Optimal Interpolation of Satellite Derived Irradiance and Ground Data

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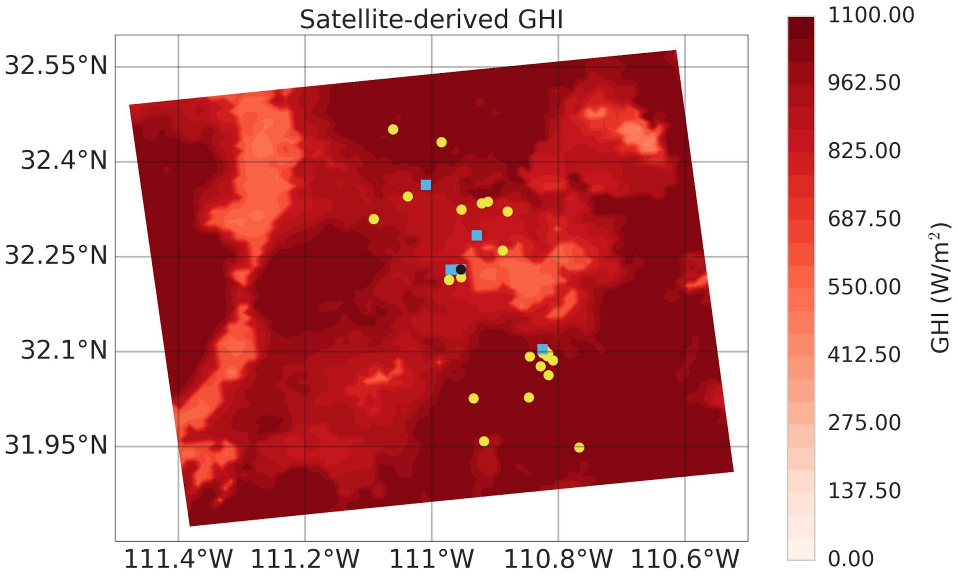
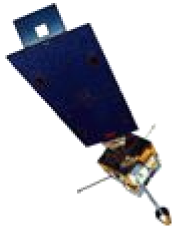
Introduction



Satellite estimates of GHI important for:

- Resource assessment
- "Behind the meter" generation estimates
- Satellite-derived irradiance forecasts

Optimal Interpolation



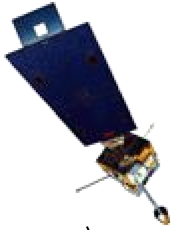
Optimal Interpolation

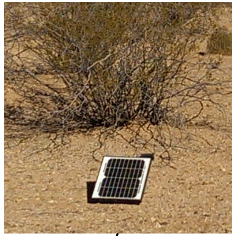
Better satellite-derived estimate of GHI

- Bayesian technique derived by minimizing the mean squared distance between the field and observations
- Is the best linear unbiased estimator of the field
- Same as the update step in the Kalman filter

Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

OI Algorithm





Maps points from satellite image to observations

Better GHI estimate

$$x_a = x_b + W(y - Hx_b)$$

$$W = PH^T(R + HPH^T)^{-1}$$

Need to a way to estimate these error covariances

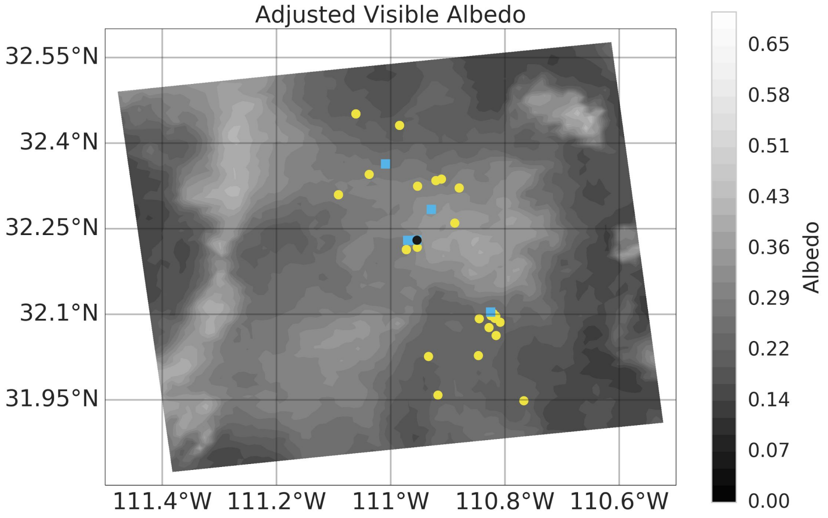
Satellite image from http://goes.gsfc.nasa.gov/text/goesnew.html

Error Covariances: P and R

- Decompose **P** into diagonal variance matrix and correlation matrix:

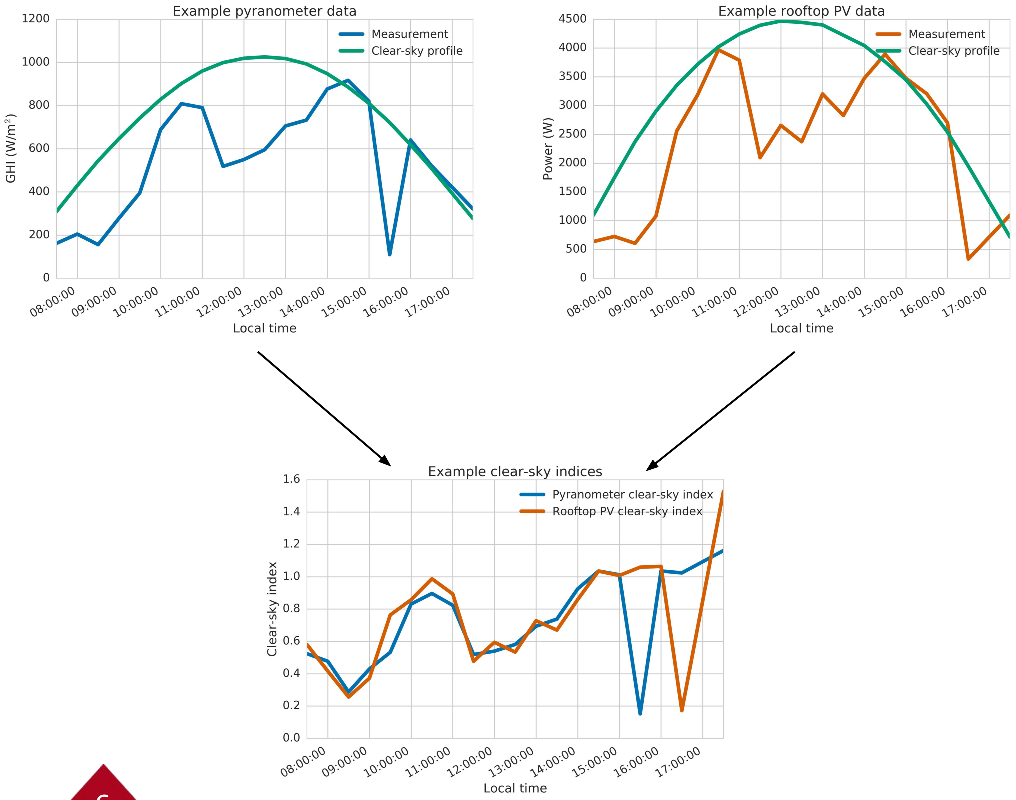
$$\mathbf{P} = \mathbf{D}^{1/2}\,\mathbf{C}\,\mathbf{D}^{1/2}$$

- Prescribe a correlation between image pixels based on the ***difference in cloudiness*** to construct **C**
- Compute **D** from processed images
- Assume observations are uncorrelated and estimate **R** from data



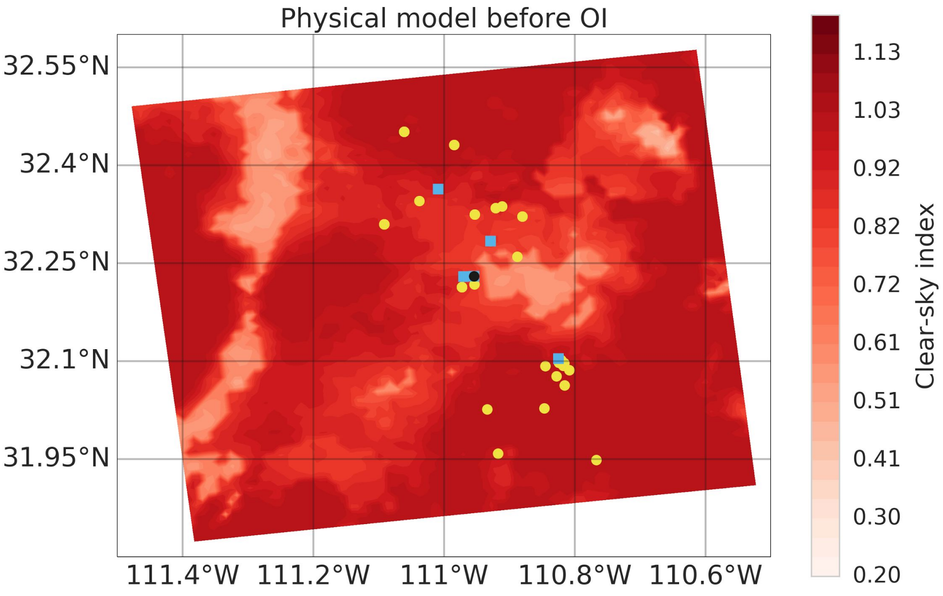
Observations

- 22 sensors (5 reserved for error analysis)
- Sources:
  - Calibrated pyranometer
  - Rooftop PV power
  - Custom irradiance sensors
- Converted to clear-sky index with clear-sky profiles

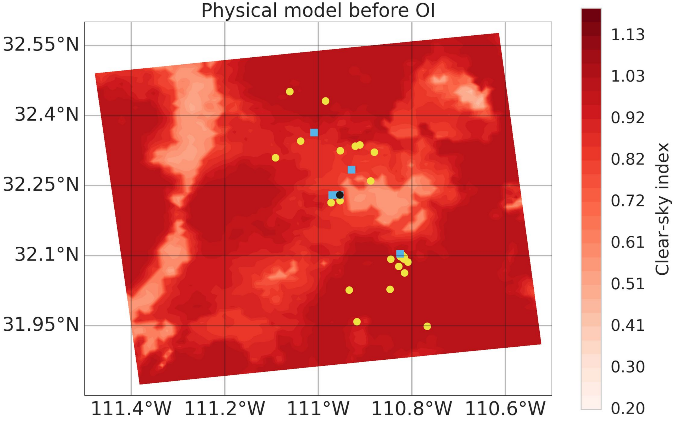


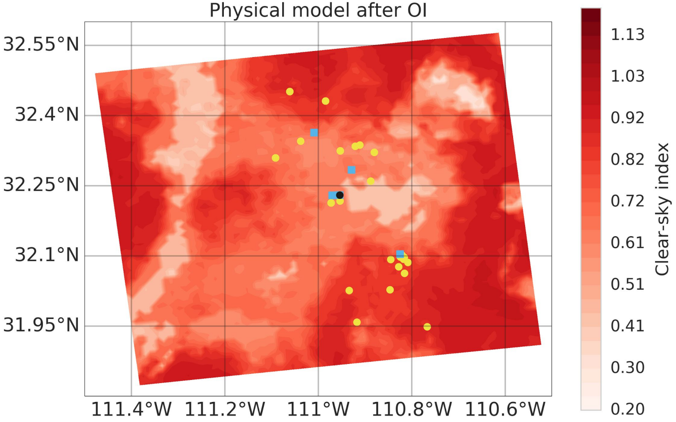
Satellite-derived GHI estimate

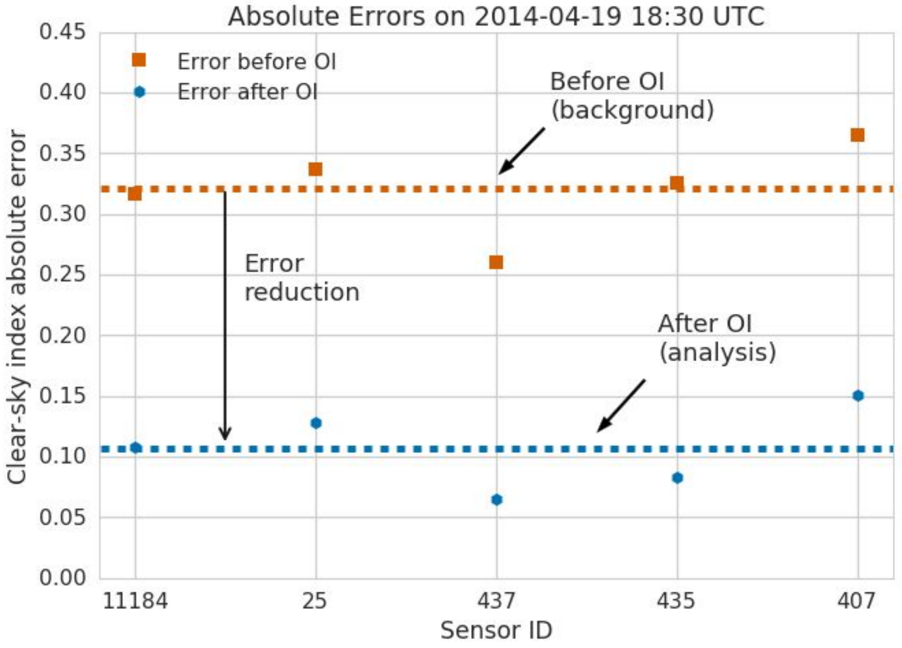
- Two conversion models:
  - An empirical model that applies some regression to data from visible images
  - A physical model using the visible and infrared images to determine cloud locations and properties
- Nominally 1 km resolution
- Using 75 km x 82 km section



Results (one image)

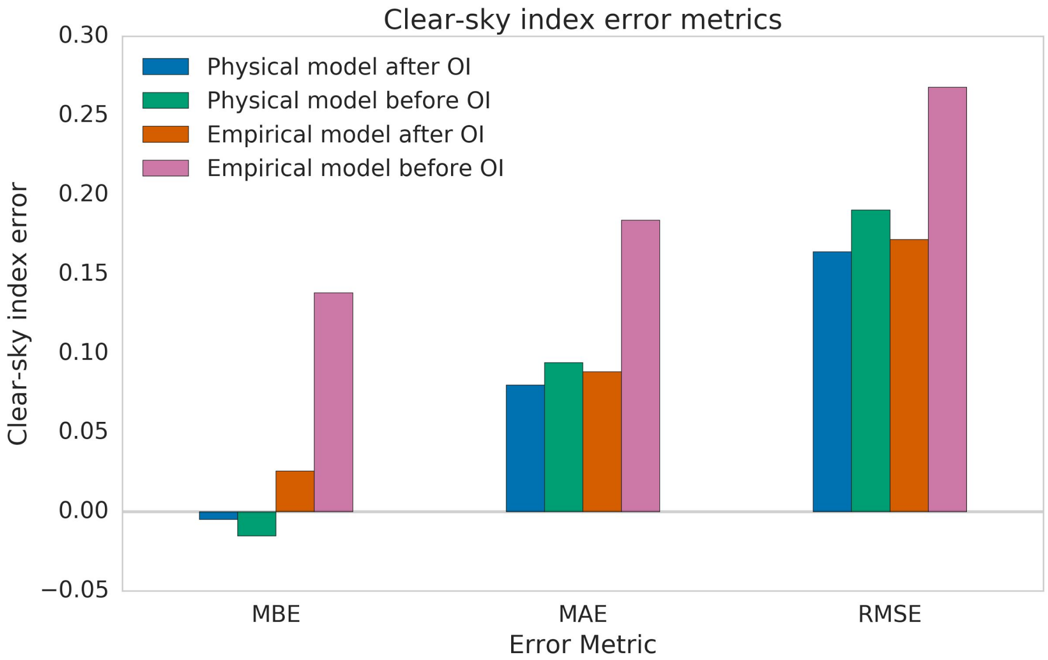




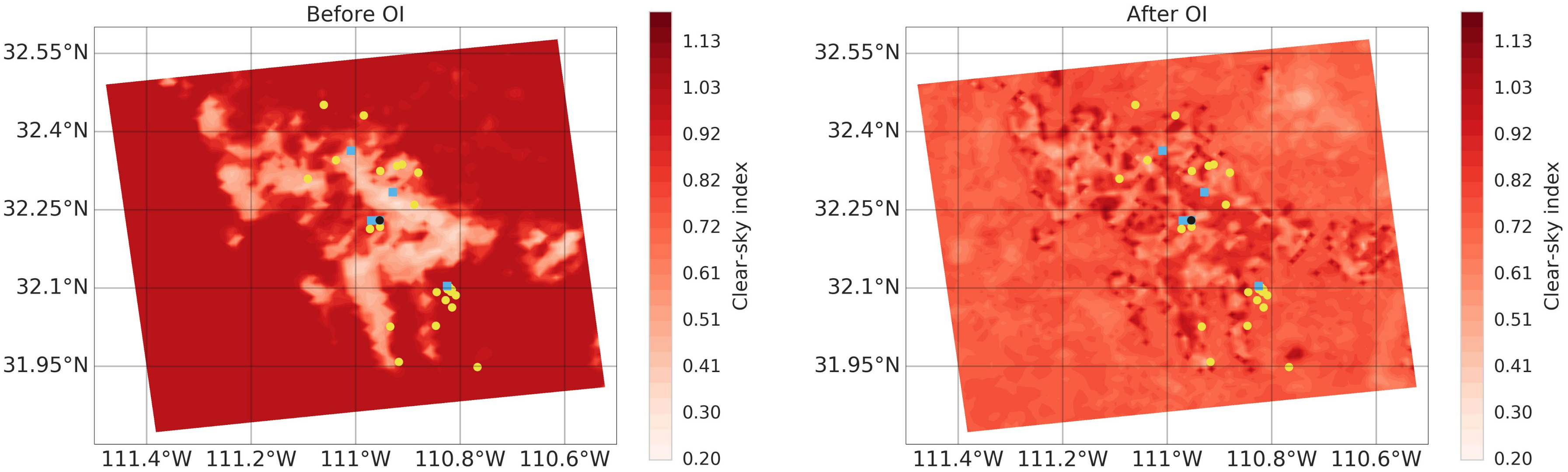


Results

- 1200 times analyzed with 700 clear and 500 cloudy times
- Evaluated against 5 sensors that were not used in OI
- The large bias for the empirical model was reduced

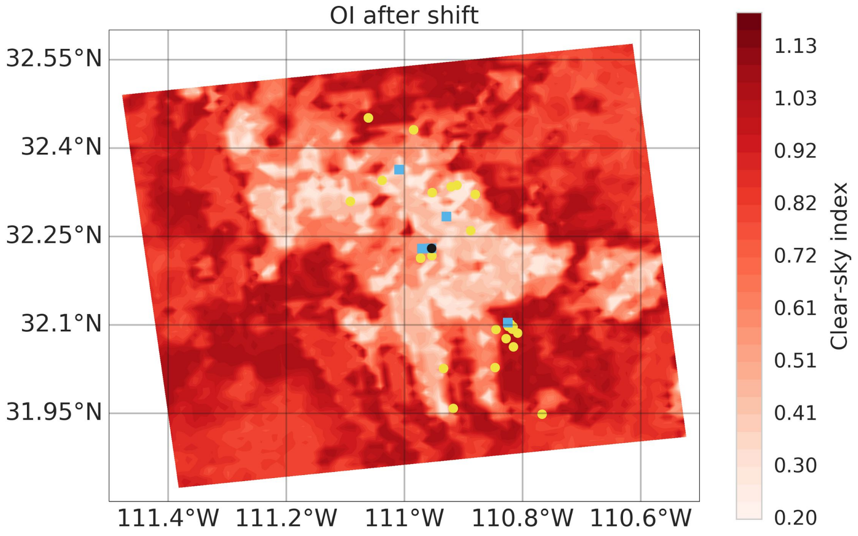


What can go wrong?



Parallax

- OI is sensitive to where the background image clouds are placed
- Cloud height and solar zenith affect where the shadow of the cloud is on the ground
- Shifting the background image slightly produces a more reasonable analysis



Future Work

- Reduce parallax error
- Study many correlation functions in depth
- Extend analysis area; can sensors in Tucson improve estimates of GHI in Phoenix?

Acknowledgments

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TEP

REN
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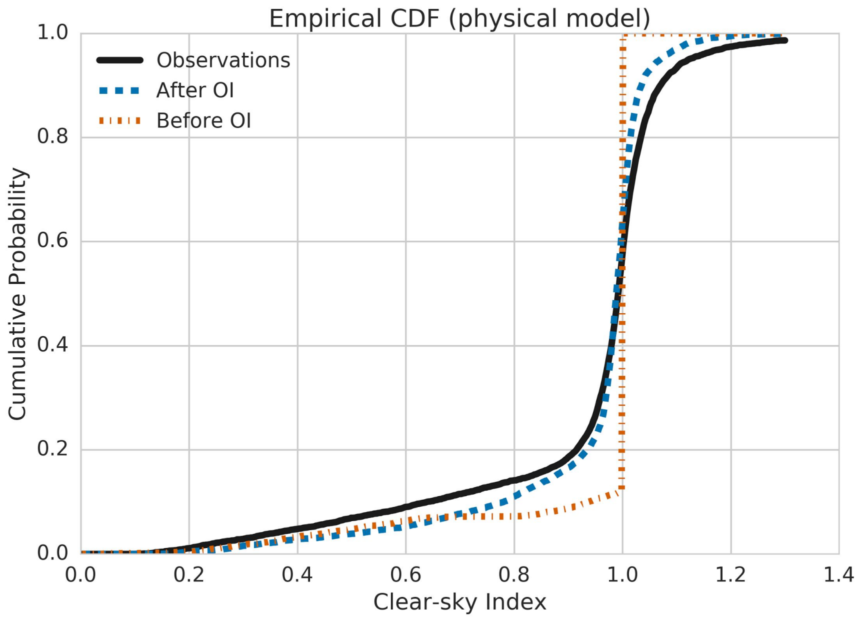
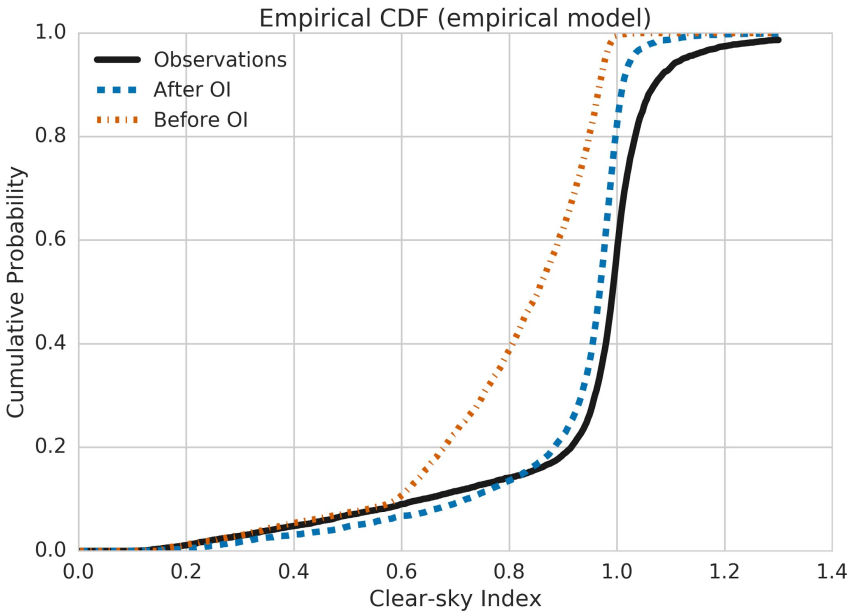
Results



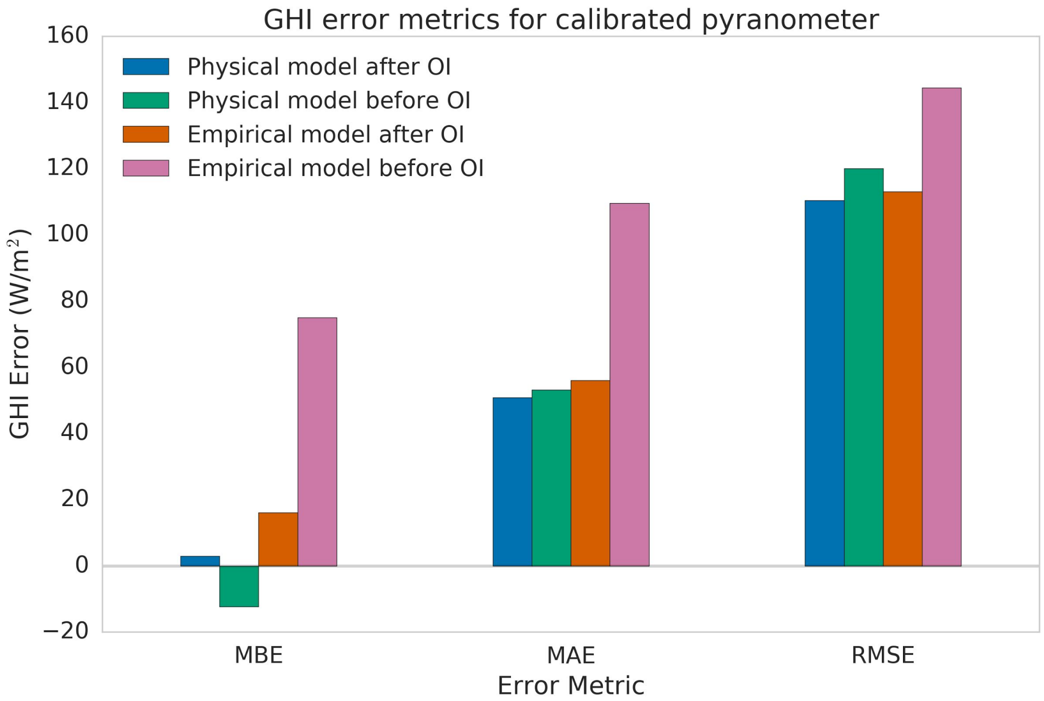
Empirical CDF (physical model)
Observations
After OI
Before OI
Cumulative Probability
Clear-sky Index
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4



Empirical CDF (empirical model)
Observations
After OI
Before OI
Cumulative Probability
Clear-sky Index
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4

Results

- GHI error metrics for the calibrated pyranometer show modest improvements for the physical model



Correlation Function

1. We take the visible brightness counts from the satellite (b_i) and convert to an adjusted albedo

$$v_i = \left(\frac{b_i}{255}\right)^2 / \cos(\phi_i)$$

2. The absolute difference between each pixel is calculated and

$$d_{ij} = |v_i - v_j|$$

3. We apply some correlation function to this "distance"

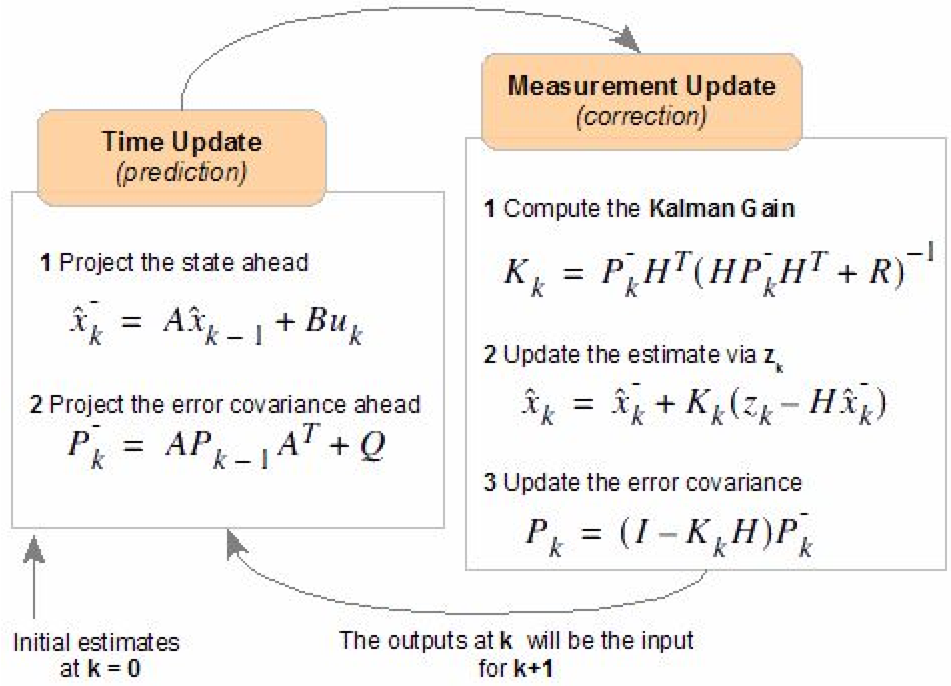
$$c_{ij} = k(d_{ij})$$

$$k(r) = \begin{cases} 1 - \frac{r}{l} & r < l \\ 0 & r \geq l \end{cases}$$

$$k(r) = \exp\left(-\frac{r}{l}\right)$$

$$k(r) = \exp\left(-\frac{r^2}{l^2}\right)$$

Extension to Kalman Filter



http://bilgin.esme.org/BitsAndBytes/KalmanFilterforDummies