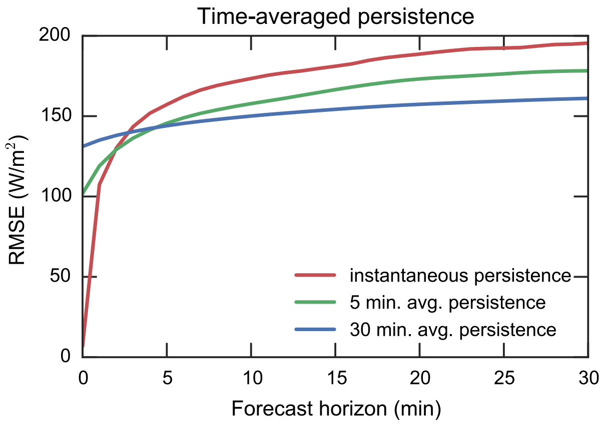

Fig. 6. Comparison of time-averaged persistence forecasts with different averaging times. The averages shown are made via a rolling average ($t_0 = 1$) with $\Delta t = 1$ s and N adjusted for each curve to give the appropriate total averaging time as described in Section 4.3. Longer time averages reduce errors at longer time horizons.

together. This average clear-sky index is then multiplied by the clear-sky expectation of the target sensor to produce a forecast for that sensor. Using N sensors, the spatially-averaged persistence for sensor n is

$$y_n^*(t+FH) = y_n^{clr}(t+FH) \times \frac{1}{N}\sum_{m=1}^{N}\frac{y_m(t)}{y_m^{clr}(t)}. \tag{10}$$

This method does not perform as well as clear-sky index persistence or measurement persistence at time horizons under a few minutes, as shown in Fig. 5, but it is more accurate (according the RMSE metric) than other persistence methods discussed here at longer (2–30 min) forecast horizons.

One could also imagine replacing the simple mean in Eq. (10) with a weighted mean by, for example, using the lasso (Yang et al., 2015) or some other shrinkage and selection method. Time and spatial averaging can also be combined as discussed in Section 5.1.

5. Results

We now present the results of the network and persistence forecasts using metrics defined in Zhang et al. (2015) and Section 3 for the study period of April, May, and June 2014. First, we evaluate persistence forecasts. Then, we study network forecast errors in depth. Finally, we compare network forecasts to other irradiance forecasting methods.

5.1. Persistence forecast results

Root-mean squared errors from the four types of persistence forecasts described above are plotted in Fig. 5. We see that for the 46 cloudy days we studied in Tucson, AZ., the two types of input averaging, spatial and temporal, both improve forecasts compared to clear-sky index persistence after time horizons of a few minutes. The cross-over time depends on the weather. As expected, clear-sky index persistence performs better than measurement persistence because it accounts for the diurnal cycle.

Though Fig. 5 shows spatially-averaged persistence outperforming time-averaged persistence, the averaging time and number of sensors averaged can change these curves significantly. Figs. 6 and 7 show various averaging times and number of sensors in the average, respectively. We see that longer averaging times reduce errors at time horizons greater than 5 min but are worse at shorter time horizons. The common auto-regressive moving average (ARMA) model similarly weights previous values and/or errors to produce a forecast. We also see that adding more sensors to a spatially-averaged persistence reduces errors except at time horizons shorter than a few minutes.

One explanation for our finding that spatially-averaged persistence performs better than time-averaged persistence is related to the number of dimensions in each average. Using kinematics ($x = vt$) we can map the time series $y_i(t)$ onto a one-dimensional transect in space downwind from the sensor. In comparison, the spatial average uses data from locations that are distributed in two dimensions including some locations that are upwind of the location of interest. By averaging over two dimensions, not one, spatial average persistence effectively uses more independent samples of the cloud field. This theory assumes that all sensors are subject to the same cloud field, which is reasonable for the size of our network.

When we average the input data over both space and time, as shown as the green line in Fig. 8, we find the RMSE is lower at longer time horizons.

5.2. Network forecast results

We now compare our network forecasts to a clear sky ($k_n^*(t) = 1$) forecast, measurement persistence, clear-sky index persistence, and spatially averaged persistence (using the same 16 sensors which were used to make the network forecast). Fig. 9 shows the MAE for these methods for only

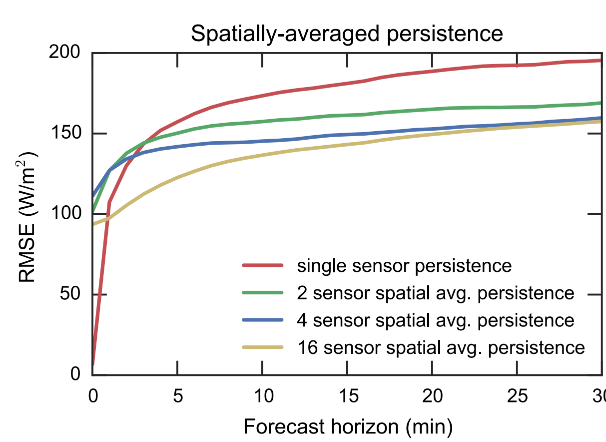

Fig. 7. Comparison of spatially-average persistence forecasts with a varying number of sensors averaged. Adding more sensors to the spatial average improves the forecast RMSE.