Final Report

California Renewable Energy Forecasting, Resource Data and Mapping

Appendix A

CURRENT STATE OF THE ART IN SOLAR FORECASTING

Regents of the University of California

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Current State of the Art in Solar Forecasting

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Abstract: As solar thermal and photovoltaic generation begin to have a larger role in electrical generation in California, the California Independent System Operators needs to accommodate their variable nature in its forecasting and dispatching. This project reviews and evaluates current knowledge and models for forecasting solar resources and considers options for improving forecasts through RD&D and additional measurements.
Satellite and numerical weather prediction (NWP) have been shown to be the best tools for hour ahead and day ahead forecasts at this time. However, NWP solar forecast performance has yet to be evaluated for California, where the coastal microclimate especially may present a significant challenge. To validate and calibrate such forecasts, an aggregated real-time production database for all metered PV systems is deemed to be the most spatially dense and economical set of "measurements." A research roadmap for improving Direct Normal Irradiance forecasts is provided.

Keywords: solar thermal, photovoltaic systems, energy, renewable, forecast, NWP, modeling

Overview: As solar thermal and photovoltaic (PV) penetration increases, the California Independent System Operators (CAISO) needs to accommodate their variable nature in its forecasting and dispatching. This project reviews and evaluates current knowledge and models for forecasting solar resources and considers options for improving forecasts through research and measurements.

Summary of recommendations (more detail is provided in section 4.3):

a) **Current Forecast Skills:** Satellite and numerical weather prediction (NWP) are currently the best tools for hour ahead (HA) and day ahead (DA) forecasts, respectively. Efforts are underway by solar forecasters and NOAA to improve mesoscale NWP for the HA market.
   - Further research should be conducted on the forecast skills of the low hanging fruit - operational NWP models - for California. The applicability of mesoscale NWP to locally enhance forecast skill should also be quantified. This research would enable wind forecast providers to adapt their existing products for the solar forecasting market and quantify the potential success of such an approach.
   - Support should be provided to CAISO to conduct a 12 months forecast 'competition' to evaluate forecast skills of forecast providers and maturity of different approaches. Careful design of such a study is critical and stakeholders should be consulted in the planning stage.

b) **Expanding ground measurements:** Ground measurements of global horizontal irradiance (GHI) (and direct normal incident irradiance (DNI) for concentrating plants) should be (and currently are) required by CAISO for utility scale solar farms. To improve HA and intra-hour forecasts statewide, more ground data are necessary. The most economical approach would be to require or incentivize 3^{rd} party data providers / aggregators to share PV output and radiometer data in real time with the ISO, utilities, and forecast providers. Models should be developed to derive solar irradiance values from such ground PV data. The advent of smart meters that can monitor residential PV outputs provides an additional avenue to implement this strategy. Also, research on sky imager deployments in areas with high PV penetration should be pursued.

c) **DNI Forecasts:** Research on radiative transfer in the atmosphere related to direct normal incident (DNI) forecasts is necessary. These forecasts should evaluate the effects of cirrus clouds, forest fire smoke, dust storms, and urban aerosol air pollution transport on concentrating solar power plants in California.

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1. Solar Forecasting Needs, Market Connection and Stakeholders (Task 1.1)

This report reviews and evaluates current knowledge and models for forecasting solar resources, and recommends ways in which forecasting can be improved. Table S6 lists the tasks and corresponding sections in this report.

Table S6: List of tasks for POB248-D76 Task 1.

Task	Section
1.1. Review the current state of the art in wind and solar forecasting in support of California grid operations including a review of opaque and transparent commercial models	Sections 1 and 2. Table S2.
1.2. Summarize and assess sources of real time wind and solar data used to calibrate day-ahead and hour-ahead forecasts.	Section 3. Table S4.
1.3. Review data on actual and forecast wind and solar thermal plant output ramp rates.	Section 2.1. and Figs. S2a and S2b. Actual plant output could not be obtained.
1.4.-1.6: Recommendations for expanded sensor deployment and data collection. Recommendations for forecasting at high renewable penetration levels.	Section 4.

Load forecasts have been an integral part of managing electric energy markets and infrastructure for many decades. Consequently, experiences, regulations, and planning by utilities and independent system operators (ISO) are the dominant consideration for this report. Furthermore the rules established by ISOs will impact the economic value of forecasting to other stakeholders such as owner-operators. Consequently, in the near-term the primary stakeholder to be considered for forecasting needs and plans is the California Independent System Operators (CAISO). Secondary stakeholders are utilities who will see greater distributed PV penetration on their urban distribution feeders. Currently on a few utilities have mechanisms in place to use solar forecasts for local automated response to voltage fluctuations caused by solar production.

The market need for better solar power integration and planning tools have been widely recognized (e.g. DOE FOA 0085, CEC PON 08-11, CSI RD&D Round 1). CAISO uses the following forecasts: The day ahead (DA) forecast is submitted at 0530 prior to the operating day, which begins at midnight on the day of submission and covers (on an hourly basis) each of the 24 hours of that operating day. Therefore, the day ahead forecast is provided 18.5 to 42.5 hours prior to the forecasted operating day. The vast majority of conventional generation is scheduled in the DA market. The hour ahead (HA) forecast is submitted 105 minutes prior to each operating hour. It also provides an advisory forecast for the 7 hours after the operating hour. CAISO also is studying in intra-hour forecasts on 5 minute intervals. FERC has issued a Notice of Proposed Rulemaking requiring public utility transmission providers to offer all customers the opportunity to schedule transmission service every 15 minutes, and requiring providers with variable renewables on their systems to use power production forecasting.

Currently, under the CAISO **Participating Intermittent Resources Program (PIRP)**, a participating intermittent resource receives special settlement treatment that nets output deviations over a month's period if the resource's scheduling coordinator submits hour ahead forecasts developed by a forecast service provider for that operating hour (de Mello and Blatchford, personal communication, 2010). Although the PIRP program does not require them, in practice DA forecasts are provided under the same contract. Wind units may participate in DA market however no special settlement treatments apply. Forecasts are integrated in CAISO planning, but there is no financial incentive to the forecast providers for accurate forecasts.

At some point PIRP may be modified and renewable generators will be required to participate in parts of the regular DA and HA markets. In that case some of the economic benefit and interest in forecasting would shift to the owner-operators of renewable power plants which would dramatically change the marketplace for renewable forecasting. An example of such a system is the Spanish 'premium tariff' for the regulation of renewable energy which allows operators of power plants to participate directly on the electricity market instead of reverting to flat-rate prices. The premium tariff option motivates operators of renewable energy plants to increasingly act like managers of conventional plants, selling electricity at the liberalized market. Just like a normal market participant, the operator places bids in advance on the DA market and is obliged to fulfill them. Thus there is the need for operators of renewable energy plants to be able to provide predictable and dispatchable energy in the profitable premium tariff.

Wind forecasting has been important for severe weather events for decades and even wind forecasting for renewable energy is a fairly mature field with several major market players. While solar radiation forecasting is standard in numerical weather prediction (NWP, the sun's energy is the primary driver of all meteorological processes), the accuracy requirements on solar radiation forecasts per se were low and the priority was on forecasting rain and air temperature. Consequently there is significant potential for improvements of solar forecasts from NWP.

For solar forecasting different types of solar power systems need to be distinguished (Table S2). For **solar concentrating systems** (concentrating solar thermal or concentrating PV, CPV) the direct normal incident irradiance (DNI) must be forecast. Due to non-linear dependence of concentrating solar thermal efficiency on DNI and the controllability of power generation through thermal energy storage (if available), DNI forecasts are especially important for the management and operation of concentrating solar thermal power plants. Without detailed knowledge of solar thermal processes and controls, it is difficult for 3rd parties (solar forecast providers and CAISO) to independently forecast power plant output.

On the other hand, CPV production is highly correlated to DNI. DNI is impacted by phenomena that are very difficult to forecast such as cirrus clouds, wild fires, dust storms, and episodic air pollution events which can reduced DNI by up to 30% on otherwise cloud-free days. Water vapor, which is also an important determinant of DNI, is typically forecast to a high degree of accuracy through existing NWP. Major improvement in aerosol and satellite remote sensing are required to improve DNI forecasts.

For **non-concentrating systems** (i.e. most PV systems), primarily the global irradiance (GI = diffuse + DNI) on a tilted surface is required which is less sensitive to errors in DNI since a reduction in clear sky DNI usually results in an increase in the diffuse irradiance. Power output of PV systems is primarily a function of GHI. For higher accuracy, forecast of PV panel temperature are needed to account for the (weak) dependence of solar conversion efficiency on PV panel temperature (Table S2).

Table S2: Quantities relevant to solar forecasting. GI: global irradiance.

Forecast Quantity	Application	Primary Determinants	Importance to market	Current Forecast Skill
Global Irradiance	PV	Clouds, solar geometry	high	medium
Cell temperature	PV	GI, air	low	high

Direct Normal Incident (DNI)	Concentrating Solar Power	temperature, wind Clouds, aerosols, water vapor	medium	Low

2. Solar Forecasting Methodologies (Task 1.1)

2.1. Forecasting Methods

The purpose of this section is to assess methodologies to forecast solar generation in California, to review best practices, and identify available data for validation and calibration of the forecasts.

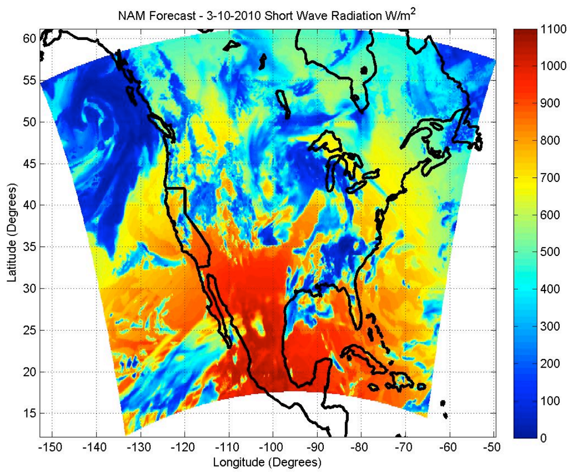
For solar forecasting very different methodologies are preferred depending on the forecast horizon (Table S1, Figures S1 and S2d):

- Persistence forecast is based on current or recent PV power plant or radiometer output and extrapolated to account for changing sun angles. Persistence forecasts accuracy decrease strongly with forecast duration as cloudiness changes from the current state.
- Total sky imagery can be used to forecast from real time (nowcast) up to 15-30 minutes. by applying image processing and cloud tracking techniques to sky photographs (Fig. S1c). The method assumes persistence in the opacity, direction, and velocity of movement of the clouds. Irradiance is predicted for the current cloud shadow and then the cloud shadow is moved forward in time based on cloud velocity and direction.
- For satellite imagery (Fig. S1b) the same methods as in total sky imagery are applied. Clouds reflect more light from earth into the satellite leading to detection and the ability to calculate the amount of light transmitted through the cloud (transmissivity = 1 – reflectivity – absorptivity). The lower spatial and temporal resolution causes satellite forecasts to be less accurate than sky imagery on intra-hour time scales. Satellite imagery is the best forecasting technique in the 1 to 5 hour forecast range. Classical satellite methods only use the visible channels (i.e. they only work in day time), which makes morning forecasts less accurate due to a lack of time history. To obtain accurate morning forecasts, it is important to integrate infra-red channels (which work day and night) into the satellite cloud motion forecasts (Perez, et al. 2010).
- NWP is the best forecasting technique for long time horizons of more than 5 hours. NWP models solar radiation as it propagates through the atmosphere including the cloud layers represented in the model. Operational National Weather Service models do not have the spatial or temporal resolution for accurate HA forecast. Consequently, NWP models are probabilistic because they infer local cloud formation (and indirectly transmitted radiation) through numerical dynamic modeling of the atmosphere. NWP models currently cannot predict the exact position of cloud fields affecting a given solar installation (Perez et al. 2009). High-resolution rapid-refresh NWP that are currently developed by NOAA and wind forecasters may be able to approach the resolution of satellite forecasts (1 km) within a few years and allow the application of high-frequency variability techniques (Mark Ahlstrom, Windlogics).

Table S1: Characteristics of solar forecasting techniques.

Technique	Sampling rate	Spatial resolution	Spatial extent	Suitable Forecast horizon	Application
Persistence	High	One point	One Point	Minutes	Baseline
Total Sky Imagery (Fig. S1c)	30 sec	10s to 100 meters	2-5 mile radius	10s of minutes	Short-term ramps, regulation
GOES satellite	15 min	1 km	US	5 hours	Load

imagery (Fig. S1b)					following
NAM weather model (Fig. S1a)	1 hour	12 km	US	10 days	Unit commitment



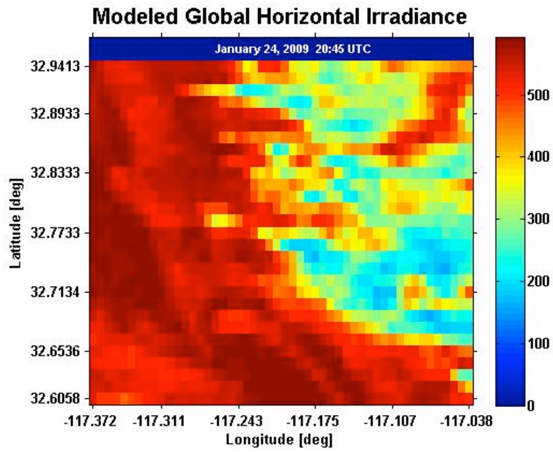


Figure S1a: Map of the forecast GHI [W m^{-2}, colorbar] in March 2010 at midday from the North American Mesoscale model (NAM).

Figure S1b: Map of the forecast GHI [W m^{-2}, colorbar] for San Diego on January 24, 2009 at 1245 PST using the GOES-SUNY satellite model.

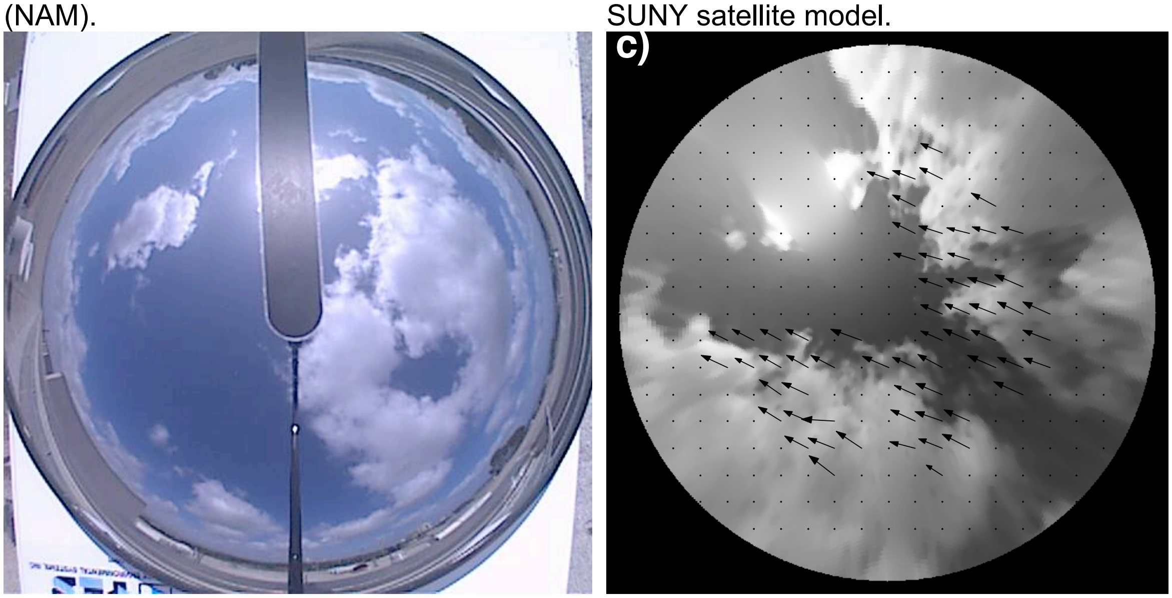


Figure S1c: Cloud motion vectors (right) and sky image (left) at the UC San Diego campus on August 19, 2009 at 1431 PDT.

Statistical methods can be applied to correct for known deficiencies of different forecasting methods through corrections for known model biases or automated learning techniques. Examples are modeled output statistics (MOS), autoregression techniques, and artificial neural network (ANN). For example, MOS uses statistical correlations between observed weather elements and climatological data, satellite retrievals, or modeled parameters to obtain localized statistical correction functions. This allows, for example, for the enhancement of low-resolution data by considering local effects (e.g. topographic shading) or for correcting systematic deviations of a numerical model, satellite retrievals, or ground sensors. A disadvantage of statistical methods is the large amount (typically at least one year) and accuracy of measurement data needed to develop statistical correlations separately for each location. This means that MOS-based forecasts are not immediately available for larger areas or for locations without prior measurements, such as most non-urban solar power plants in the California.

2.2. Evaluation of Numerical Weather Prediction Solar Forecasts in California

For Task 1.3 we conducted an analysis of the intra-day solar forecast skill of the current operational NWP model – the North American Mesoscale (NAM) model for February to June 2010 using California Irrigation Management Information System (CIMIS) GHI measurements. NAM provides hourly forecast up to 72 hours ahead on a 12 km grid within the Continental US.

A 24 hour persistence forecast was more accurate forecast in clear sky conditions than in overcast conditions (Fig. S2b). This indicates that clear conditions are persistent, but during times of transitional weather patterns P is inaccurate. Generally, P is an inaccurate method for more than 1 hour ahead forecasting and should be used only as a baseline forecast for comparison to more advanced techniques.

The original NAM forecast for GHI consistently over-predicts solar irradiation during clear sky situations, but under-predicts GHI for cloudy conditions (Fig. S2c). On average, these bias errors can exceed 25%. The consistent errors in NAM motivate application of a bias correction, termed model output statistics (MOS), as a function of solar zenith angle and clear sky index. Through the use of MOS, the bias error was eliminated and the root mean square error (RMSE) was significantly improved (Fig. S2b). The RMSE for the corrected forecasts ranges from 25% under very cloudy conditions to 8% under clear conditions.

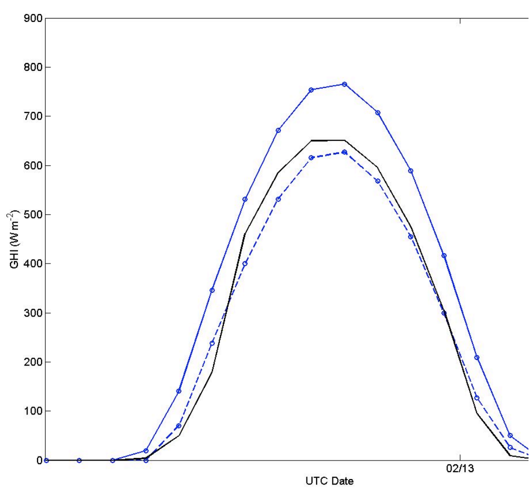


Fig. S2a: Camarillo, CA original NAM forecast N and MOS corrected N_C forecasts compared to CIMIS ground data on Feb 13, 2010. Blue: Original NAM forecast, dashed blue: bias corrected NAM forecast, black: CIMIS measurement. The MOS reduces forecast error by nearly 200 W m^{-2} at mid day.

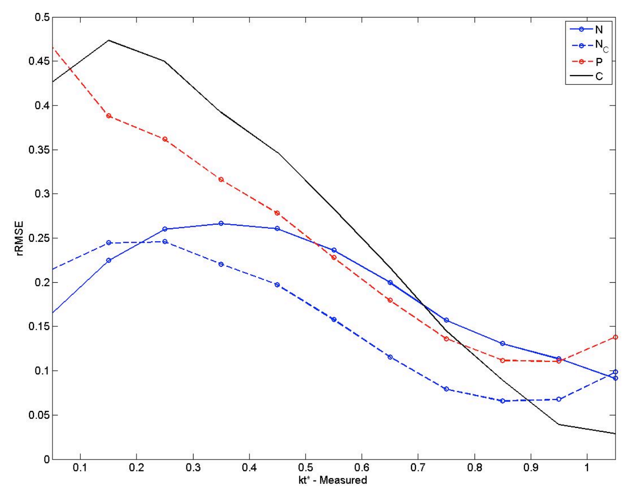


Fig. S2b: Relative root mean square error (y-axis, normalized by 1000 W m^{-2}) of different forecasts as a function of total cloud cover (x-axis) for February-June 2010 in California. Blue solid: original NAM model; blue dashed: bias corrected NAM model; red dashed: persistence forecast; black: clear sky forecast.

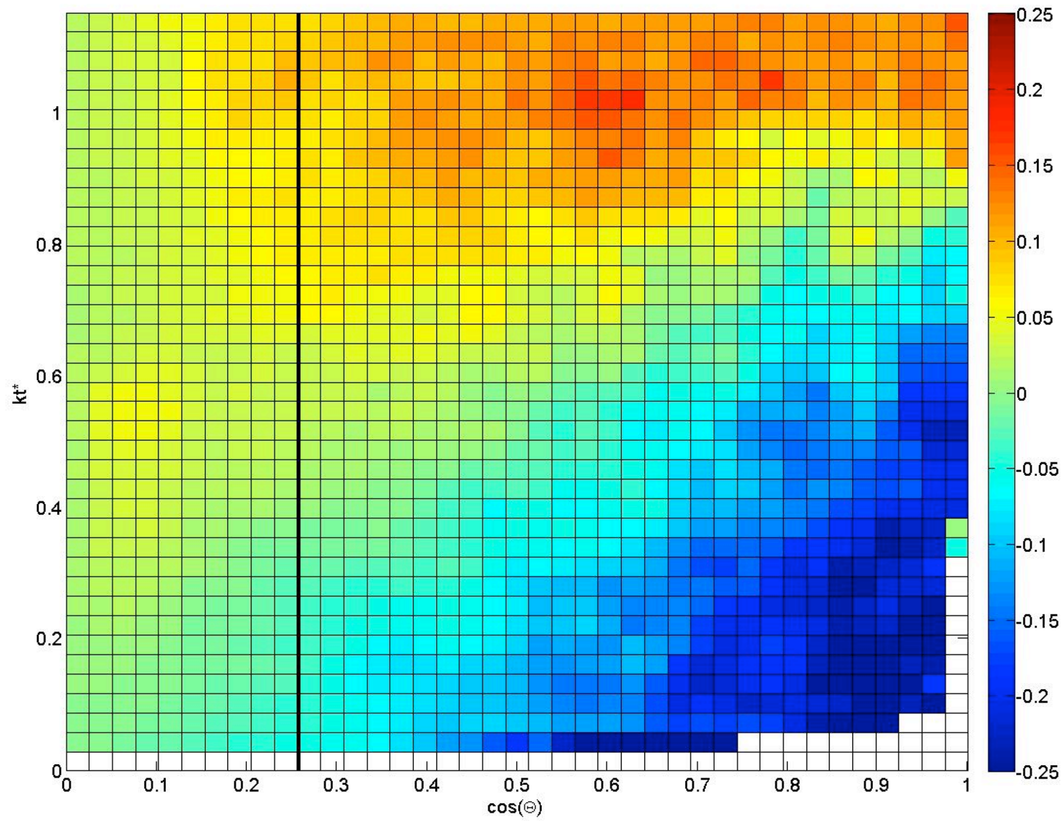


Figure S2c: Relative mean bias error [%/100, colorscale] of NAM forecast N as a function of solar zenith angle (θ) and forecasted clear sky index (kt*) from February to June 2010 compared to CIMIS measurements.

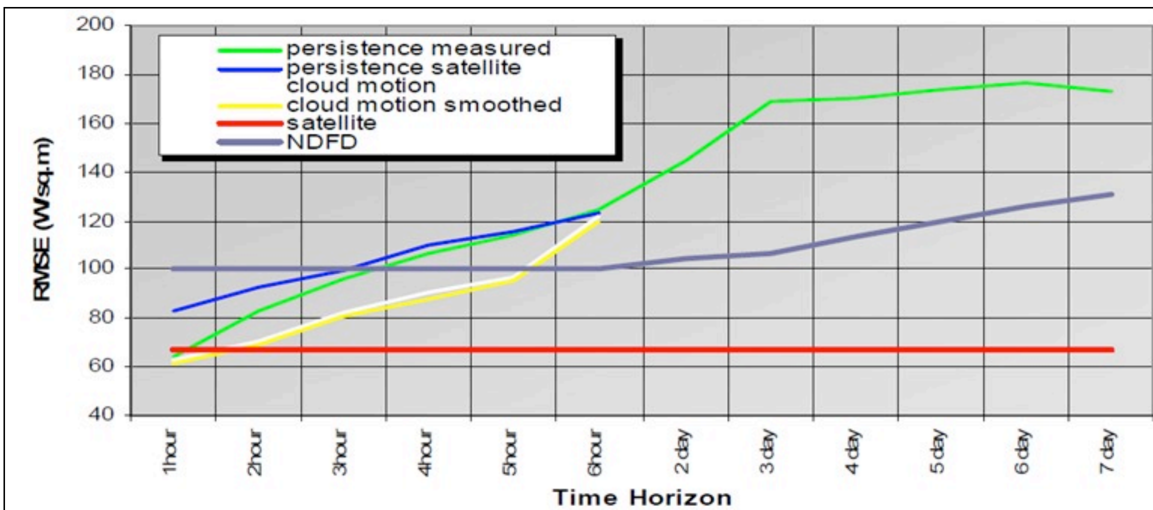


Fig. S2d: Root mean square error (RMSE) of different solar forecasting techniques obtained over a year at seven SURFRAD ground measurement sites (from Perez et al. 2010). The red line shows the satellite nowcast for reference, i.e. the satellite 'forecast' for the time when the satellite image was taken. Cloud motion forecasts derived from satellite (yellow and white lines) perform better than numerical weather prediction (NDFD) up to 5 hours ahead. Numerical weather prediction has similar accuracy for 1 hour to 3 days ahead.

2.3. Literature Survey of Forecasting Applications

2.3.1. Peer-reviewed research

Table A1 in the appendix provides an overview of studies validating solar forecasting methods. The most extensive body of research is from Germany by the groups of Prof. Heinemann at the University of Oldenburg and Dr. Schroedter-Homscheidt at the German Aerospace Agency. No studies exist that examine forecasts for California, partly because there is no high-quality SURFRAD measurement site in California for forecast validation. A comprehensive study of forecasts at seven SURFRAD sites in the US (Perez et al. 2010, Fig. S2d) is probably generally applicable to most inland areas of California. The coastal California meteorology poses unique challenges and forecast models will have to be independently validated there. Generally, published results of forecast error have to be examined with care. The forecast error strongly depends on the amount and variability of cloudiness, making comparison between studies performed in different seasons and climates difficult. Nevertheless, a few general **conclusions** can be drawn **from the literature survey:**

a. Surprisingly, significant bias errors (i.e. persistent high or low deviations) exist in NWP models. However, these errors could be corrected through MOS. NWP model errors should be carefully examined in California.
b. Only for clear sky conditions can accurate forecasts be obtained with as low as 6% RMSE.
c. For all conditions (cloudy and clear) all forecasts that are compared to ground data have RMSEs of at least 20% but as large as 40-80% for cloudy conditions. The main reason for these large errors is the difference in spatial scale between a satellite pixel or NWP model grid cell and the measurement station. Unless local techniques with a finer resolution are employed such as sky imagery, the forecast error will always be large, especially for sub-hourly intervals and cloudy conditions.
d. DNI forecasts are associated with about twice the RMSE than GHI forecasts.

The recommendations for the best solar forecasting approach are well summarized by Schroedter-Homscheidt et al. (2009), who propose to use

- deterministic NWP schemes in the day-ahead market with ensemble prediction technologies for GHI. Post-processing of NWP should be used to derive hourly DNI from NWP.
- aerosol optical depth modelling from air quality applications in the day-ahead prediction (for DNI).
- nowcasting of cloud fields and irradiance from satellites. Cloud motion vector forecasting including both visible and infrared channels should be used for the 1 to 5 hour forecast horizon (satellite-based aerosol added for DNI).
- ground measurements for intra-hour forecasts.

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2.3.2. Solar forecast providers

For this section solar forecast providers were invited to describe their forecasting model, quantify forecast accuracy, and comment on research needs. Generally there are two camps of solar forecast providers. Especially established wind forecast providers apply techniques developed for wind forecasting to solar, which implies running dedicated mesoscale NWP together with machine learning (MOS, ANN) techniques to nudge the forecast to a particular site. Providers specializing in solar forecasts tend to use (government supplied) NWP data for DA forecasts, but use satellite cloud fields for intra-day or HA forecasts. **We believe that for HA forecasts in the coming 3 years the satellite-based method has the greatest maturity, highest spatial resolution, and accuracy. However, as NWP approaches smaller grid sizes and NWP and mesoscale models are improved to assimilate satellite data, NWP may become superior to satellite-based methods. For DA forecast NWP is and will always**

be the most promising forecasting method. A review of models from different providers follows (in alphabetical order):

3Tier does not provide details on solar forecasting capability on its website, but since it uses satellite-based technologies for its solar resource assessment it is likely to possess cloud forecasting capability. 3Tier was invited to comment, but has not responded.

AWS Truepower (AWST): "The production of forecasts in the AWST solar forecasting system is based on the dynamic weighting of an ensemble of forecasts generated by a combination of physics-based (also known as Numerical Weather Prediction (NWP)) models, advanced statistical procedures and cloud pattern tracking and extrapolation techniques. The individual members of the ensemble are weighted for each look-ahead time period (e.g. 1–hour, 2-hours etc.) according to their relative performance in a relevant sample (e.g. a rolling period prior to the forecast time or a set of cases that are similar to the current weather regime). The independent weighting for each look-ahead period allows the system to shift from heavy reliance on one method for a particular look-ahead interval to a heavy weighting of another method for a subsequent look-ahead interval according to the statistical performance characteristics of each method for each look-ahead interval. Currently, the AWST cloud pattern tracking procedure is under development and not yet used as part of the operational ensemble. AWST expects this approach to be added to its operational ensemble once development and testing is completed shortly.

The current operational version of the AWST's solar forecasting system consists of four major components. The first is the generation of a set of mesoscale NWP simulations using the MASS, WRF and ARPS models. These models are run from several sets of initialization and boundary conditions to generate an ensemble of mesoscale NWP forecasts. Most of the simulations employ the standard government-center 6-hour NWP update frequency. However, a small subset are operated in a rapid update cycle mode, which initializes a new simulation every 1 or 2 hours using the latest available data including synthetic moisture data inferred from cloud patterns in satellite images. This is intended to improve the short-term NWP prediction of cloud patterns and characteristics and is still being refined.

The second phase of the forecast production process employs statistical models such as multiple linear regression, Artificial Neural Networks (ANN) and support vector regression to create an ensemble of forecasts of irradiance and other relevant parameters (such as panel temperature). The input into these models includes the output from the NWP simulations, recent time series data from the forecast site and off-site locations and in the future the output from the cloud pattern tracking schemes. The statistical models serve to correct system errors in the NWP simulations as well as to adjust the NWP forecasts to account for recent trends revealed by the on-site or off-site measurement data. The output is an ensemble of forecasts for the site.

The third major component is the generation of a either a (1) deterministic forecast by statistically weighting members of the ensemble according to their performance in a relevant training sample or (2) a probabilistic forecast based on quantile regression using information about the dispersion of the forecasts in the ensemble and also trained on a relevant training sample.

The fourth component is the transformation of forecasted irradiance and other meteorological parameters to power output power output values by using a statistical or physics-based solar plant model. This can be done prior to or after the construction of the ensemble composite (i.e. applied to the individual members of the forecast ensemble or the ensemble composite predictions of the meteorological parameters)."

Provided by John Zack, AWS Truewind, john@meso.com

Clean Power Research offers the SolarAnywhere® solar resource assessment and solar forecasting service. Hourly GOES satellite images are processed using the most current algorithms developed and maintained by Dr. Richard Perez at the University at Albany (SUNY). The algorithm extracts cloud indices from the satellite's visible channel using a self-calibrating feedback process that is capable of adjusting for arbitrary ground surfaces. The cloud indices are used to modulate physically-based radiative transfer models describing localized clear sky climatology. Near term irradiance datasets are produced hourly and are accessible via the SolarAnywhere website or programmatically via web services.

SolarAnywhere provides hourly forecasts up to 7 days in advance using a cloud motion algorithm for short term forecasts and a NWP algorithm for longer term forecasts. The transition point between the short term and long term forecasts is automated in order to produce a unified dataset every hour containing 1 to 168 hours of forecast irradiance for each location. The accuracy of the forecast technique is reviewed in several papers Perez et al. (2009, 2010)

Clean Power Research and SUNY are in the process of increasing the spatial resolution from 10km to 1km and temporal resolution from one hour to one minute as part of the California Solar Initiative Advanced Modeling and Verification for High Penetration PV study. Other improvements in the near term include the imminent release of the v3.0 SUNY algorithm which will incorporate the four infra-red channels from the GOES satellites. Access to the new IR channels will enable early morning cloud motion forecasts during a time period that currently has an inadequate visual image history. Incorporation of the infra-red channels will achieve significant improvements in high albedo locations by enabling better differentiation between naturally highly reflective locations and intermittent snow cover.

Garrad Hassan is an established wind forecast provider. The entry into the solar market will likely be based off of existing NWP and mesoscale modeling capabilities. Garrad Hassan was invited to comment, but has not responded.

Green Power Labs (http://www.greenpowerlabs.com/services_forecasting.html)
"provides solar radiation and power production monitoring and forecasting for utilities, independent system operators and solar power producers. The technology developed by Green Power Labs for broadband modeling of solar radiation at the Earth's surface is based on the analysis of GOES satellite visible spectrum images. The model software is implemented as plug-in for ESRI's ArcGIS9.3 suite.

Solar radiation monitoring is based on a physical model that relates the satellite-derived Earth-atmospheric reflectivity from the visible spectrum channel of the satellites to the transmissivity of the atmosphere. The model calculates the sun's position, air mass and extraterrestrial radiation and, in conjunction with digital databases of surface elevation, Linke turbidity data, produces estimates of clear-sky global radiation at the Earth's surface. The amount of solar radiation reflected by clouds is determined from the satellite-derived data. The resulting data of overcast global radiation at the Earth's surface are produced at a resolution of 1x1 km at the satellite's nadir, at 30 minute intervals. The SolarSatData results are adjusted to the site-specific conditions using World Meteorological Organization - grade weather monitoring stations initially set up at solar power generation sites.

Solar radiation forecasting works on a basis of physical relationship between cloud cover and solar radiation. The forecast system is based upon the cloud cover forecasts from two

Numerical Weather Prediction systems. These are the high resolution Nonhydrostatic Mesoscale Model (NAM) provided by the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction, covering North America and adjacent waters at 10 km resolution, and the Global Environmental Multiscale model provided by Environment Canada at 15 km resolution in its regional configuration. The solar radiation and solar energy generation system performance forecasts for the next 48 hours at hourly intervals are produced daily from the 00Z and 12Z runs and are made available online. GPLI solar radiation forecasts are well correlated with ground observations.

Solar power generation forecasting utilizes recognized models of solar power generation technologies. The service currently offers PV power generation forecasting for utility-scale and distributed systems as well as spatial aggregation of solar power generation in utility areas of service. " (Tony Daye, Senior Manager, Green Power Labs Inc., tony.daye@greenpowerlabs.com)

Solarcasters (http://www.solarcasters.com/dayahead.htm, http://www.solarcasters.com/hourahead.htm, http://www.solarcasters.com/minuteahead.htm):
"offers a line of technical and engineering support services for utility-scale solar power generation. The line includes forecast services for the day-ahead (DA) and hour-ahead (HA) time frames. A service for forecasts in the 0-60 minute time frame is also under development.

SolarCasters DA forecasts predict irradiance and resulting power production in 3-hour average time blocks. Forecasts are made twice each day for the following 24-hour period (...). SolarCasters provides both irradiance forecasts and plant-specific power generation forecasts using its TRNSYS-based plant simulation software. Integration of these forecasts with electrical dispatch master controls systems from Siemens and GE is underway.

DA forecasts are based primarily on numerical weather prediction (NWP) with proprietary algorithms used to forecast cloud cover based on NWP results. The forecasts also use proprietary radiative transfer models to predict the irradiance reaching the ground. A proof-of-concept study at a desert location generated mean average errors (MAE) of around 1% and an RMS error of 11%. Forecasting in a humid semi-tropical environment proved more difficult with a MAE of -7% (the model under predicts the observed) and an RMS error of 38%.

HA forecasts predict 1-hour average power production for the 2-5 HA time frame and are generated using a series of proprietary algorithms based on analysis of satellite images, together with the SolarCasters radiative transfer modeling. The MAE at the desert site in this time period was typically 2% with 12% RMS error. Again the semi-tropical site proved more problematic with MAE of -8% and RMS errors near 25%.

The proof-of-concept studies were conducted on short time series and the results presented here may not be representative. All forecast results are expected to improve when site-specific corrections (MOS) derived from long-term observations are applied.

The forecast technology for the 0-60 minute time frame involves on-site imaging equipment and the use of geometric transforms to track and predict cloud-related transients affecting all or only a portion of a generating site. An X-band radar system for predicting cloud cover in this time frame has also been tested and may prove useful for the largest generating sites. Neither of these technologies has yet been subject to a proof-of-concept."
Provided by: Steve Ihnen, CTO, SolarCasters, Inc., Redmond, WA 98052, o. (425) 736-4631, steve@solarcasters.com

Solardatawarehouse.com is an aggregator and data provider of solar irradiance data from 3600 stations throughout the US. Solardatawarehouse also offers a forecast product based on the dense ground measurements, airport METAR observations, and National Digital Forecast Database data. “The forecasting model has two separate components: One predicts solar radiation based on meteorological observations, while the second learns to recognize seasonal climate patterns at the site. Outputs from the two models are combined to forecast solar radiation one hour and three hours into the future. The models are adaptive and capable of self-learning based on the training data presented them.” (James Hall – JHtech, (719) 748-5231, JamesHall@jhtech.com).

Windlogics has been developing expertise in solar resources and forecasting (e.g. Ahlstrom and Kankiewicz, Utility-scale PV variability workshop, 2009; Kankiewicz et al. American Solar Energy Society conference, 2010) and may be entering the market with new solar forecasting products soon.

3. Data Sources for validation and calibration (Task 1.2)

Solar forecasts from NWP or satellite models are of limited accuracy. Clouds are not resolved or modeled poorly in NWP. Satellites can observe large clouds directly, but they measure only the light *reflected* by clouds, atmosphere, and ground. Solar irradiance reaching the ground has to be modeled using various assumptions. Consequently, accurate data from ground stations is required to validate and calibrate NWP and satellite model forecasts.

In Table S4 sources of real time solar data are listed. Unlike for wind, there is an extreme shortage of publicly available ground based solar irradiance measurements. The following observations apply:

- There are only three stations in California (NOAA-ISIS at Hanford and NREL-MIDC in LA and Rancho Cordova) that provide publicly available, measured, real-time data. However, due to lack of funding and/or supervision even for these stations data quality is a concern (Manajit Sengupta, NREL, personal communication).
- The California Irrigation Management Information System (CIMIS) measurement network covers the entire state at decent resolution, but data are only available in hourly intervals and are only downloaded 1x / day in the evening making these data largely useless for solar forecasting applications.
- CAISO also presently has very little solar generation data, since many solar power plants have gas-fired backup generators which are not separately metered.
- GOES satellite data is currently the most promising resource due to real-time availability, large coverage, and decent accuracy.
- A powerful, but so far untapped resource are the more than 2000 metered PV systems around the state. Since PV power output is near linearly related to solar irradiance, these systems effectively act as distributed solar irradiance sensors. If the measurements could be linked to a national database in real-time, they would be a very valuable and economical resource for solar forecasting.

Also note, that recently NOAA and NREL (Michalsky et al. 2010) have proposed the upgrade of Climate Reference Network (CRN) to measure GHI, DNI, and DIF. However, with only 7 CRN stations in California these measurements would not be sufficient in their spatial density for California’s solar forecasting needs. NOAA estimates that the cost of expanding the CRN network would be $1.5 M for the 7 sites in California. NREL also runs the SOLRMAP initiative to provide quality control for 3rd party installed irradiance sensors, but the data remain proprietary to the operator.

Table S4: Available irradiance measurements in California. ISIS: Integrated Surface Irradiance Study; CIMIS: California Irrigation Management Information System; ASOS: Automated Surface Observation System; PBI: Performance Based Incentive; MIDC: Measurement and Instrumentation Data Center.

Name	Type	Resolution / # of stations	Time step	Real Time?	Accuracy for GHI
GOES	Satellite	1 km	15 min	Yes	Low
NOAA ISIS	Ground GHI, DNI, DIF	1 (Hanford)	3 min	Yes	Medium – High
NREL MIDC	Ground GHI, DIF	2 (LA, Rancho Cordova)	1 min	Yes (30 min)	Medium – High
CIMIS	Ground GHI	134	1 h	No (1x / day download)	Medium
NOAA ASOS	Cloud height and density	82 (airports)	10 min	Yes	Low
CSI PBI	PV output, some GHI	>2070	15 min	No, NDA required[1]	Low
UCSD Sky Imager	Sky Image	50 m	30 sec	Yes	Low

4. Discussion

4.1. Evaluation of forecast accuracy

4.1.1. Error Metrics

Due to the binary nature of solar radiation (cloudy or clear) the choice of error metric is very important for the evaluation of solar forecast models. The root mean square error (RMSE) metric is problematic as it is dominated by large errors. Thus if a forecast model is usually correct but occasionally off by a large amount it may score worse than a model that is always slightly off but never way off. We recommend adding the mean absolute error (MAE) or mean absolute percentage error (MAPE) as a standard evaluation metric since it is less sensitive to large errors.

4.1.2. Economics versus Irradiance

All forecast evaluations (given for reference in Table A1) calculate the forecast error in W m^{-2} or % of solar irradiance. This has the advantage of comparability, but is not the most economically relevant metric. For example, a forecast error during peak load is likely both economically and operationally more significant than an error during off-peak times. To quantify the economic value of radiation forecasts and forecast errors we recommend that researchers use the CAISO OASIS site which continually updates prices in the HA and DA market.

4.2. Single site versus Regional Forecasts

Solar forecast quality dramatically improves when several sites are aggregated over a region (e.g. Lorenz et al. 2009), because average cloudiness in a region can be forecast more accurately than cloudiness at a particular site. Since shorter time-scale fluctuations in power output are uncorrelated across sites only a few miles apart (i.e. the clouds responsible for these fluctuations are usually smaller than the distance between sites) aggregation of power output

[1] May be available real-time in the future through smart meters.

from several sites mitigates the issue of large ramps over short time-scales. The larger the forecast region and the larger the number of sites within that region, the less important small scale variability becomes. For example, Mills and Wiser (2010) showed that 1 minute fluctuations are uncorrelated over distances as small as 20 km meaning that the relative variability standard deviation decreases with the square root of the number of sites – 4 sites means half the relative variability. They concluded that the increase in spinning reserve costs for solar are smaller than those for wind.

In the current market, prices are set at each node in the electric grid. Consequently, the economic value of forecasting is primarily in localized forecasting for a particular solar plant or an urban distribution feeder. However, for other applications such as congestion management and grid operation on larger scales, often aggregate or ensemble forecast are sufficient or desirable.

Likewise for solar forecasting in urban areas, the PV sites are distributed across different rooftops and aggregate forecasts are of greater relevance than forecasts for individual PV systems.

4.3. Recommendations

a) **Type of solar forecast:** GOES satellite and NWP data are the most accurate solar forecast sources for hour-ahead (HA) and day-ahead (DA) forecasts, respectively. An overwhelming body of research (Section 2.2) shows that solar forecast based on satellite models outperform NWP forecasts up to around 5 hours ahead. In turn, persistence forecasts give similar results as satellite forecast up to 1 hour ahead.

   Mesoscale Numerical Weather Prediction (NWP)
   Why: In the long term as computing power and models improve, NWP will be the most promising tool to forecast solar irradiance. This research would enable wind forecast providers to adapt their existing products to solar forecasting and quantify the potential improvement in accuracy.
   What to do: Research should be conducted on the forecast skills of operational numerical weather prediction models for California and the applicability of mesoscale meteorological models to locally enhance forecast skill.
   Who can do it: In collaboration with NREL (Bill Mahoney) and NOAA scientists (Stan Benjamin), California researchers should conduct modeling and evaluation studies for California. Scripps Institution of Oceanography researcher Masao Kanamitsu has significant experience in mesoscale meteorological modeling in California.

   Conduct a forecast competition: CAISO has successfully conducted a wind forecast competition in 2008/2009 and would like to repeat a similar project for solar forecasting. Any forecast providers could bid and provide forecasts for a few representative sites to the ISO for one year. The following parameters should be forecast: Global Horizontal Irradiance, Diffuse Horizontal Irradiance, Direct Normal Irradiance, Global (diffuse + direct) plane of array irradiance for fixed tilt PV, PV panel temperature for fixed tilt PV mounted onto a flat area, Global (diffuse + direct) irradiance for a two-dimensional tracking CSP plant. The California Solar Energy Collaborative (CSEC) could provide independent analysis of such a dataset for CAISO to evaluate operational forecast skill for different providers. Similar

to a previous study on wind forecasting, forecast providers would need to be reimbursed for these services by CAISO and their input to the design of such a study should be sought.[2]
Why: No peer-reviewed studies exist that evaluate solar forecast performance for California. With its unique microclimates California presents a significant challenge to forecast models.
What to do: Contact CAISO's James Blatchford as to the timeline and support required to conduct such a study.
Who can do it: CSEC has the experience, knowledge, and independence to work with CAISO in planning, execution, and analysis of such a study.

b) **Ground measurement networks:** More ground measurements of solar irradiance would improve HA and intra-hour forecasts. Ground measurements of GHI (and DNI for concentrating plants) should be (and currently are) required by CAISO for large solar farms (similar to wind measurements in the PIRP program). However, we believe that establishing and maintaining a separate dedicated network of solar irradiance sites in California would not be the most economical approach to improving forecast skill. High-quality irradiance sites are labor intensive to install and operate as most DNI sensors require daily cleaning. E.g. NOAA estimates that the cost of upgrading the Climate Reference Network to conform to solar resource and forecasting needs would be $1.5M for just 7 sites in California. Yet the high accuracy does not necessarily translate to reduced forecast error since clouds are spatially localized and their detection and prediction would require extremely dense networks. No peer-reviewed research study exists that shows advantages of non-local measurements networks for solar forecasting. However, if other energy meteorology networks were established (e.g. for wind forecasting for which the advantages of such networks are more obvious), it would be useful and economical to 'piggyback' off of these sites and install low-maintenance GHI silicon pyranometers.

The most economical approach to enhance ground measurements would be to require and/or incentive 3rd party data providers (e.g. SunPower, Energy Recommerce, Fat Spaniel) to share their data in real time with the ISO and/or solar forecast providers which – under NDAs – could operate a data warehouse for utilities, and forecast providers. The cost to sharing such data is minimal as the infrastructure is in place such as more than 2000 sensors, meters, telemetry, and databases (Table S4). The only change to the current mode of operation is that database access would be provided in real-time instead of sending monthly summaries to CSI as is done currently. This approach would be expected to cost a fraction of a new station network and could be operated by CAISO and the energy industry in an open market. The advent of smart meters that can monitor residential PV outputs provides an additional avenue to implement this strategy.

Why: There is a lack of solar irradiance measurements in California.
What to do: Research should be funded by the California Solar Initiative or PIER or both in collaboration to develop models to derive solar irradiance values from ground PV data and

[2] John Zack from AWS Truepower comments that "A rigorous competitive evaluation of forecast providers is fundamentally a good idea to establish level of performance expectations and an estimate the variation in forecast performance among providers. However, it is important to realize that the information obtained from such a study will be limited by the design of the study. A particular method may perform very well for one objective but not as well for another. (e.g forecasting of routine events vs anomalous events) and some methods may perform much better if certain types of data are available but may not have any advantage if those data are not available. The danger is that conclusions derived from a specific set of forecast evaluation conditions will be extrapolated to general conclusions, which may to lead to erroneous decisions on how to best address other forecasting objectives. We have encountered this issue in many of our wind forecasting applications."

demonstrate the potential and feasibility of such an approach to improve the accuracy of solar forecasting.
Also research on total sky imager (Figure S1c) deployments in areas with high PV penetration should be pursued. Sky imagers can survey a large area from a single site. The reduced accuracy in the irradiance measures determined by a sky imager (compared to a pyranometer) will be more than overcome by the spatial density and cloud tracking capability of the observations.
Who can do it: Kleissl is conducting Total Sky Imager work at UC San Diego. For the data aggregation work, collaborators with a background in data assimilation would be useful.

c) **Forecast aerosol optical depth for DNI:** Depending on the expected market share of concentrating solar power (CSP) plants in California, research should be conducted on DNI forecasts examining the integration of aerosol models into weather forecast models. These forecasts should especially be able to consider cirrus clouds, forest fire smoke predictions, dust storms, and urban aerosol air pollution transport that may affect CSP in California.
Why: Aerosols can significantly decrease DNI which could impact CSP plants.
What to do: Evaluate satellite remote sensing products of aerosol optical depth and their assimilation into solar forecasting.
Who can do it: Since aerosols may not be detectable on the ground, satellite remote sensing techniques hold the most promise, especially if coupled with NWP. A joint NASA-NOAA-EPA effort seems to be the most advanced (http://www.star.nesdis.noaa.gov/smcd/spb/aq/). With the exception of work in Germany (Breitkreuz et al. 2009), prior AOD work is focused on air quality applications. Additional research is required to determine the skill in determining solar irradiance.

5. Glossary

The NREL '**Glossary of Solar Radiation Resource Terms'** defines the following:

AOD: Aerosol Optical Depth: AOD is the "extinction per unit path length due to aerosols alone". Extinction of solar radiation occurs due to water vapor, ozone, mixed gases, and 'equivalent extinction' represented by Rayleigh scattering of atmospheric molecules, and what is 'left over' is the aerosol extinction.

DIFF: Diffuse Sky Radiation (or Diffuse Horizontal Irradiance): The radiation component that strikes a point from the sky, excluding circumsolar radiation. In the absence of atmosphere, there should be almost no diffuse sky radiation. High values are produced by an unclear atmosphere or reflections from clouds.

DNI: Direct Normal Irradiance: Synonym for beam radiation, the amount of solar radiation from the direction of the sun.

GHI: Global Horizontal Irradiance: Total solar radiation; the sum of direct, diffuse, and ground-reflected radiation; however, because ground reflected radiation is usually insignificant compared to direct and diffuse, for all practical purposes global radiation is said to be the sum of direct and diffuse radiation only.

Irradiance: The rate at which radiant energy arrives at a specific area of surface during a specific time interval. This is known as radiant flux density. A typical unit is W/m^2.

MBE: Mean Bias Error: Metric to compare the b. MBE can be negative (forecast is too small, on average), zero (forecast has no bias), and positive (forecast is too large, on average).

Mesoscale: Scale of numerical weather prediction models with domain sizes on the order of 1000 km and grid cells on the order of 1 to 5 km. Mesoscale models provide more fine-grained information than macroscale models (which predict weather for the entire US or even the globe), but are limited in the area over which they forecast.

MOS: Model Output Statistics: Statistical method to correct model errors in postprocessing based on predetermined bias errors.

NWP: Numerical Weather Prediction: Weather forecasting using computer models.

PV: Photovoltaic: Technology for converting sunlight directly into electricity, usually with photovoltaic cells.

Pyranometer: An instrument with a hemispherical field of view, used for measuring total or global solar radiation, specifically global horizontal radiation; a pyranometer with a shadow band or shading disk blocking the direct beam measures the diffuse sky radiation, as is illustrated in the picture below. A picture of the Eppley PSP pyranometer is included in the PSP definition above.

RMSE: Root Mean Squared Error: Metric to compare forecasts to actual data.

Rotating Shadow Band Radiometer: An instrument that determines total solar radiation and diffuse sky radiation by periodically shading the total sky sensor from the sun with a rotating shadow band. Below is a picture of a rotating shadow band radiometer at the Solar Radiation Research Laboratory. The curved black shadowband at the right of the instrument is at rest; once every minute, it rotates 180° to obscure the sun for a few seconds, then returns to its resting position.

Scattered Radiation: Radiation that has been reflected from particles, disrupting the original direction of the beam

Silicon Sensor: A photovoltaic cell that is being used to measure solar irradiance. Because its spectral response is not as exact as that of thermopile instruments, it has a higher uncertainty.

Solar Concentrator: A solar collector that enhances solar energy by focusing it onto a smaller area through mirrored surfaces or lenses

Solar Thermal Electric: Technology for using the sun's energy to produce steam to run turbines that generate electricity.

Transmittance: The fraction or percent of a particular frequency or wavelength of electromagnetic radiation that passes through a substance without being absorbed or reflected.

Turbidity: A measure of the opacity of the atmosphere. A perfectly clear sky has a turbidity of 0, and a perfectly opaque sky has a turbidity of 1. Turbidity is affected by air molecules and aerosols.

Zenith Angle: The angle between the direction of interest (of the sun, for example) and the zenith (directly overhead).

6. Acknowledgments

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Appendix

Table A1: Review of studies for solar energy forecasting. Modica et al. (2010) showed first results for forecasts with sky imagery. NDFD: National Digital Forecast Database (National Weather Service, NOAA, Washington, DC); ECMWF: European Center for Medium-range Weather Forecasting; Meteosat: Geostationary european satellite.

Study	Location	Quantity	Forecast Source	Averaging Interval	Time Horizon	Error Metric	Error Value	Comment
Schroedter et al(2009), Breitkreuz et al (2009)	121 sites in Europe	GHI	NWP (ECMWF)	1 h	1 - 72 h	RMSE MBE	10% (clear) – 40% (all) -10%	For clear-sky situations aerosol modeling significantly improves GHI and especially DNI irradiance forecasts relative to ECMWF. On the other hand, for cloudy conditions the AFSOL forecasts leads to significantly larger forecast errors.
		GHI	Aerosol + Mesoscale Model (AFSOL)	1 h	1 - 72 h	RMSE MBE	8% (clear) - 60% (all) 5% up to -25% (all)	
		GHI	Meteosat	1 h	1 - 72 h	RMSE MBE	6% (clear) – 22% (all) 0	I believe Meteosat was calibrated to data
		DNI	NWP	1 h	1 - 72 h	RMSE MBE	30% (clear) – 82% (all) -25% (clear) up to -35% (all)	Overall: 31.2% or 159 W m-2 -26.3% or -134 W m-2
		DNI	AFSOL	1 h	1 - 72 h	RMSE MBE	20% (clear) - 85% (all) 10% (clear) up to -15% (all)	18.8% or 96 W m-2 11.2% or 57 W m-2
		DNI	Meteosat	1 h	1 - 72 h	RMSE MBE	15% (clear) – 38% (all) <3%	15.6% or 80 W m-2 -1.7% or -9 W m-2
	Forecast length has a significant impact on forecast accuracy, as long as cloudy situations are included in the analysis: for the AFSOL system, this can be quantified by RMSEs of 49.7% for the first day, 62.4% for the second day, and 67.7% for the third day. When considering only cloud-free cases, forecast length has no effect on bias or RMSE for any of the model systems analyzed. Thus, it can be deduced that this error tendency is caused exclusively by difficulties in cloud forecasts that increase with growing forecast duration.							
Wittman (2008)	1 site in Spain, July 2003	GHI	NWP (ECMWF)	1 h	1 - 72 h	RMSE MBE	18.5% or 109 W m-2 -11.1% or -65.6 W m-2	Similar order but better results for clear skys only. AFSOL GHI on 5% RMSE.
		GHI	AFSOL	1 h	1 – 72	RMSE	25.1% or 148 W m-2	

					h	MBE	-2.2% or -12.7 W m-2	
		DNI	ECWMF	1 h	1 – 72 h	RMSE MBE	41.7% or 184.9 W m-2 -23.3% or -103.2 W m-2	
		DNI	AFSOL	1 h	1 – 72 h	RMSE MBE	47.0% or 208.6 W m-2 15.6% or 69.4 W m-2	
Lorenz et al. (2009)	Europe	GHI	ECMWF	1 h	3 h -	RMSE MBE	12% (clear) to 85% (cloudy) 0% (clear) to 25% (cloudy)	For both ECMWF and ECMWF + MOS: Day 1: RMSE = 35%, Day 2: RMSE = 40%, Day 3: RMSE = 55%.
			ECMWF + MOS	1 h		RMSE MBE	12% (clear) to 80% (cloudy) <5%	
	Study also shows confidence intervals for prediction. For ensembles distributed over a region of a size of 3o x 3o, the RMSE of the forecast is about half the RMSE of a single site. The RMSE is reduced to one third of the site-specific RMSE for regions of a size of about 8o x 8o.							
Perez et al. (2007)	Albany, NY	GHI	NDFD	3 h	3-72 h	RMSE MBE	32% (<4) to 40% (>26h) -10% (<4 h) to -4% (>26 h)	National Digital Forecast Database only output cloud cover
Hammer et al. (1999)	Central Europe, April - June	GHI	Meteosat - Heliosat	instantaneous	0.5 – 2 h	RMSE	18% for 30 minutes (vs 26% persistence), 22% for 1 h, 28% for 2 h, 38% for 3 h.	RMSE is satellite forecast versus satellite actual, i.e. no ground station data were used. Numbers were estimated from graphs. Filtering improves the forecast quality.
Bacher et al. (2009)	Denmark	P_{out}	Autoregressive models based on P_{out} (t-1) and NWP	1 h	1 h – 30 h	RMSE	40 - 100% (normalized by mean power) for same day, 5% - 13% (normalized by peak power) for next day	For horizons below 2-h solar power is the most important input, but for next day horizons no considerable improvement is achieved from using available values of solar power, so it is adequate just to use NWPs as input.
Hamill & Nehrkorn (1993)	Eastern 2/3 of US	Brightness	GOES cross-correlation	instantaneous	0.5 h – 2.5 h	RMSE	9% (0.5 h) to 18% (2.5 h) for fall, winter, spring. 11% to 25% for summer	RMSE is satellite forecast versus satellite actual in gray-shade values. Persistence was 12% to 21%. Using 500 mbar wind field nearly as good as crosscorrelation

								method. 11 km pixel resolution.
Heinemann (2006)	Germany Saarbruecken 8 Stations	GHI	Meteosat – Heliosat from Hammer et al. (1999)		0.5 h – 6 h	RMSE	25% (0h) to 42% (6 h) with motion & smoothing. 25% (0h) to 55% (6 h) with persistence	With increasing forecast the influence of smoothing becomes more important than the application of motion vector fields.. Variability in the cloud field has a strong effect on forecast RMSE.
	Same as above	GHI	MM5	1 h	1 h to 48 h	RMSE	with MOS: 33% for day 1 and 36% for day 2 with MM5: 52% for day 1, 55% for day 2	40 days in summer 2003
Jensenius (1981)			MOS on NWP			RMSE MBE	25% for 1 day 2% for 1 day	
Bofinger and Heilscher (2004)	32 sites in Germany		MOS on ECMWF			RMSE MBE	32% for hourly and 19% for daily. Persistence was 55% for hourly and 48% for daily. 2.9% for hourly and 2.8% for daily	1 year
	same		Meteosat - Heliosat	1 h		RMSE MBE	26% for hourly and 12% for daily 3% for hourly and daily	
Perez et al. (2009)	6 sites in US	GHI	Satellite	1 h	1 h to 6 h	RMSE MBE	53 to 64 Wm-2 (1h) to 100 to 133 Wm-2 (6h) (persistence: 53 to 65 Wm-2 (1h) to 108 to 125 Wm-2 (6h) -3 to 12 Wm-2 (1h) to -3 to -13Wm-2 (6 h) (persistence: 2 to 11 Wm-2 for 1h, 6 to -23 Wm-2 for 6h)	8/23/2008-1/31/2009. Persistence forecast included extrapolating measured irradiances using a constant GHI/GHIclear ratio. Forecast errors for Boulder, CO, are much higher due to local topography and are excluded.
	same	GHI	NDFD	1 h	1 (same day) to	RMSE MBE	75 to 114 Wm-2 (same day) to 97 to 146 Wm-2 (7 days) (persistence: 150 to 211	All NDFD forecasts originate at 11:00 GMT.

					7 days		Wm-2 (7 days)) -25 to 32 Wm-2 (same day) to -18 to 41 Wm-2 (7 days) (persistence: -8 to 10 Wm-2)	
	Cloud-motion forecasts are more accurate than NWP up to 4-5 hours ahead with a performance gain approaching nearly 40% for the 2-hour forecast. The forecasts also perform better than on-site measurement extrapolation with performance gain peaking at hour 4. NDFD overpredicts irradiance, even after it was adjusted empirically to prevent overprediction. Comparing range of mean monthly values within a 2^{o} by 2^{o} gridbox to absolute RMSE errors at the site shows that the RMSE errors are much smaller.							
Remund et al. (2008)	3 sites in CO, NV, MS	GHI	NDFD	1 h	1 day	RMSE MBE	18% (NV), 41% (CO), 36% (MS) 2% (NV), 3% (CO), -4% (MS)	April – September 2007. The breakeven of persistence is reached after 2-4 hours. The breakeven is dependent on the uncertainty. For ECMWF and NDFD this value is reached at 2 hours for GFS/WRF at 3 hours. The errors for same day and 2 day forecast are only marginally different from 1 day (shown on left).
			EMCWF V2			RMSE MBE	18% (NV), 40% (CO), 32% (MS) 3% (NV), 11% (CO), 6% (MS)	
			GFS/WRF			RMSE MBE	18% (NV), 50% (CO), 41% (MS) 2% (NV), 19% (CO), 18% (MS)	Also conducted Kolmogorov-Smirnov test.