Table 1
Summary of error statistics for network forecasts for the 46 days with clouds. Error statistics were calculated for the entire dataset at once. Only forecasts and data with solar zenith angle less than 75° were used. The mean irradiance was $\bar{y} = 662\ \mathrm{W/m^2}$ and the mean clear-sky index was $\bar{k} = 0.92$.

FH (min)	rMAE (%)	MAE (W/m^2)	MBE (W/m^2)	rRMSE (%)	RMSE (W/m^2)	Avg. skill (%)
1	4.96	30.97	−1.44	11.90	82.55	22.96
3	7.51	48.13	−1.39	15.89	110.46	23.09
5	9.29	59.59	−3.91	18.67	127.06	19.65
10	11.39	71.38	−8.59	22.11	141.44	18.63
20	13.23	82.39	−10.46	24.03	152.84	18.66
30	13.95	86.57	−7.52	24.49	154.15	21.21
60	15.45	95.59	−6.65	26.59	160.72	21.00
120	17.02	106.51	−2.01	29.20	172.45	19.58

30 min, our new method performs well. We only used 3 months of data from our real-time network while Lonij et al. used one year of data.

Chu et al. (2015b) produced a cloud tracking forecast of PV power with an ANN applied to a deterministic forecast using a sky imager at a site near the Nevada/Arizona border. The initial deterministic forecast model does not perform well compared to persistence, with negative skills at 5, 10, and 15 min forecast horizons. However, the re-forecast using an ANN technique improves the result with skills of 15.1%, 21.8%, and 26.2% at forecast horizons of 5, 10, and 15 min respectively, which are comparable to our technique. Similar optimization could be applied to our deterministic network forecasts to further improve skill. A Taylor diagram of both the initial deterministic forecast and ANN re-forecast would be useful as another method to assess the forecasts.

Compared to the regression methods in Yang et al. (2015), our forecasts perform comparably at the 5 min forecast horizon. Yang et al. used 1 s irradiance data from Oahu and applied the lasso and ordinary least squares regression methods to make very short term (< 5 min) forecasts. At shorter horizons, both methods can outperform the reference persistence forecast. Since our forecasts approach the clear-sky index persistence model, regression methods are likely a better choice if sub-five minute time horizons forecasts are needed, at least for the region studied here.

6. Conclusion

We presented a deterministic method to forecast irradiance that uses data from a network of irradiance sensors as the primary input. This method can combine the benefits of clear-sky index persistence and spatially-averaged persistence into one forecast. It outperforms a reference clear-sky index persistence model for 1–120 min forecast horizons. Much of this improvement is due to spatial averaging, which shows surprising utility for the region and time period studied. However, network forecasts still exhibit more variability than spatially-averaged persistence, thus we claim network forecasts are better at forecasts horizons less than 30 min. The results presented here used numerical weather model winds at a single layer of the atmosphere to perform cloud advection, so complex cloud movement or incorrect cloud motion vectors likely limited the accuracy. The limited size and density of the network also limits the accuracy of network forecasts.

We showed that forecast skill can be a misleading metric, and we instead used a Taylor diagram to better understand the differences among forecast methods. This lead us to reinterpret our finding that network forecasts show significant skill to 2 h forecast horizons so now we make a more informed claim that network forecasts show meaningful skill out to 30 min forecast horizons. We encourage other authors to make use of Taylor diagrams when assessing the quality of forecasts.

While the method presented may have a limited useful maximum forecast horizon, the irradiance sensor network will be a valuable asset to make other types of forecasts. For instance, regression methods using a network can improve very short time horizon forecasts (Yang et al., 2015). In the future, we could use the network of sensors to improve satellite image forecasts similar to Marquez et al. (2013) and to validate numerical weather model forecasts. We may also study how different interpolation methods affect the results of our network-based forecasting method in a detailed comparison.

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Appendix A. Analysis for both clear and cloudy days

Table A.2 presents error statistics calculated over all 91 days in the study period. As expected, the magnitude of errors is smaller when more clear days are included.