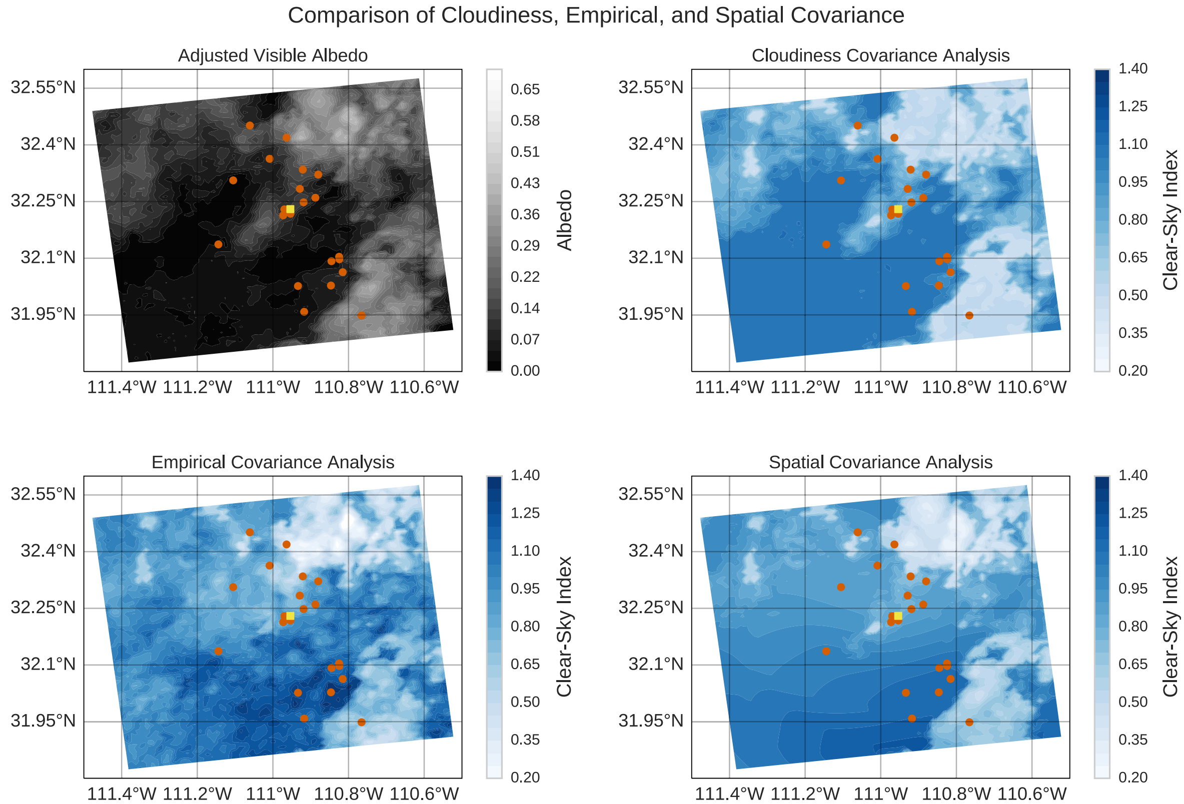

Fig. 6. Example of OI using empirical, spatial, and cloudiness covariance with the UASIBS model. The upper left shows the visible image taken from the satellite with the surface albedo removed. The upper right shows the analysis using cloudiness covariance that generally agrees with the visible albedo image. The analysis computed with an empirical covariance matrix (bottom left) generates clouds in the lower left of the image that are not present in the visible albedo image. The spatial covariance analysis (bottom right) shows a smoothly varying and thin "background cloud" that is inconsistent with the visible albedo image.

semi-empirical model with optimal interpolation and still obtain irradiance estimates that are comparable in quality to estimates from more complicated, physics-based models. This also suggests that the optimal interpolation routine that we have presented is likely to work with satellite image to irradiance models that were not studied here.

OI assumes that the background error is unbiased and Gaussian as described in Eq. (4). However, it is clear from Fig. 5 that the SE background is biased. From Fig. 4, it also appears that the UASIBS background is not Gaussian. Thus, we cannot assume that this application of OI yielded the best linear unbiased estimate, but we show that OI still produces measurable improvements.

The results in Table 3 indicate that any of the three methods to compute the background error covariance matrix produce an analysis that improves upon the background. However, when we subjectively compare the analysis of the covariance models, as in Fig. 6, we see that analysis using the cloudiness covariance method better represents the cloud pattern depicted in the visible satellite image. Clouds produced using the spatial and empirical covariance methods are physically inconsistent with the clouds depicted in the visible albedo image. For example, the lower left corner of the images in Fig. 6 should have no clouds present according to the visible albedo image, but the empirical covariance analysis has clouds present in that region. The analysis produced using spatial covariance shows a thin and smoothly varying "background cloud" that is simply not observed in the visible albedo image. Furthermore, the cloudiness covariance parameterization is calculated for each satellite image individually which likely leads to a better modeling of the spatial heterogeneity of irradiance. Thus, we recommend the cloudiness covariance parameterization as the method of choice, but additional verification sensors evenly distributed throughout the study area may help to better distinguish the parameterizations through objective measures.

8. Conclusions

We presented an application of optimal interpolation that combines ground irradiance sensor data with a satellite derived estimate of irradiance. We systematically analyzed three methods to choose an error covariance matrix for the satellite derived GHI estimates. This covariance matrix is critical to the success of OI. We observed the best results by assigning covariances based on the differences in cloudiness rather than spatial or empirical covariances. Our implementation of OI was trained and evaluated using three months of data in Tucson, AZ. We tuned the model parameters over one-third of the data, and presented the results of OI over the remaining two-thirds.

The results show that OI improves the entire satellite derived irradiance field with data from only a small number of point locations. Furthermore, the success of OI with different satellite derived irradiance models indicates that OI is likely applicable to satellite derived irradiance models not described in this paper.

In future work, we wish to study if OI is applicable to larger areas than the city scale studied here. If, for example, clouds form because of the same physical forcings, OI using cloudiness covariance may be able to use sensors in Tucson to improve irradiance estimates 100 miles away in Phoenix. Furthermore, OI as described in this paper can be extended to a Kalman filter with the use of a cloud advection model. This allows forecasts to be made that also incorporate previous satellite and ground sensor data instead of relying on a single snapshot in time.