Solar Energy Forecast Validation for Extended Areas & Economic Impact of Forecast Accuracy

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Abstract **— This article evaluates the accuracy of solar energy forecasts as a function of geographic footprint ranging from a single point to regions spanning several hundred km. The forecast models that are evaluated include SolarAnywhere®, ECMWF, GFS, HRRR, NDFD and satellite-based cloud motion. The forecast time horizons range from one hour ahead to 2 days ahead. In addition, a new accuracy metric is introduced: this metric quantifies the cost of remedying forecast errors with backup generation if the forecasts overpredict, or with curtailment in case of underprediction.**

Index Terms **— solar forecast, solar resource, backup, curtailment, storage.**

I. Introduction

Operational solar forecasts are increasingly applied regionally to support grid operators to account for the impact of dispersed PV generation on their load forecasts [e.g., 1]. However, while regional aggregate forecast error reduction has been noted (e.g., [2]), in depth quantitative validations have typically been site-specific (e.g., [3, 4]). In this article we systematically analyze the influence of the solar generation footprint on the accuracy of operational solar forecast models.

Starting from a single point and gradually extending the area to a subcontinental region, we analyze the evolution of forecast accuracy. In addition to standard model evaluation metrics we also pay attention to the logistical accuracy of PV output forecasts by estimating the cost of missed forecasts from the underlying drivers of energy markets: specifically, we estimate the amount and cost of backup energy and capacity as well as solar output curtailment needed to make-up for forecast errors, hence to provide the equivalent of firm, guaranteed forecasts with 100% reliability.

II. Methodology

We consider two climatically distinct US regions centered respectively on the SURFRAD measurement stations of Desert Rock, NV, and Bondville, IL. Around each station we also analyze concentric regional footprints ranging from one single intermediate resolution satellite model cell (~ 10 x 8 km) to 110x110 such cells (amounting to a region the size of Texas and Oklahoma.) For extended areas, the forecasts are evaluated against SolarAnywhere historical data. This extended area evaluation benchmark is justified by: (1) the fact that single point forecast errors gauged against ground measurements and satellite data are comparable (see Figure 1); (2) the satisfactory performance of new satellite models compared to ground [5], and (3) the observation that satellite model errors diminish considerably when gauged against an aggregate of points.

The forecast models that are analyzed in this article include the recently deployed SolarAnywhere V4 [4] as well as its constituting underlying forecast models, including NOAA's Global Forecasting System (GFS), High Resolution Rapid Refresh (HRRR) and National Digital Forecast Database (NDFD), The European Center for Medium Range Weather Forecasts (ECMWF), and satellite-derived cloud motion vectors forecasts. The time horizons considered for this analysis include 1, 3, 24 and 48 hours-ahead.

Experimental data: Forecasts and benchmarking data span nearly one year from June 2015 to April 2016. Validations are based on global irradiance (GHI) as a proxy for PV output, noting that other factors influencing PV output, temperature wind speed and soiling are second order effects, and, to the exception of soiling, can be accurately forecasted.

Validation Metrics: These include standard model validation metrics such as mean absolute and root mean square errors (MAE and RMSE). In addition, a new set of metrics is introduced to quantify the cost of missed forecasts on the basis of first operational principles: these metrics quantify the amount of backup capacity and backup energy necessary to make up for any forecast overestimation through the period analyzed. The cost of missed forecast can then be estimated from the cost of backup technology, e.g., electrical storage via batteries. These operational metrics also quantify the amount of solar that must be curtailed in case of forecast underestimation. In essence the metrics estimate the cost of providing 100%

accurate solar forecasts from the added hardware and operational losses associated with solar production.

III. RESULTS

Figure 1 compares the relative single point RMSE statistics for all models obtained when using ground measurements and satellite irradiances as a benchmark. The similarity of these statistics warrants the use of satellite-data for regional validations.

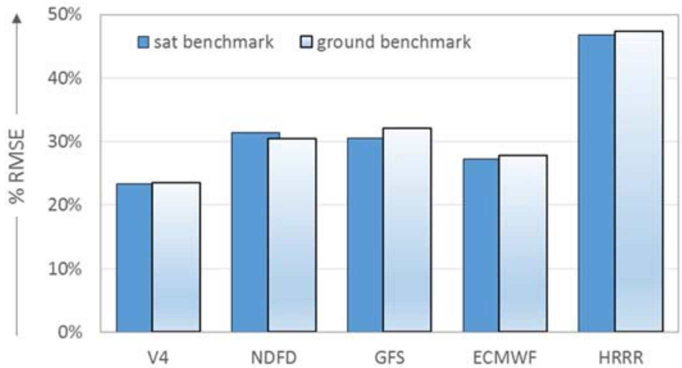

Fig. 1. Comparing single-point mean relative RMSE statistics across all time horizons and locations as benchmarked with ground measurements and satellite data.

Table I reports the relative MAE (MAPE) of all forecast models at one-hour ahead as a function of footprint. Table II shows the same but for 24 hours ahead. Note that MAPEs normalized to mean observed GHI and not to a peak irradiance of 1000 Wm^{-2} (i.e., corresponding to rated PV capacity) as is current practice in the industry, particularly the wind industry [6]. A MAPE peak normalization would reduce the numbers presented in Table I and II by well over 50%.

For both eastern and western locations, the impact of footprint on model performance is noteworthy. At one hour ahead, MAPEs of less than 5% are achieved by SA-V4 for regional footprints of ~ 50x50km for the western location and ~ 200x200km for the eastern location. Day-ahead MAPEs of the order of 10% are achieved for a regional footprint of ~ 20x20 km in the west. In the eastern US, day-ahead MAPEs of 15% are achieved for footprints greater than 200X200 km.

In all instances the SolarAnywhere V4 performance is superior to that of its underlying models. This is illustrated in Figure 2 were the RMSE of SA V4 is compared to ECMWF (the best of the underlying models) as a function of regional footprint and time horizon up to 48 hours ahead.

The scatterplots in Figure 3, 4 qualitatively illustrate the influence of footprint on hour ahead and day-ahead model performance for Desert Rock. The plots correspond respectively to a single location, and to 2^o x 2^o, 4^o x 4^0, and 7^o x 7^o, extended areas, i.e. corresponding to regions roughly equivalent to of Massachusetts, New York, and California. These scatterplots show that forecast reliability becomes remarkable for both hour-ahead and day-ahead horizons as the

TABLE I
HOUR-AHEAD MAPE STATISTICS

BONDVILLE						
Footprint lat x long Degrees	SA V4	NDFc	GFS	ECMWF	HRRR	CMMM
0.1 x 0.1	12.2%	21.6%	25.7%	23.1%	34.2%	11.3%
0.3 x 0.3	9.5%	20.5%	24.1%	21.3%	32.9%	8.7%
0.5 x 0.5	8.2%	20.0%	23.3%	20.3%	32.0%	7.4%
1 x 1	6.7%	19.0%	22.4%	18.7%	30.6%	5.9%
2 x 2	5.4%	17.5%	20.3%	16.3%	28.1%	4.6%
4 x 4	4.2%	15.0%	17.6%	13.6%	25.4%	3.7%
7 x 7	3.4%	12.7%	15.5%	11.3%	23.5%	3.1%
11 x 11	2.9%	10.8%	13.9%	9.8%	21.8%	2.8%
DESERT ROCK						
Footprint lat x long Degrees	SA V4	NDFc	GFS	ECMWF	HRRR	CMMM
0.1 x 0.1	8.4%	13.5%	10.6%	11.0%	20.8%	8.2%
0.3 x 0.3	6.0%	12.2%	9.4%	9.2%	20.3%	6.1%
0.5 x 0.5	5.1%	12.0%	8.8%	8.4%	19.9%	5.2%
1 x 1	4.2%	12.1%	7.7%	7.5%	19.3%	4.3%
2 x 2	3.4%	11.4%	7.0%	6.5%	17.3%	3.7%
4 x 4	2.7%	10.6%	6.3%	5.6%	14.5%	3.3%
7 x 7	2.5%	9.2%	6.5%	5.5%	12.3%	3.2%
11 x 11	2.3%	7.2%	6.6%	5.0%	10.5%	3.1%

TABLE II
DAY-AHEAD MAPE STATISTICS

BONDVILLE						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMMM
0.1 x 0.1	21.2%	23.3%	28.2%	24.7%	NA	NA
0.3 x 0.3	19.4%	22.1%	26.7%	22.8%	NA	NA
0.5 x 0.5	18.6%	21.6%	26.0%	22.0%	NA	NA
1 x 1	17.2%	20.7%	24.9%	20.5%	NA	NA
2 x 2	15.2%	19.1%	23.0%	18.3%	NA	NA
4 x 4	12.5%	16.7%	19.9%	15.5%	NA	NA
7 x 7	10.0%	13.9%	16.8%	12.6%	NA	NA
11 x 11	8.1%	10.9%	14.6%	10.5%	NA	NA
DESERT ROCK						
Footprint lat x long degrees	SA V4	NDFD	GFS	ECMWF	HRRR	CMMM
0.1 x 0.1	10.8%	13.9%	10.8%	11.5%	NA	NA
0.3 x 0.3	8.9%	12.7%	9.8%	9.7%	NA	NA
0.5 x 0.5	8.1%	12.5%	9.2%	8.9%	NA	NA
1 x 1	7.2%	12.6%	8.3%	7.9%	NA	NA
2 x 2	6.3%	12.0%	7.6%	7.1%	NA	NA
4 x 4	5.3%	11.0%	6.8%	6.1%	NA	NA
7 x 7	4.9%	9.3%	7.1%	5.9%	NA	NA
11 x 11	4.7%	7.6%	7.3%	5.5%	NA	NA

considered balancing area increases. The scatterplots in Figure 5 qualitatively contrast the performance of SA V4 at the one-hour ahead horizon compared to HRRR and the two global NWP models, GFS and ECMWF, for a 4º x 4º region.

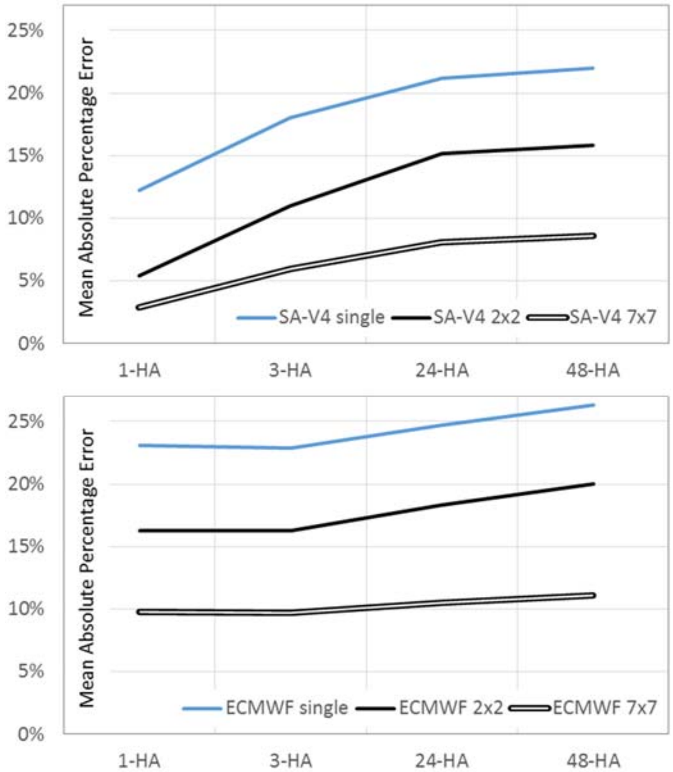

Fig. 2. Comparing the performance of SA-V4 (top) and ECMWF (bottom) in Bondville vs. time horizon (1, 3, 24 and 48 hours ahead) and footprint (point, 2ºx2º and 7ºx7º).

The new operational/financial metrics are reported in Table III. These include:

- The percentage of PV output that must be curtailed and, vice versa, supplied via backup generation to make up for any SA-V4 forecast deficit or overestimation, i.e., to render the forecasts 100% accurate.
- The cost of battery storage that would be sufficient to absorb excess production and provide backup generation if storage was applied to absorb excess and provide backup generation – assuming $300/kWh for battery CAPEX and 80% roundtrip efficiency.

Results show that offering operational forecast guaranties at the regional level could be achieved with either a minor amount of PV output curtailment/backup (e.g., less than 3% in the Western US for day-ahead guaranty for a balancing area of ~60K square miles) or the operation of storage systems amounting to a small fraction of PV CAPEX.

TABLE III
PERCENT PRODUCTION CURTAILED/BACKUP & CORRESPONDING ELECTRICITY STORAGE COST PER PV KW TO INSURE 100% FORECAST ACCURACY

	footprint (degrees)			
	point	**2 x 2**	**4 x 4**	**7 X 7**
Western US Hour Ahead Forecast Guaranty				
% curtailed & backup	4.0%	1.6%	1.2%	1.0%
Battery cost per PV kW	$ 328	$ 174	$ 122	$ 76
Western US Day Ahead Forecast Guaranty				
% curtailed & backup	5.8%	3.3%	2.8%	2.3%
Battery cost per PV kW	$ 560	$ 523	$ 463	$ 224
Eastern US Hour Ahead Forecast Guaranty				
% curtailed & backup	5.9%	2.7%	2.1%	1.5%
Battery cost per PV kW	$ 349	$ 128	$ 109	$ 73
Eastern US Day Ahead Forecast Guaranty				
% curtailed & backup	11.5%	8.4%	7.0%	4.5%
Battery cost per PV kW	$ 753	$ 715	$ 533	$ 334

TABLE IV
BATTERY COST PREMIUM AND CURTAILMENT REQUIREMENTS INCREASE WHEN USING OTHER FORECASTS INSTEAD OF SA-V4 TO DELIVER 100% FORECAST ACCURACY

	ECMWF	NDFD	GFS
Battery cost premium compared to SA V4 (West US)			
short time horizons (1 &3 hours ahead)	174%	306%	197%
All time horizons (1-48 ours ahead)	147%	267%	167%
Curtailment/backup increase relative to SA V4 (West US)			
short time horizons (1 &3 hours ahead)	129%	197%	138%
All time horizons (1-48 ours ahead)	121%	182%	130%
Battery cost premium compared to SA V4 (East US)			
short time horizons (1 &3 hours ahead)	195%	285%	233%
All time horizons (1-48 ours ahead)	153%	216%	196%
Curtailment/backup increase relative to SA V4 (East US)			
short time horizons (1 &3 hours ahead)	183%	190%	230%
All time horizons (1-48 ours ahead)	153%	158%	191%

Achieving forecast guaranties with any of the underlying NWP models could also be achieved, but the curtailment/backup and/or battery cost premium relative to SA-V4 would be consequential as shown in Table IV

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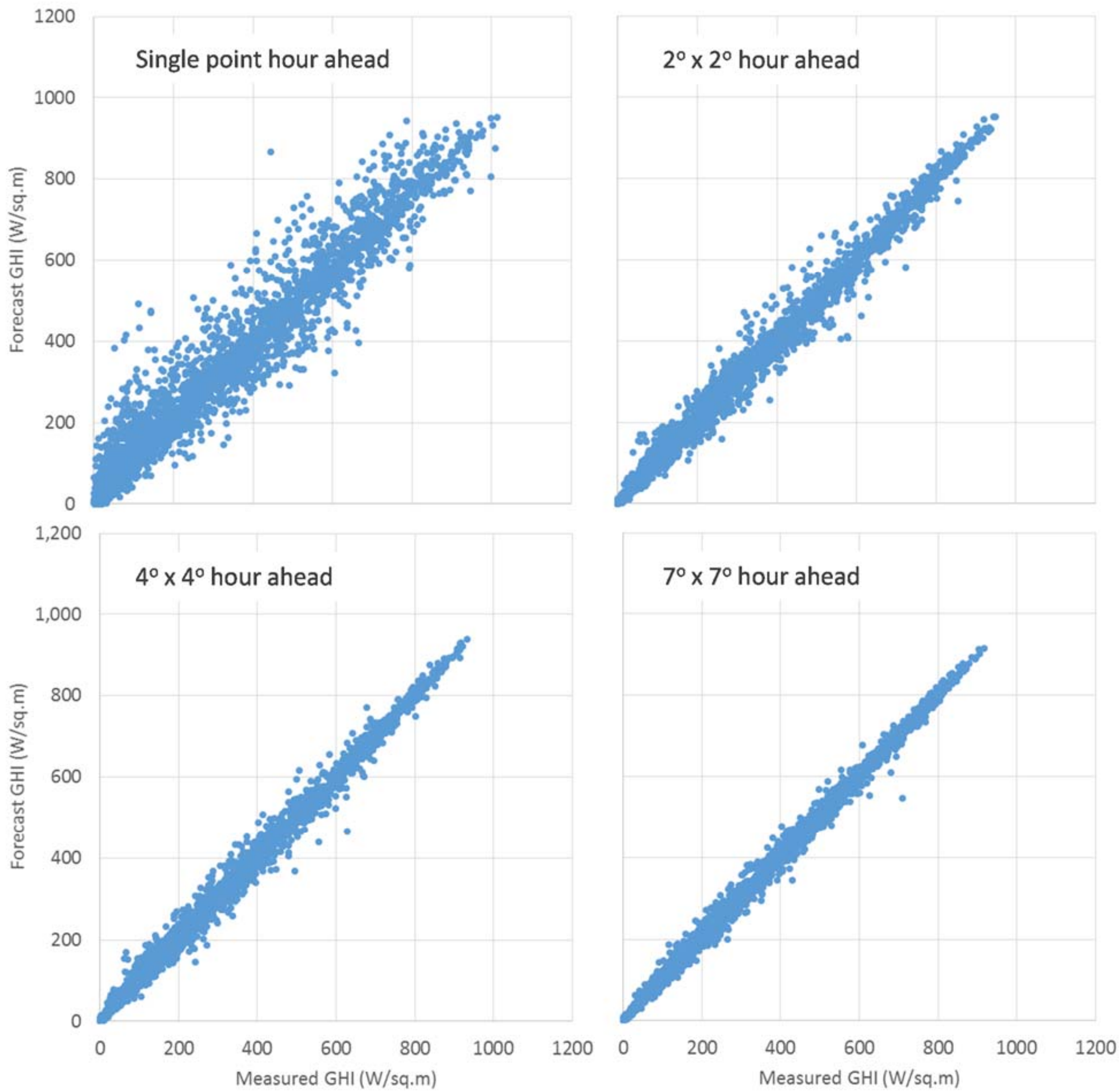

Fig. 3. Hour Ahead Forecast vs. Actual GHI in the Southwestern US as a function of balancing area footprint

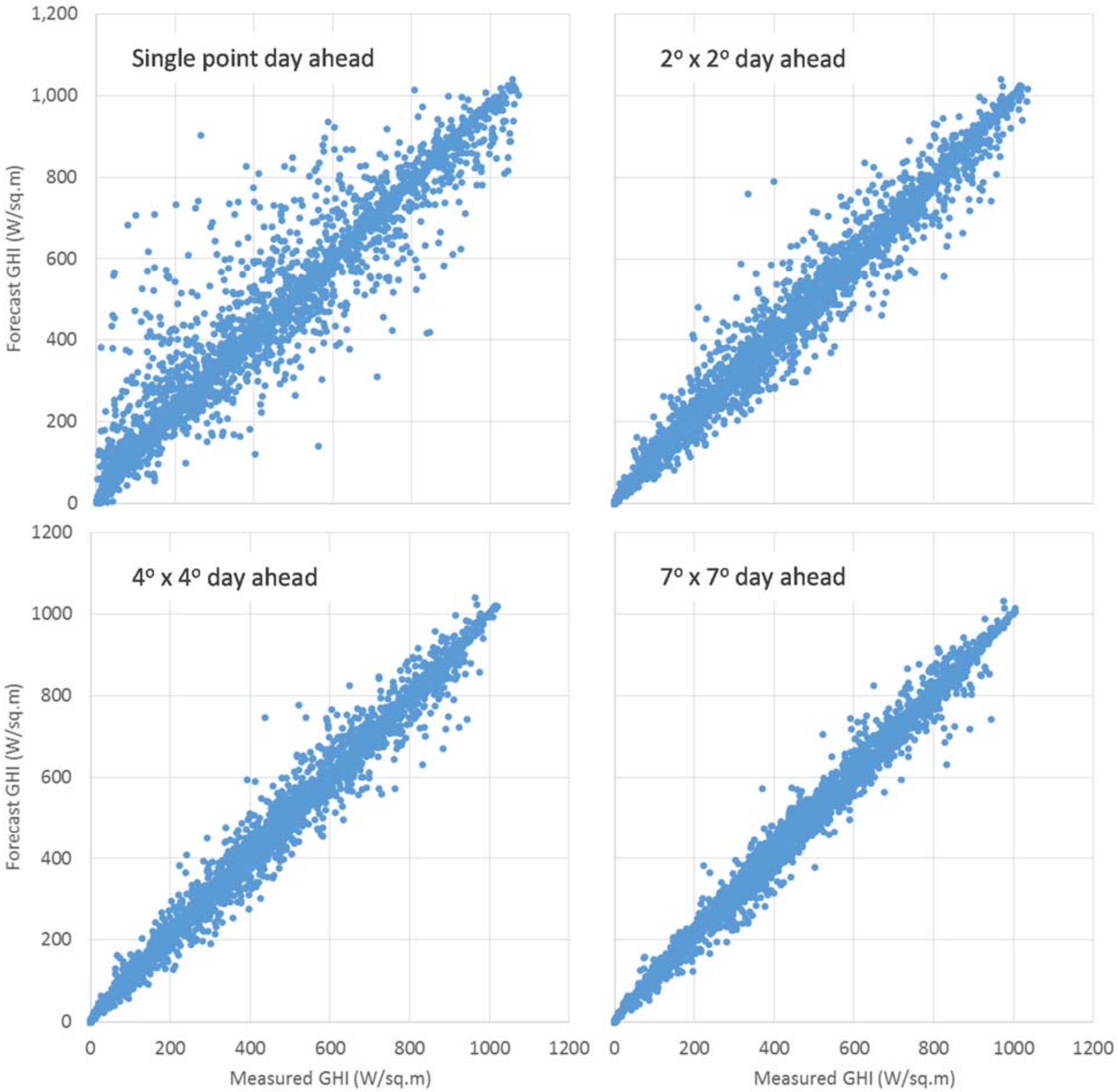

Fig. 4. Day Ahead Forecast vs. Actual GHI in the Southwestern US as a function of balancing area footprint

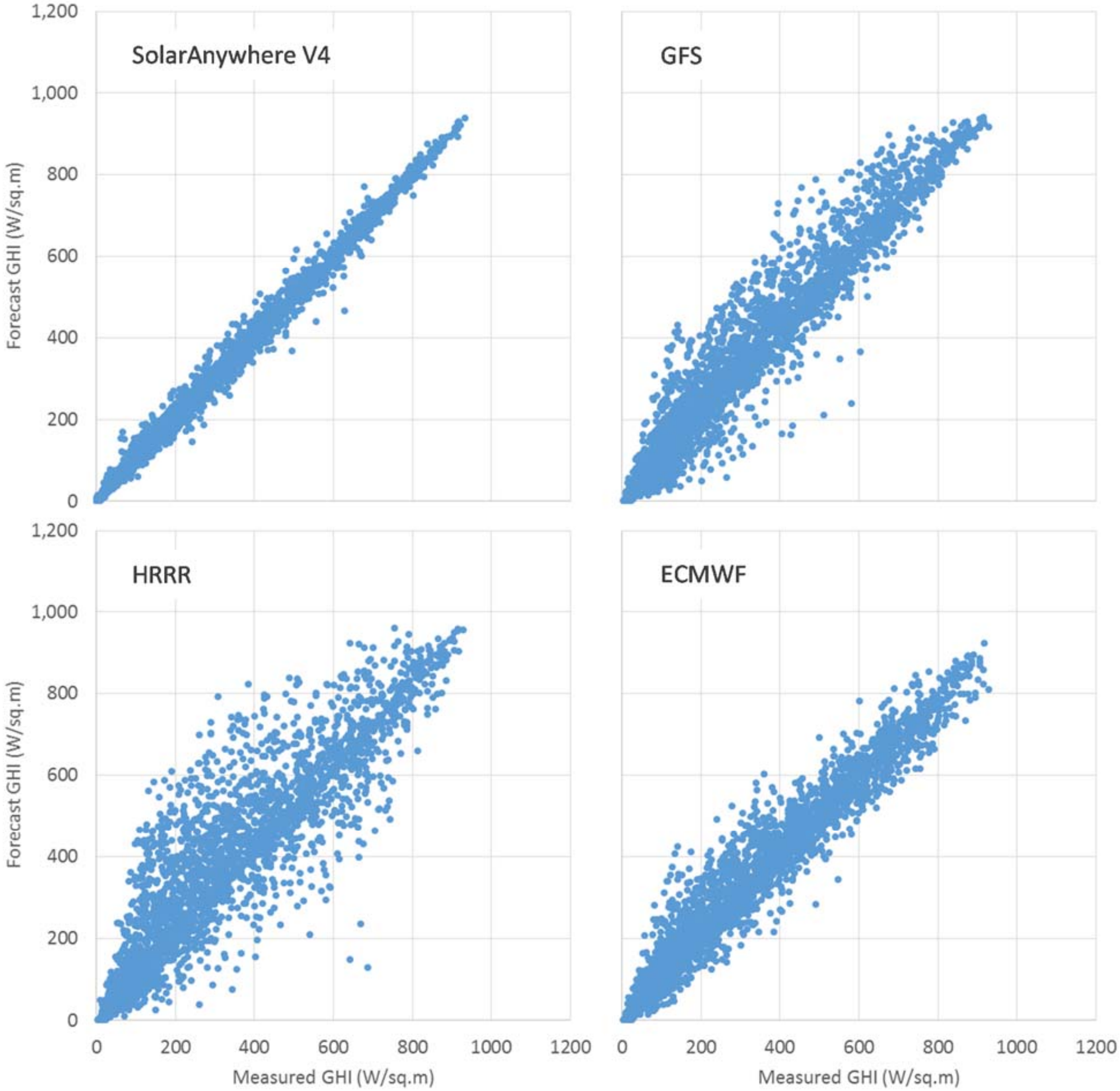

Fig. 5. Comparing Hour Ahead Forecasts in the eastern US for a 4°x4° footprint.