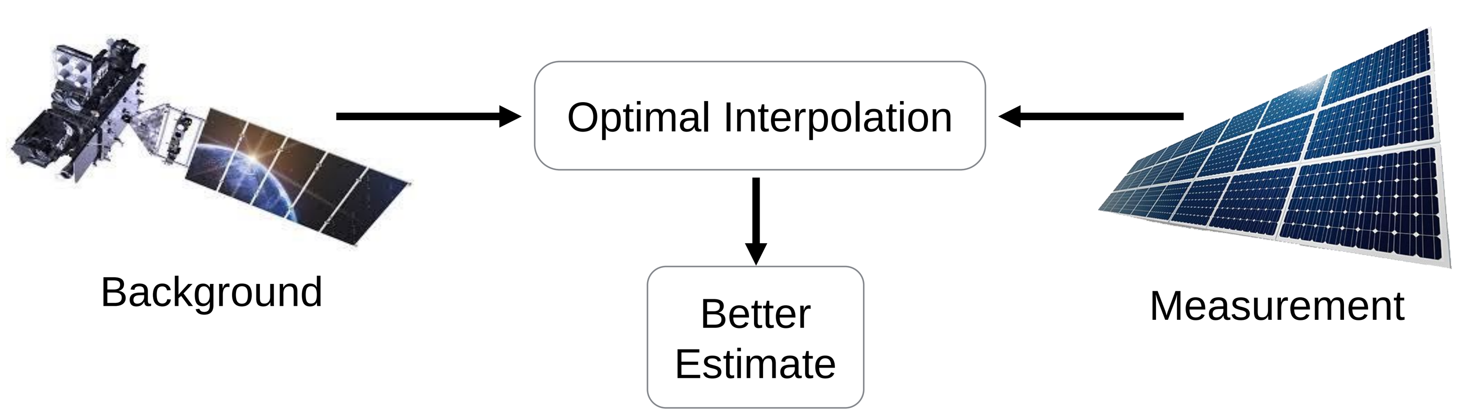
- Call your estimated value x_b and the measurement y.
- The error variances, σ_y^2 and σ_b^2, measure how large of an error you expect from each estimate.
- Optimal interpolation (equivalent to least squares) is the best, linear, unbiased estimate of the true value.
- The optimal interpolation result (known as the analysis) is given by:



$$x = x_b + w(y - x_b)$$

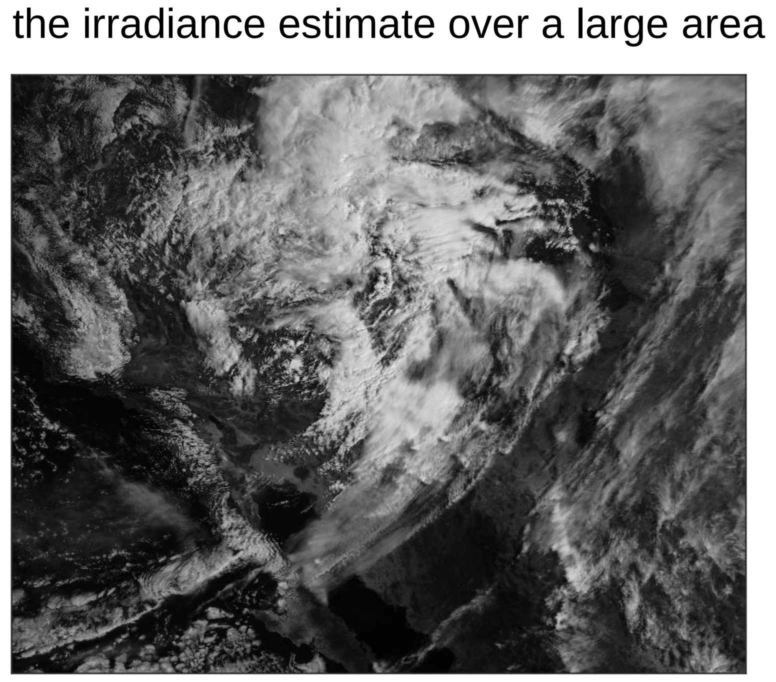
where

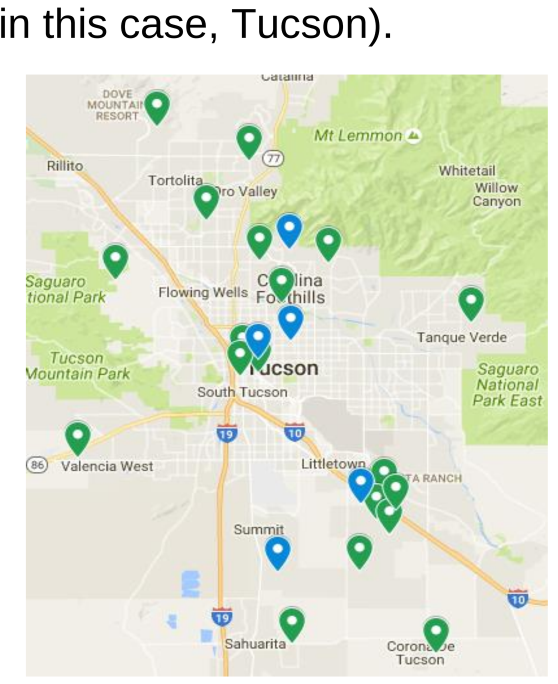
$$w = \sigma_b^2(\sigma_y^2 + \sigma_b^2)^{-1}$$



Satellite and ground data

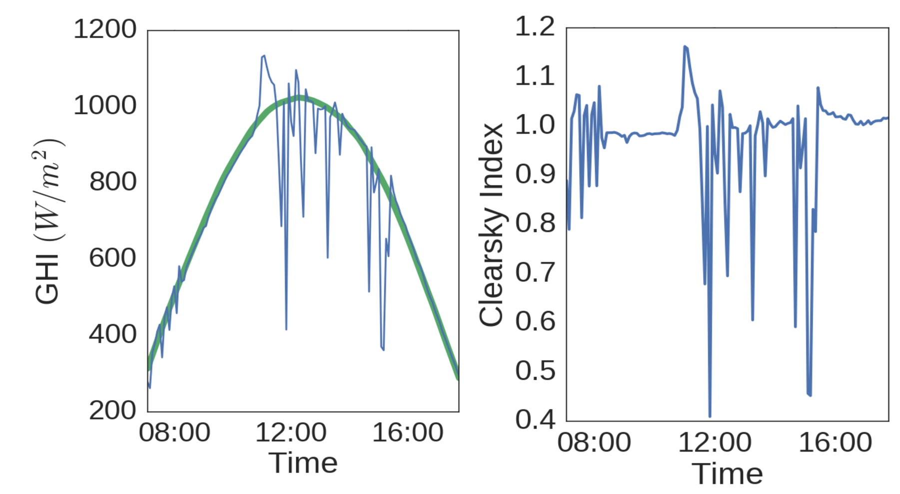
- Data are derived from two sources, geostationary satellite images and ground irradiance measurements from sensors and PV cells.
- Optimal interpolation enables accurate but sparse ground data to improve the irradiance estimate over a large area (in this case, Tucson).

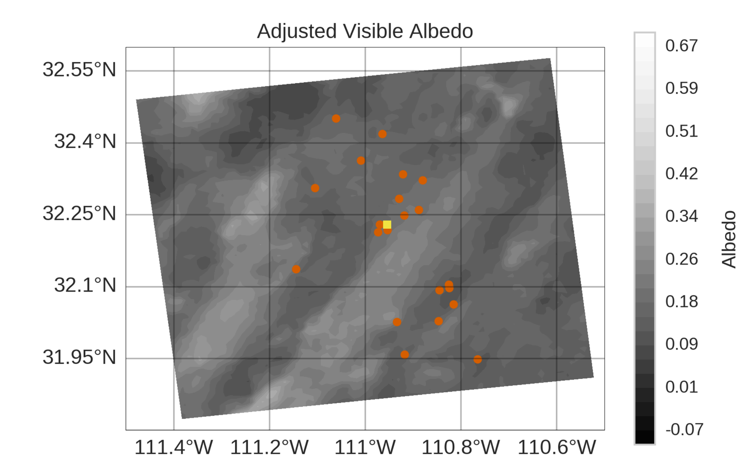




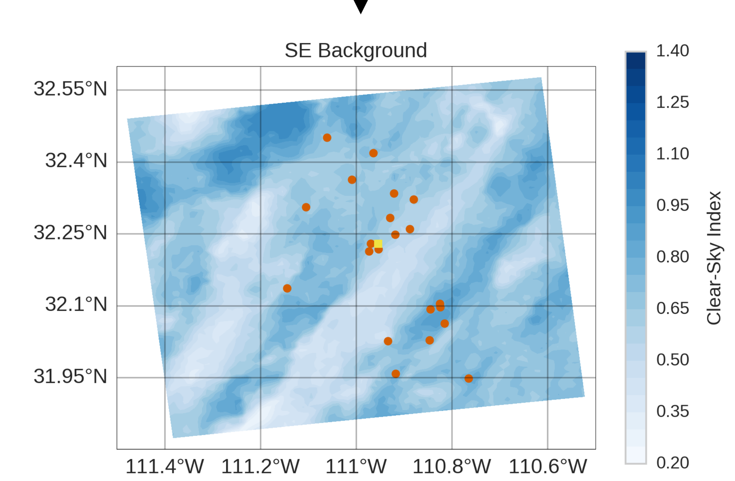
Optimal interpolation with satellite data

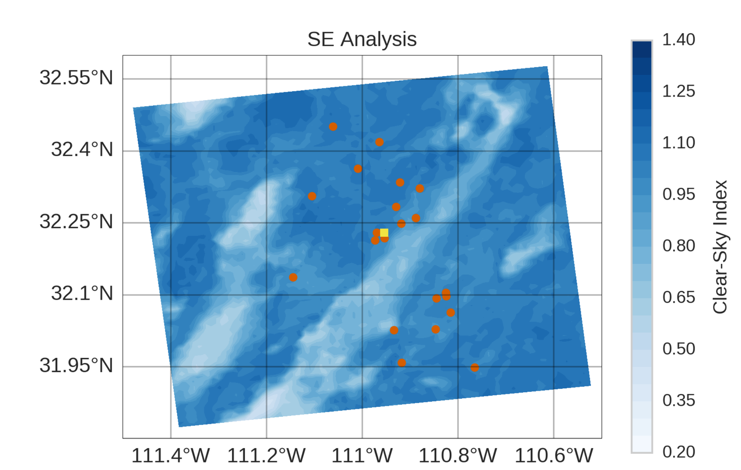
We remove the effects of time of day, time of year and unit of measurement by converting sensor and PV data to a clear sky index. This is done by dividing the measured irradiance or power production by the irradiance or power production under a clear sky.





Visible satellite images are converted to a surface irradiance estimate using two models: a physical model (UASIBS) and a semi-empirical model (SE). The background, $\mathbf{x}_b$, is this surface irradiance divided by the clear sky expectation. Optimal interpolation (OI) combines measurements, $\mathbf{y}$, with this background to form the analysis, $\mathbf{x}_a$.



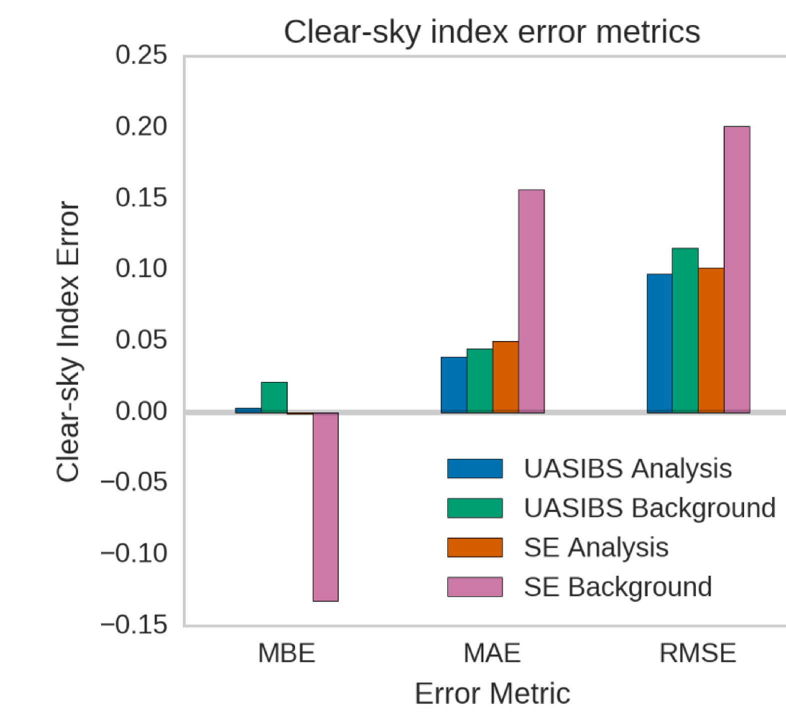


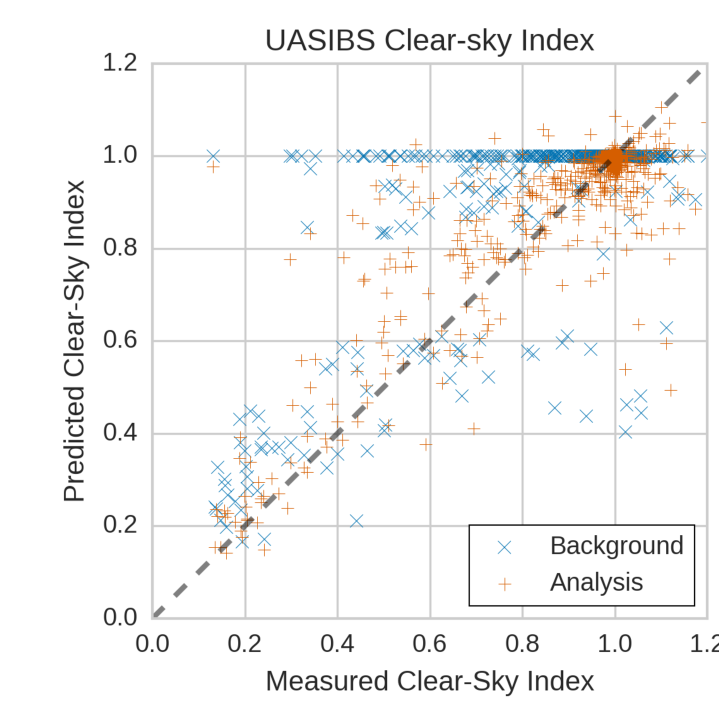
$$\mathbf{P} = \mathbf{D}^{1/2}\mathbf{C}\mathbf{D}^{1/2}$$
$$\mathbf{W} = \mathbf{P}\mathbf{H}^T(\mathbf{R} + \mathbf{H}\mathbf{P}\mathbf{H}^T)^{-1}$$
$$\mathbf{x}_a = \mathbf{x} + \mathbf{W}(\mathbf{y} - \mathbf{H}\mathbf{x}_b)$$

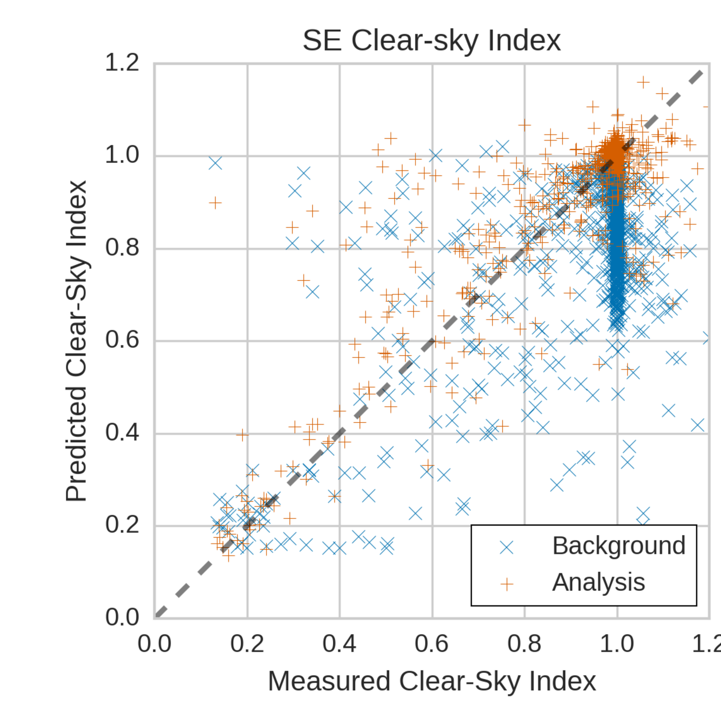
- $\mathbf{C}$ is the satellite correlation matrix. Points in the background are more correlated if they have a similar visible satellite image pixel value. For example, if two points have a similar pixel value in the visible satellite image the clouds over the two points will likely have similar properties.
- $\mathbf{D}$ is the background error variance. It describes how far from the truth one can expect the background irradiance estimate to stray.
- $\mathbf{P}$ and $\mathbf{R}$ are the satellite and sensor error covariance matrices. If we know the error at one location this will tell us what to expect at others.
- $\mathbf{R}$ is a diagonal matrix because we expect the *error* correlation between sensors to be negligible.
- $\mathbf{H}$ maps points in the satellite image to sensors on the ground.
- $\mathbf{W}$ is the weight matrix. The larger the weight the more we trust our ground observations.
- Parameters for calculating $\mathbf{C}$ and $\mathbf{D}$ (including the correlation variable and inflation parameter) have been optimized over a tuning dataset.

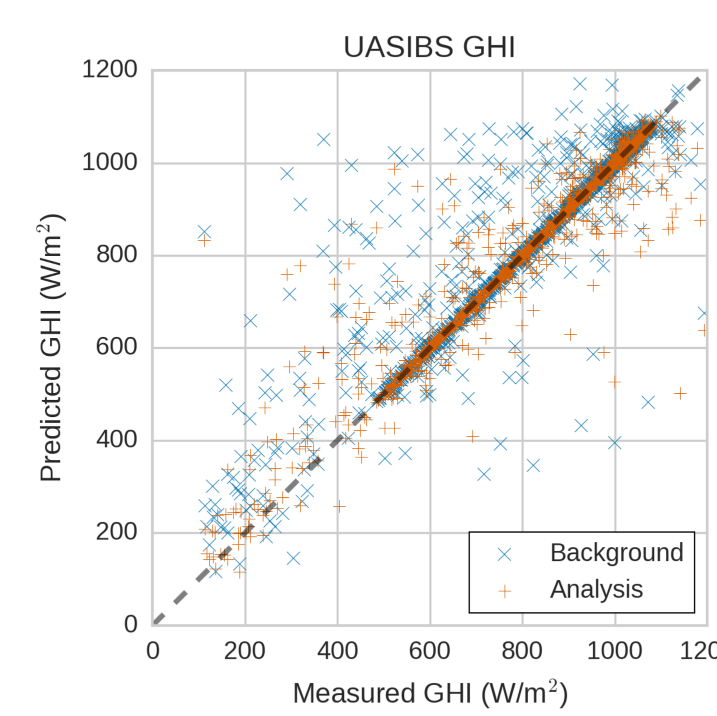
Results

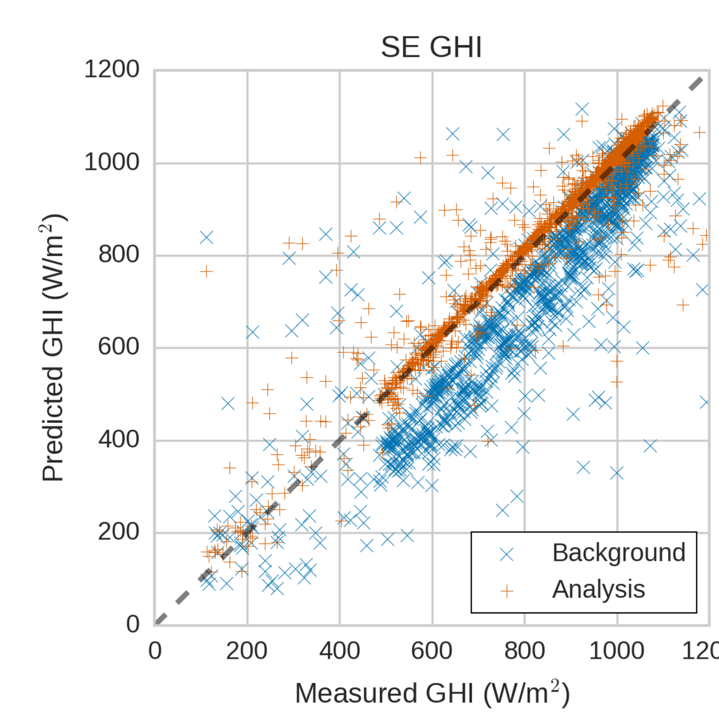
- Errors are calculated for sensors not included in the OI routine for 3 months of data
- MBE is nearly eliminated for both satellite models
- After OI, the two models have similar RMSE
- RMSE has decreased by nearly 50% for the SE model
- Scatterplots of predicted vs measured GHI and clear-sky index further illustrate the improvements of the analysis (after OI) over the background (before OI)











Future work

- Combine satellite images with a numerical cloud advection model and ground irradiance measurements using a Kalman filter in order to create forecasts.
- Determine the feasibility of using sensors in Tucson to improve satellite estimates 100 miles away when weather patterns allow.

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