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# Optimal interpolation of satellite and ground data for irradiance nowcasting at city scales

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ABSTRACT

We use a Bayesian method, optimal interpolation, to improve satellite derived irradiance estimates at city-scales using ground sensor data. Optimal interpolation requires error covariances in the satellite estimates and ground data, which define how information from the sensor locations is distributed across a large area. We describe three methods to choose such covariances, including a covariance parameterization that depends on the relative cloudiness between locations. Results are computed with ground data from 22 sensors over a $75 \times 80$ km area centered on Tucson, AZ, using two satellite derived irradiance models. The improvements in standard error metrics for both satellite models indicate that our approach is applicable to additional satellite derived irradiance models. We also show that optimal interpolation can nearly eliminate mean bias error and improve the root mean squared error by 50%.
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## 1. Introduction

Estimates of global horizontal irradiance (GHI) are essential at many stages of photovoltaic (PV) system deployment and operation. A widely used technique is to compute GHI from geostationary satellite images, which are typically available every 15–30 min and cover large areas of the globe. Such satellite derived estimates of GHI are commonly used to design and site PV power plants (Vignola et al., 2013), to forecast the output of a fleet of PV generators (Kühnert et al., 2013), and to provide real-time estimates of distributed generation (DG) or "behind the meter" generation of rooftop PV systems (Saint-Drenan et al., 2011). Satellite derived estimates have also been used to detect failures in PV systems (Drews et al., 2007).

In addition to satellite derived GHI estimates, one may have access to ground sensors that provide more accurate GHI measurements, but are often sparsely distributed. We present a method that combines the broad areal coverage of satellite derived GHI with the accurate point measurements from ground sensors in order to provide more accurate GHI estimates for city-scale areas.

Similar techniques have used ground measurements to improve satellite derived irradiance estimates in the context of improving daily (or longer) irradiance estimates. Much of this work studies so called site adaptation techniques with the goal of improving multi-year satellite irradiance estimates using a limited measurement campaign from ground sensors (Polo et al., 2016). A number of studies use Kriging methods that rely on spatial interpolation of the ground data along with satellite derived estimates (D'Agostino and Zelenka, 1992; Journée et al., 2012; Frei et al., 2015). Others use linear bias corrections (Polo et al., 2015), polynomial bias corrections (Mieslinger et al., 2014), or apply a polynomial to correct the satellite cumulative distribution function (Schumann et al., 2011). Ruiz-Arias et al. (2015) used optimal interpolation (OI) with numerical weather prediction solar radiation data and monthly-averaged daily GHI values from ground sensors.

OI is a Bayesian technique often used in geophysics, in particular numerical weather prediction, to combine models and observations. OI is mathematically equivalent to 3D variational methods, Kriging, and Gaussian process regression (Low et al., 2015). OI and 3D variational techniques are often used in the field of meteorology, Kriging is used in the context of geostatistics, and one often encounters Gaussian process regression in the context of machine learning. Thus, each method seeks a solution with the approach and quantities, like covariances, appropriate for each context.

In the context of this study, the satellite derived GHI estimates represent the model and the ground sensor data are the observations for OI. We focus on improvements to GHI estimates from a single satellite image using OI rather than improving the

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