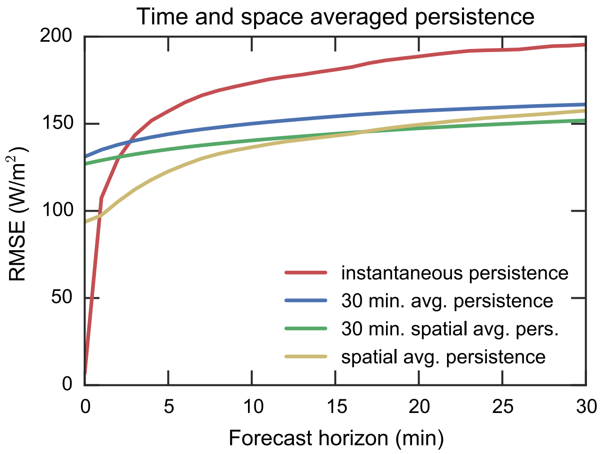

Fig. 8. Comparison of a persistence forecast made by first averaging over space and then averaging over time (green line) to other persistence methods. Averaging in time and space marginally improves forecasts at longer time horizons. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

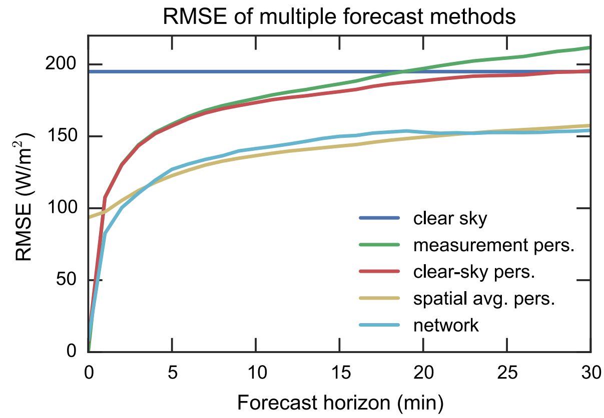

Fig. 10. RMSE of many types of forecasts averaged over 46 cloudy days. Clear sky refers to a forecast where one assumes the sky is always clear ($k_n^*(t) = 1$).

cloudy days while Fig. 10 shows the RMSE. Plots of CRMSE show similar trends. Note that network forecasts have nonzero error at zero forecast horizons because of the smoothing applied when making the interpolated clear-sky index map and due to limiting the maximum forecasted clear-sky index to 1.25. We see that network forecasts have lower MAE than other methods for time horizons from 1 min to 30 min. We only graph up to 30 min forecast horizons because the 30 min to 2 h errors are similar and uninteresting. Fig. 10 shows that the network forecasts have lower RMS errors than the other methods at forecast horizons less than about 4 min and then have slightly higher RMSE values than spatially-averaged persistence. This difference between RMSE and MAE suggests that network forecasts have fewer small errors but more large errors than spatially-averaged persistence forecasts. For completeness, we also present error metrics for all 91 days in the study period in Appendix A. Clear days show similar trends

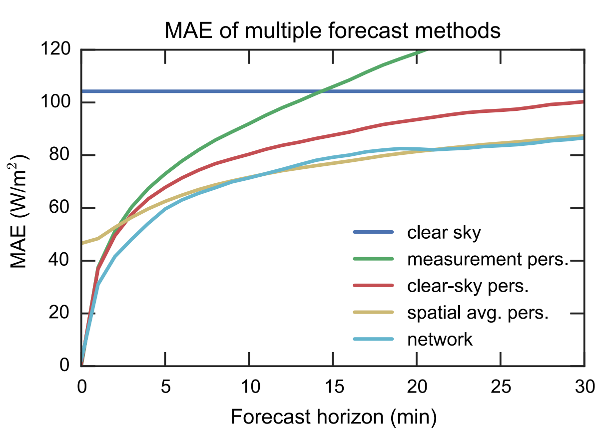

Fig. 9. MAE of many types of forecasts averaged over 46 cloudy days. Clear sky refers to a forecast where one assumes the sky is always clear ($k_n^*(t) = 1$). Network forecasts have the lowest MAE at all time horizons shown.

but with smaller errors which lowers the 91 day average RMSE by 40–50% depending on the time horizon.

We also compute forecast skill as defined by Marquez and Coimbra (2012). Fig. 11 illustrates the regressions used to calculate the average skill of our forecasts. At low clear-sky index persistence RMSE values (e.g. clear days), we see that the skill is negative (network RMSE > clear-sky index persistence RMSE). For days with larger clear-sky index persistence RMSE values, we see that our network forecasts have positive skill. The average skill found from regressions, typically 20%, is plotted in Fig. 12 as a function of forecast horizon.

5.3. Exploration of forecast errors

The forecast skill of the network-based forecasts remains at a surprising +20% at time horizons through 2 h. This was unexpected because the finite domain of the network is usually transited by clouds in 10–20 min. To explain this finding, we revisited the underlying statistics of forecast skill. The root mean squared error can be written as

$$\mathrm{RMSE} = \sqrt{\sigma_f^2 + \sigma_o^2 - 2\sigma_f\sigma_o\rho + \mathrm{MBE}^2}, \qquad (11)$$

where σ_f is the forecast standard deviation, σ_o is the measurement standard deviation, ρ is the correlation coefficient, and MBE is the mean bias error (Taylor, 2001). When correlations and biases are small, the RMSE reduces to a sum in quadrature of the observation and measurement standard deviations. Under these conditions, a smoother forecast will have a lower RMSE, and thus a more positive forecast skill, than a more variable forecast. Of course, this does not mean that the smoother forecast is more skillful under most definitions of the word.

As an alternative means of understanding the relative merits of our forecast methods, we turned to Taylor diagrams (Taylor, 2001). The Taylor diagram in Fig. 13 shows the CRMSE, correlation coefficient, and standard