

Fig. 3. An example of a 5 min ahead network forecast compared to measured data. Forecasts were generated every 1 min and the forecast for 5 min in the future is shown. The forecast and measurements at 12:00 show excellent agreement. For reference, the MAE for this entire period is 105 W/m² and the RMSE is 140 W/m², and for 11:45 to 12:00 the MAE is 68 W/m² and the RMSE is 82 W/m².

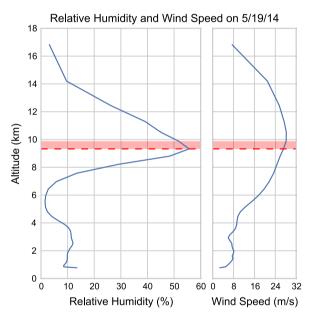


Fig. 4. Example vertical profiles of relative humidity and wind speed made by a numerical weather model on 5/19/14 at noon. To find the altitude at which clouds are most likely to form, we find the height with the greatest relative humidity (red dashed line). The winds at this height and heights within 90% of the maximum relative humidity (red shaded area) are averaged to produce an estimate of the cloud motion vector. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

dewpoint as a function of altitude/pressure) from the Weather Research and Forecasting (WRF) model run by the Univ. of Arizona, Dept. of Atmospheric Sciences (Leuthold, 2015). First, we compute a profile of relative humidity as a function of altitude averaged over the Tucson area from the WRF model. To estimate the cloud motion vectors, we find the altitude at which relative humidity is greatest (dashed line in Fig. 4), similar to Lave and Kleissl (2013). We then find all nearby heights

that have a relative humidity that is within 90% of the maximum (shaded area in Fig. 4). The wind speed and direction is then averaged for these altitudes and over the entire Tucson area to provide an estimated cloud motion vector. A new cloud motion vector is estimated in this way from each hourly output of the WRF model and then interpolated to 1 min time resolution. This simple estimation method has a number of limitations including only recognizing a single cloud layer and possibly selecting the wrong layer of the atmosphere i.e. one in which there are no clouds. This cloud motion estimation method along with the modest size and density of our network likely limits the overall accuracy of the network based forecasts presented here. Still, this network based method produces forecasts with lower errors than several standard persistence methods, as we discuss next.

3. Error metrics

We assessed the accuracy of forecasts using standard error metrics that are defined in Zhang et al. (2015). Each error metric is computed for forecast horizons, FH, ranging from 1 min to 30 min (FH = 0, 1, ..., 30) by comparing forecasts, $y^{FH}(t_i)$, to subsequent instantaneous measurements, $y(t_i)$, of a single irradiance sensor. Errors were only computed when the solar zenith angle was less than 75°. Unless otherwise noted, only the 46 cloudy days in the study period were used to calculate error metrics and each metric is computed over this entire cloudy data set. Data and forecasts for a sensor (star in Fig. 1) in the middle of the network and near many large PV installations were used. Comparisons are always made with an instantaneous measurement, not averaged data, even when the forecast uses averaging.

In addition to root-mean squared error (RMSE) and mean absolute error (MAE), we also compute the centered root-mean squared error (CRMSE) for irradiance

CRMSE(FH) =
$$\left(\frac{1}{N}\sum_{i=1}^{N} \left[(y^{FH}(t_i) - \bar{y}^{FH}) - (y(t_i) - \bar{y}) \right]^2 \right)^{1/2}$$
, (3)

where an overbar indicates the sample mean of the quantity (Taylor, 2001). The CRMSE removes forecast bias and will become important later.

We also compute errors for forecasted clear-sky indices. This is valuable because, as opposed to irradiance, clear-sky index errors are not weighted based on the position of the sun in the sky.

We also define *relative* metrics in terms of clear-sky indices in order to present errors in percentages. The relative RMSE is

$$rRMSE(FH) = \bar{k}^{-1} \left(\frac{1}{N} \sum_{i=1}^{N} (k^{FH}(t_i) - k(t_i))^2 \right)^{1/2}.$$
 (4)

Relative MAE is similarly defined as