Bilionis et al., 2014). For time horizons from several hours to up to a week in advance, numerical weather models often give the best predictions (Mathiesen and Kleissl, 2011; Diagne et al., 2014; Perez et al., 2013). Combinations of techniques are also being studied to extend the useful time horizon of a forecast (Marquez et al., 2013; Lauret et al., 2014).

Networks of irradiance sensors overcome some challenges typically associated with sky imagers or satellite images. For example, data from networks of irradiance sensors do not have the issue of converting pixel brightness to irradiance as sky imagers and satellite image methods have. Sky imagers and satellite images have the additional challenge of estimating cloud height to correctly project irradiance at cloud height to a location on the ground.

In this paper, we describe GHI forecasts that utilize a network of sensors placed throughout Tucson, AZ for April, May, and June 2014. The ideas behind this work are similar to those of Lonij et al. (2013), however the data sources and implementation are different. The rooftop PV network in Lonij et al. (2013) was limited to historical reports of 15 min average power, whereas the irradiance sensors used in the present research report 1 s resolution data with 1 min latency. This allows us to make higher resolution and, as we will see, more accurate forecasts.

We will show that our sensor network based forecasting method has significant skill when compared to a clear-sky index persistence forecast from 1 min to beyond 2 h time horizons. While the limited area and density of the network likely limits the skill and forecast horizon of our network-based forecasting method, the geographic diversity of measurements provide several advantages including improved persistence estimations. We will also explore why the forecasts exhibit such significant skill and explain this result is due to smoothing after 30 min forecast horizons.

First, we describe our network of irradiance sensors. Then, we describe how we use the network to make forecasts. A discussion of different types of persistence forecasts follows. Finally, we present and discuss our results and offer a concluding summary.

2. Irradiance sensor network forecasts

Our forecasting method relies on a network of sensors that sample the global horizontal irradiance at a number of locations. Our network consists of 12 irradiance sensors we developed, plus three rooftop PV power systems and one calibrated, commercial sensor. The calibrated sensor is part of a National Renewable Energy Laboratory (NREL) Solar Resource and Meteorological Assessment Project (SOLRMAP) site at the Univ. of Arizona (Wilcox and Andreas, 2010). Converting the data to clear-sky indices using an expected clear-sky profile for each sensor allows us to combine sensors that measure different quantities to make forecasts. These sensors are distributed throughout Tucson as shown in Fig. 1. The irradiance sensors we developed collect 1 s data and transmit it to a database every minute via cellular data networks (Lorenzo et al., 2014). Some use commercial pyranometers while others use photodiodes. Since we use clear-sky indices with data driven clear-sky profiles, the absolute error of the sensor is not a concern. However, the sensor used to evaluate the forecasted irradiance is a commercial sensor (Apogee SP-212) and agrees with the calibrated sensor to within 2% on average on clear days. The data were plotted for each day and for each sensor and verified by eye to provide some measure of quality control. See Lorenzo et al. (2015) for access to the dataset that was used in this study.

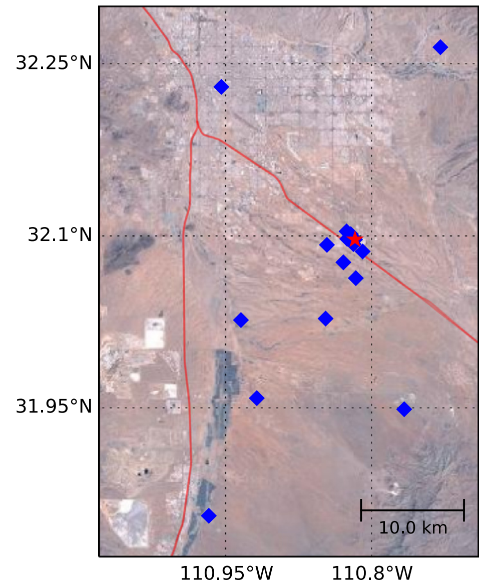

Fig. 1. Map of irradiance sensors used for this study in Tucson, AZ. The red star indicates the position of the sensor that was used to evaluate forecasts in Section 5. The sensor was chosen because of its proximity to 25 MW of installed PV power in and around the University of Arizona Science and Technology Park Solar Zone. The forecast area extends from 31.83° N to 32.28° N and 110.7° W to 111.15° W. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The first step in making our forecasts is to convert irradiance and PV power data to clear-sky index data. The clear-sky index for a sensor n at time t is defined as

$$k_n(t) = \frac{y_n(t)}{y_n^{clr}(t)}, \tag{1}$$

where $y_n(t)$ is the measured data and $y_n^{clr}(t)$ is the clear-sky expectation. Clear-sky expectations for each sensor are generated by fitting the measured data on a clear day in the recent past. An advantage of using this data-driven method of generating clear-sky expectations rather than a clear-sky model, such as the REST2 model (Gueymard, 2008) or Ineichen model (Ineichen and Perez, 2002), is that the data-driven method inherently accounts for sensor orientation, permanent obstacles, and sensor calibration errors. Furthermore, because our forecasting method relies on forecasting clear-sky index and then converting back to