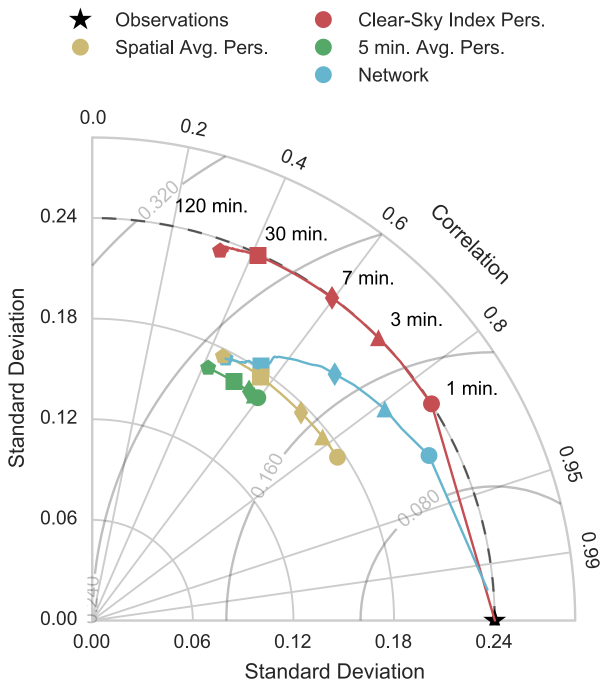

Fig. 13. Taylor diagram for clear-sky index persistence (red), spatially-averaged persistence (yellow), 5-min time-averaged persistence (green), and network (light blue) forecasts for 1 min (circle), 3 min (triangle), 7 min (diamond), 30 min (square), and 120 min (pentagon) forecast horizons. The black dashed line indicates the standard deviation of the data. Solid contours around the observations point are lines of constant CRMSE. Forecasts for clear-sky index were used so all quantities are dimensionless. At the 120 min forecast horizon, the spatially-averaged persistence and network points overlap. Network forecasts start with a standard deviation near that of the measurements, but this decreases at longer time horizons as the network forecast begins to resemble spatially-averaged persistence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

less than 30 min. Regardless of their forecast skill metric scores, assessing the utility of network and spatial-average persistence forecasts past 30 min is challenging. We therefore suggest that researchers restrict their use of forecast skill to methods which have similar mean bias errors and standard deviations.

Fig. 13 also shows how network and spatially-averaged persistence forecasts always have lower RMSE than clear-sky index persistence after a certain horizon. This is a result of the combination of lower standard deviation and higher correlation for the network and spatially-averaged persistence forecasts. This trend holds for even longer forecast horizons. Unfortunately, Eq. (11) does not simplify for the forecasts and data shown here so both correlation and standard deviation need to be considered to understand RMSE.

5.4. Limitations and comparisons to other work

One limitation of the current network algorithm is that it does not account for multiple cloud layers. Satellite images from many of the studied days confirm that multiple cloud layers were moving in different directions. We also studied incorporating data from times in the past appropriately shifted by cloud motion vectors but found no noticeable improvement, likely due to this complex motion.

On a day with a single cloud layer coming from the southwest shown in Fig. 14, we see that a single upstream sensor greatly improves network forecasts at around the 7 min forecast horizon. This demonstrates that the network method can perform quite well if the velocity of the clouds is well defined and the sensors are appropriately located.

Another limitation is the size of the irradiance network. Depending on the wind motion vectors clouds can pass from the edge of the network to the center in 10 min. Since the boundary is set to the spatial average of sensors, network forecasts converge to spatially averaged persistence.

Still, our current method of network forecasting performs as well as or better than both clear-sky index and spatially-averaged persistence. Error statistics for network forecasts for cloudy days are presented in Table 1.

When we compared our current network method and high resolution data with the previous work of Lonij et al. (2013), we see that our new method performs favorably. Lonij et al. use a network of 80 rooftop PV systems in the Tucson area with 15 min averaged power data to make short-term forecasts of power. Their method uses a similar cloud translation method as this work, but wind vectors are obtained from NOAA forecasts, via optimization of the wind vector to minimize RMS forecast errors, or via a Kalman filter applied to optimized vectors. At 15 and 30 min forecast horizons, the best forecasts of Lonij et al. had skills of −8.0% and 2.4%, respectively, while our new method has skills of 17.7% and 21.2%. Even compared to the optimized "forecasts" (which were not true forecasts) with skills of 1.6% and 34.5% at 15 and

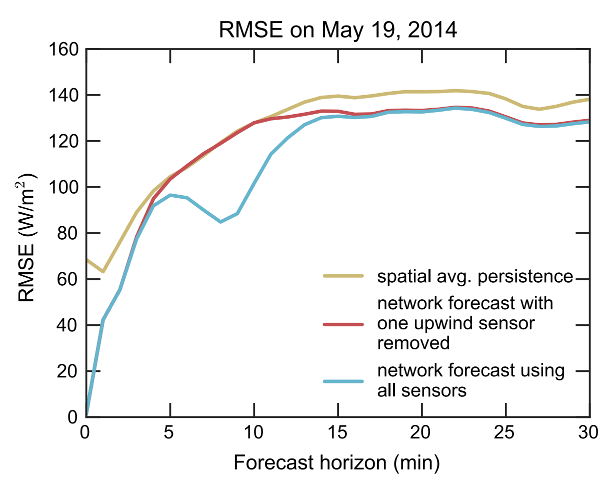

Fig. 14. RMSE vs forecast horizon on May 19, 2014 for network forecasts made with all the sensors in the network (blue) and with one upwind sensor removed (red), along with a spatially-averaged persistence forecast (yellow). The dip at 7 min for the forecast using the full network illustrates that properly placed upstream sensors do improve forecasts over a simple spatial average. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)