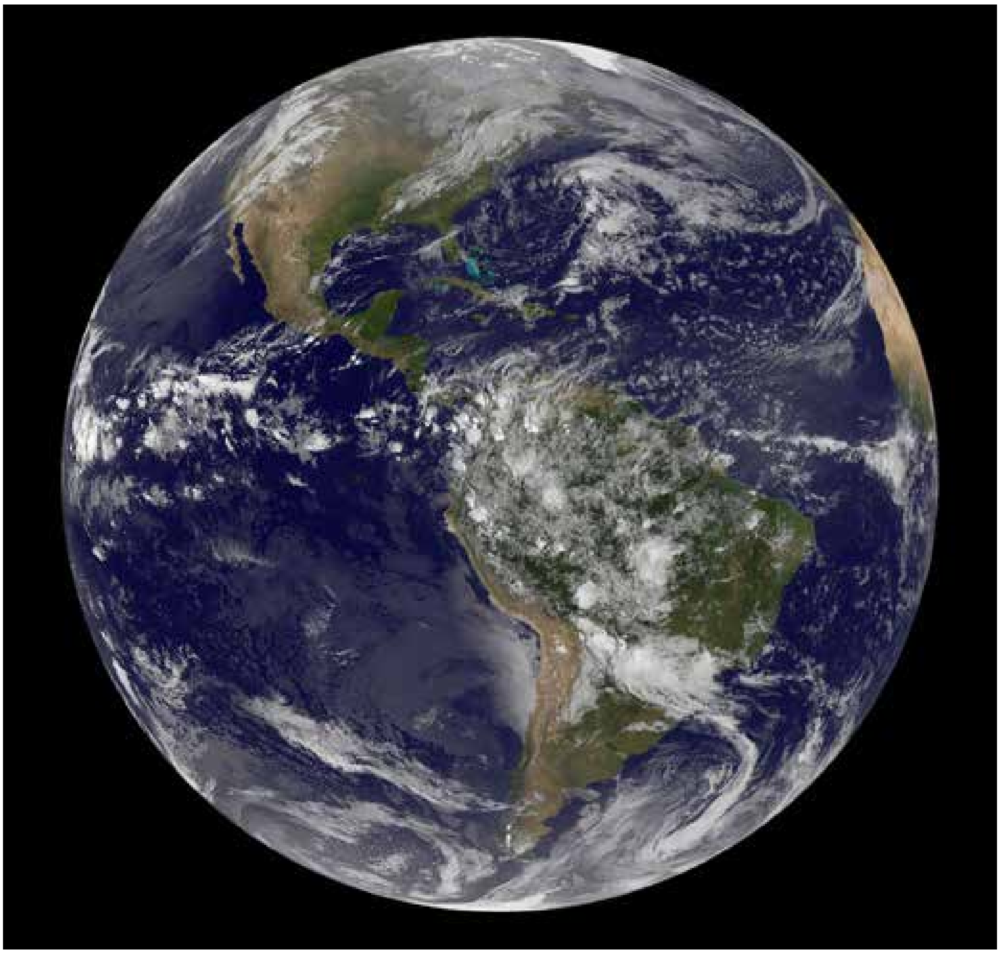
Towards accurate PV power forecasting

Forecasting | Predicting the power production of a PV plant offers a multitude of benefits to plant owners and grid operators. Jose Ruiz-Arias looks at the challenges of accurate forecasting across different timescales and in different climate zones



Credit NASA

The weather system is chaotic and cannot be controlled at will. Neither can solar power, which can only be anticipated with some level of uncertainty. In general, solar power increases the need for operating power reserves to compensate for production drops due to weather fluctuations. However, improved scheduling using solar power forecasting allows minimising such reserves as well as reducing the need for PV power curtailment. For electricity trading, it maximises revenues by minimising the penalties due to mismatches in production bids. All in all, solar power forecasting facilitates the matching of production and demand curves in distribution and transmission grids.

The benefit of solar power forecasting extends over applications at multiple time ranges. For instance, at sub-hourly time scales, forecasting of power ramp rates is used to make a more efficient operation of power storage units. A few hours ahead, solar forecasting is helpful in the operation of secondary electricity markets, in which solar power forecasting is combined with other system variables such as foreseen demand, state of transmission grid or expected generation from other sources in order to come up with the best operating decisions. For day-ahead time periods, solar power forecasting is used to schedule the operation of conventional power plants to accommodate the foreseen solar power generation. At even longer timescales, solar power forecasting is useful to schedule plant maintenance operations.

Expected improvements in satellite and weather observation sensors are expected to boost the quality of solar radiation forecasts at all timescales

PV power forecasting

Forecasting PV power production involves two modelling aspects: 1) modelling the weather, and 2) modelling the PV system. Among the weather factors determining PV production, solar radiation is the most important one, followed by air temperature.

The level of detail and accuracy at which a PV power system can be described are much higher than for describing the weather system. For instance, the layout and technology of PV panels, thermal and electrical losses or inverter performance are all aspects that can be accurately characterised. In contrast, the observation of weather is comparatively highly uncertain. Given the large scale of the Earth's weather system, its observation requires the use of remote measurement techniques (e.g., sensors onboard satellites). Indeed, most often there are no other means of observation.

All in all, the characterisation of weather is at least as blurry as even the loosest characterisation of a PV system. As a practical example, just consider that the uncertainty of solar radiation measurements—starting at 3% in the best use case—is one order of magnitude higher than the uncertainty of power measurements. At the same time, however, the uncertainty of solar radiation forecasts is nearly one order of magnitude higher than that of solar radiation measurements. Therefore, the

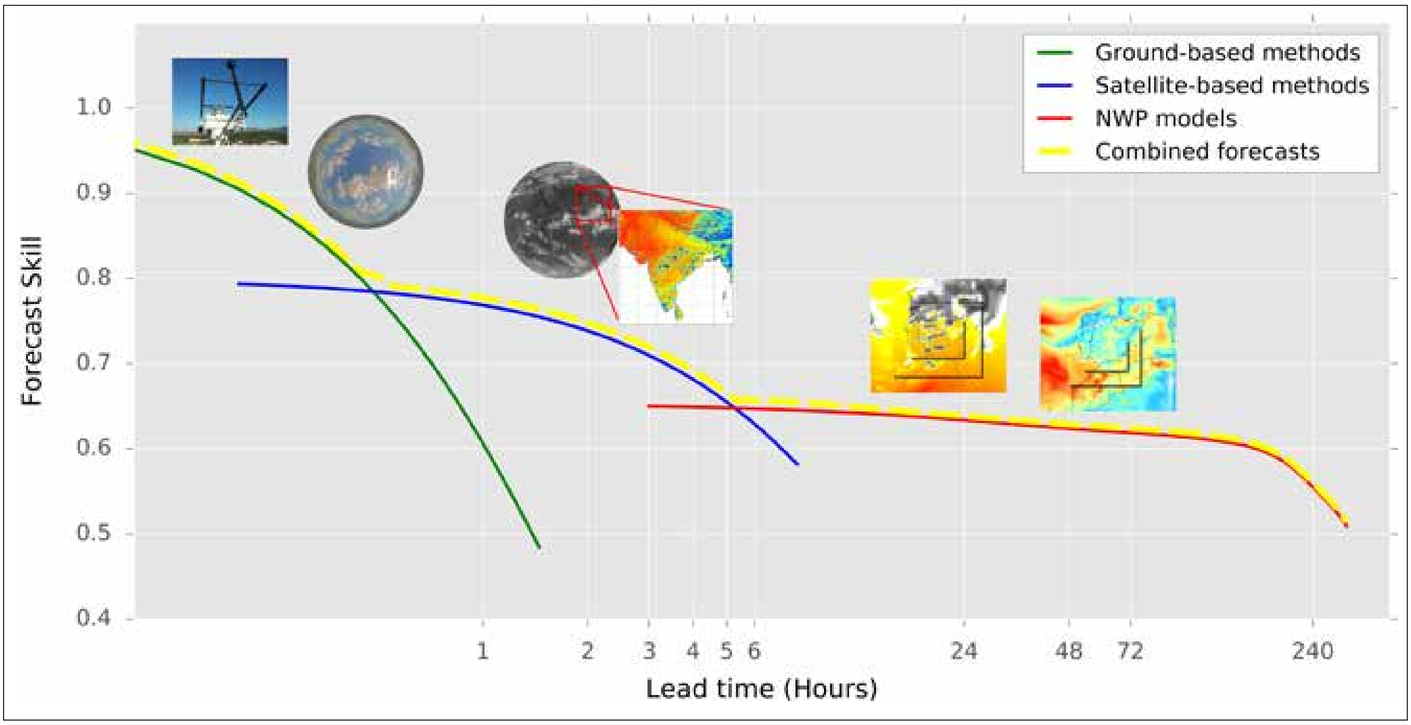


Figure 1. Conceptual plot of forecast skill vis-á-vis forecast lead time for ground-, satellite- and NWP-based forecast methods. The forecast skill values, shown for illustration purposes, are only approximated. The pyranometer and sky camera photos are courtesy of the University of Jaén, Spain

uncertainty at forecasting solar radiation turns out as the dominating factor in the forecast of PV power production. Based on this fact and the worldwide scarcity of public PV production data, the subsequent discussion will be primarily focused on solar radiation forecasting. However, the results here presented are similar to the ones expected for PV forecasting. The focus on solar radiation forecasting allows us to expand our discussion to virtually any location worldwide.

Solar radiation forecasting

Solar radiation forecast can be tackled using purely statistical methods or physically based ones; or, the trend nowadays, using combinations of both. However, what ultimately defines the most suitable approach for each particular application is, most often, the intended forecast lead time, and factors such as computational burden or availability of on-site observations, possibly with near real-time feedback to the forecaster. Lead time, in our context, means the time between the forecast being issued and the time to which it refers. Likewise, horizon lead time is normally used to refer to the maximum lead time involved in each forecast. For example, for some applications, the interest in solar power forecast relies mostly on lead-time ranges of up to six hours ahead or, equivalently, six hours' horizon lead time.

The various solar forecasting methods are here introduced by intended forecast lead time. In this sense, Figure 1 shows a conceptual comparison of the expected forecast skill as a function of forecast lead time for the most important families of forecast methods: i) Ground-based methods, ii) satellite-based methods and, iii) numerical weather prediction (NWP) models. The maximum forecast skill (one) is for a perfect forecast, i.e., matching the uncertainty of actual observations.

Less than one hour ahead

At sub-hourly forecast lead times, the methods based on on-site ground observations provide the highest skill (see Fig. 1) because, at this timescale, weather patterns often change very little and are affected only by local features. In other words, the correlation of weather phenomena stays high. Thus, statistical methods do a great job at casting the current observed conditions into near future times. The forecast is normally issued in the form of solar radiation time series representing the average conditions in the surroundings of the location of interest. These forecasts are most frequently based on the combination of solar radiation measurements with sub-hourly time resolution (ideally, 10 minutes or shorter) and statistical methods such as auto-regressive or state-space models. A trivial model, particularly ubiquitous by its simplicity, is the so-called 'smart persistence', which assumes clouds do not change throughout forecast lead time and only the changes due to the deterministic course of the sun are modelled. However, in general, more sophisticated assumptions are used in production models.

A somewhat different approach to forecasting sub-hourly solar radiation is based on the observation of the cloud field over the location of interest using on-site cloud sky cameras. These are essentially camera systems (as simple as plain surveillance cameras or more specialised and sophisticated systems) staring at the sky. By comparing two or more consecutive images, the overall speed and trajectory of cloud structures can be inferred and used to cast the cloud locations into the future (using similar techniques to the ones used by the satellite-based methods described below). Then, the spatially-distributed solar radiation over the measurement field can be calculated from the predicted cloud field. This technique potentially offers a detailed description of the passing clouds over the PV field, being even able to resolve cloud shades in different sections of a PV power plant.

However, it is a relatively new approach, still under heavy research to solve multiple challenges that prevent its implantation as a widespread forecasting technique. It requires the on-plant deployment of dedicated hardware systems, with stringent maintenance requirements, and sophisticated software to store, manage and process the large volume of data. There are also technological barriers that limit the ability of the systems to distinguish clouds near the circumsolar region or to detect the altitude of clouds. So far, the proposed solutions involve increasing the complexity and cost of the detection systems but still with too limited improvements. Typically, the forecast horizon using sky cameras does not extend beyond 15 minutes ahead.

Few hours ahead

As the forecast lead time moves from sub-hourly to various hours ahead, the relative importance of remote weather features prevails over local features. In essence, clouds far from the site of interest will be affecting local weather in a matter of tens of minutes to a few hours. As a consequence, local observations are not enough to account for future events and the observation area needs to be expanded. The satellite-based methods then come naturally to the playing field. Figure 1 shows that the forecast skill of ground-based methods is eventually surpassed by the forecast skill of satellite-based methods for horizon forecasts of about half an hour.

Sensors aboard modern satellites provide images of cloud fields that extend over thousands of kilometres. They describe clouds with a spatial resolution in the order of 3 km (even finer for some spectral channels) and a refresh rate between 10 and 30 minutes depending on the satellite. As with sky cameras, the forecasting principle consists of a similarity analysis of two or more consecutive cloud images. From it, the positions of matching cloud structures in the two images are used to determine the speed and trajectory of clouds, which are represented by a spatial field of vectors customarily referred to as cloud motion vectors (CMV). Then, assuming CMV stay the same for the next hours, the future position of clouds is inferred, from which solar radiation is computed.

A major limitation of CMV-based techniques (using both sky cameras and satellite imagery) occurs when the vertical movement of clouds is not negligible with respect to the horizontal displacement, which typically happens with convective and orographic clouds. Contrarily to sky cameras, satellite-based forecasting does not require costly on-site equipment and maintenance. Moreover, the new and forthcoming satellite systems promise spatial and temporal resolutions never seen so far, being soon capable of reaching spatial resolutions comparable to large PV power plants.

Beyond few hours ahead

As shown in Fig. 1, the skill of satellite-based forecasts decreases with increasing forecast lead time. This happens because the spatio-temporal correlation of current and future weather patterns drops off. NWP-based forecasting methods tend to provide higher forecast skill than satellite-based methods beyond typically five or six hours ahead. They simulate the temporal evolution of the entire weather system by solving the equations that describe the atmospheric physical processes. The physical foundations of NWP models make up for the lack of valid information at forecasting times from current observations. NWP models are routinely used by public and private weather services to provide forecasts on a regular basis. They can run over the entire Earth, then being known as global NWP models, or over only a limited area, then being referred to as limited area or mesoscale NWP models. Global models—which are run virtually only by public weather services and research centres due to their huge computational demands—provide worldwide coverage at the expense of limited spatial resolution (currently in the approximated range from nine to 25km) and temporal resolution (currently hourly or three-hourly). The typical refresh rate is once every six or 12 hours, with each new forecast normally providing values up to about 10 days ahead. However, some particular configurations of these models—not precisely focused on solar radiation—simulate the atmosphere up to several months ahead.

Probably the most widely used global NWP models are the Integrated Forecasting System (IFS) of the

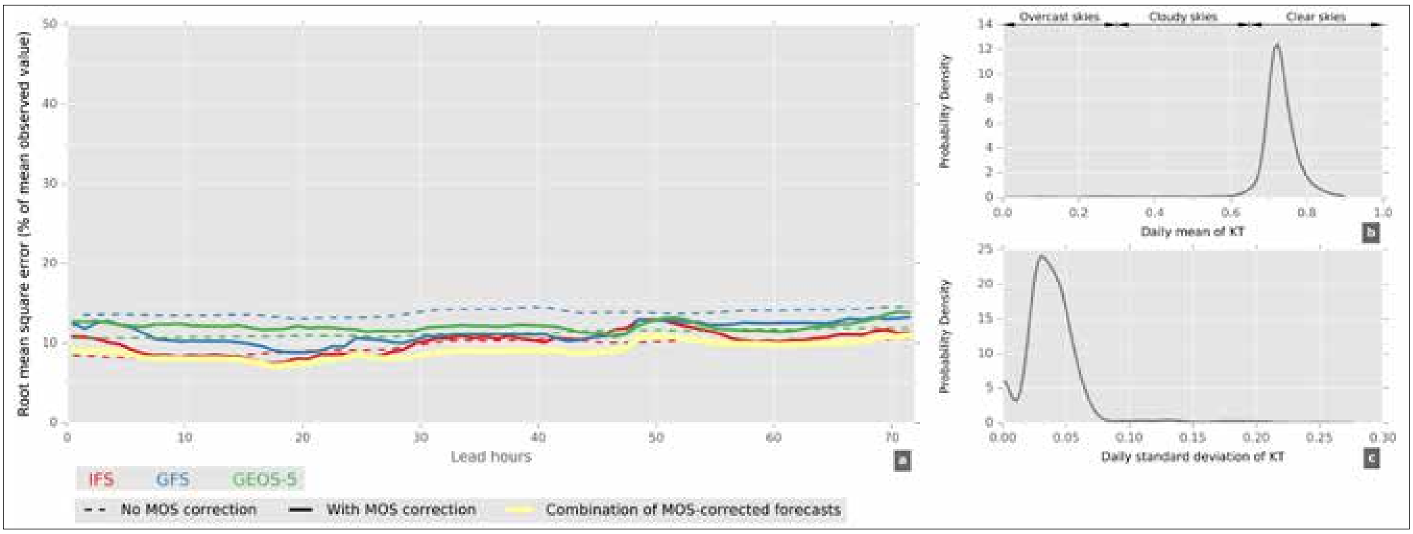


Figure 2. Validation of solar radiation forecasts at a location in the Atacama Desert, Chile. (a) Root mean square error as a function of forecast lead hours for IFS (red), GFS (blue) and GEOS-5 (green). (b) Distribution of daily mean clearness index, KT. (c) Distribution of daily standard deviation of KT. Validation conducted against the Solargis solar radiation satellite model. Validation period: 2016/09 – 2017/04 (eight months)

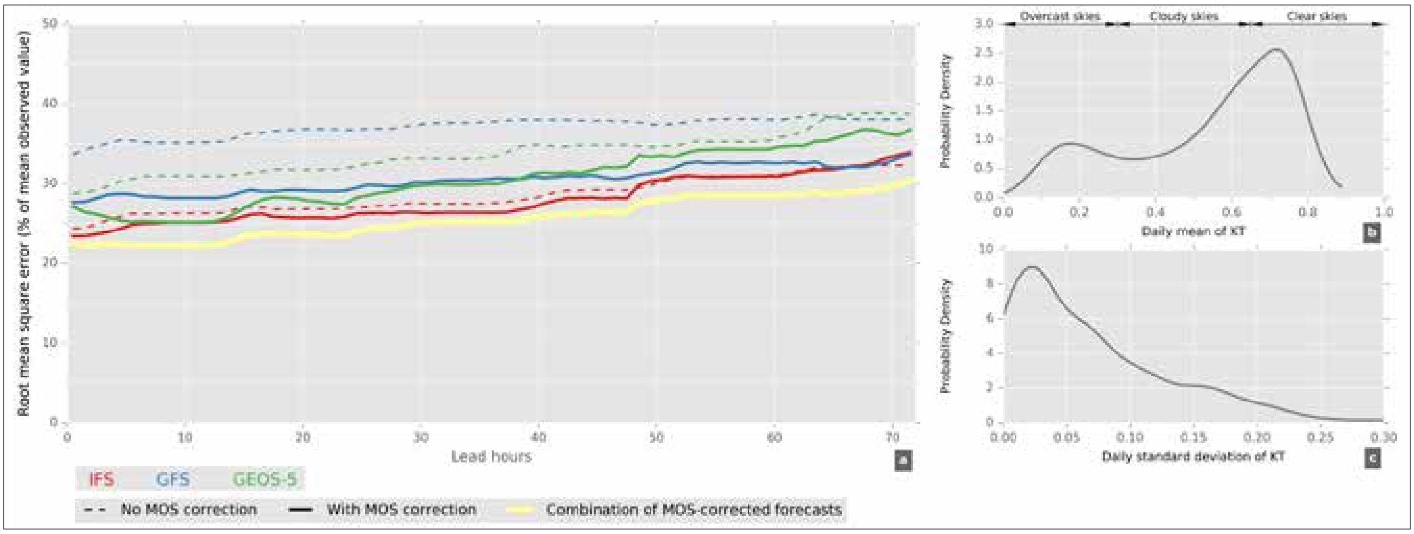


Figure 3. As Fig. 2, but for a location in Tokyo, Japan

European Centre for Medium-range Weather Forecast (ECMWF) and the Global Forecast System (GFS) of the National Centers for Environmental Information (NCEI) of the United States. In contrast, mesoscale NWP models focus on a limited area (e.g., country-wide) and simulate the weather system with increased spatial and temporal resolutions, in the order of few kilometres with sub-hourly outputs. Due to their reduced computational requirements compared to global models, they are often operated also by private entities since they can be adapted to the specific needs of final users.

The development of NWP models—especially as regards global NWP models—has never been particularly focused on solar radiation, with only very few and recent exceptions. Therefore, to forecast solar radiation, post-processing approaches are often used to adapt the forecasts to local features not considered by the NWP model as well as to increase the temporal and spatial resolution. In addition, although all NWP models are physically based and are mostly founded on the same major physical assumptions, some other assumptions are different. For instance, the modelling of convective clouds or the calculation of solar radiation may originate discrepancies in the forecast skills of different models. Overall, the best forecasting approach is normally the use of consensus forecasts that optimally integrate forecasts from various NWP models. Below, some examples of NWP forecasts are shown.

Long-term forecasting

This sort of forecast is required during the early development stages of PV projects for feasibility and bankability studies. Essentially, the foreseen resource for the next years and decades is required to trace down a reliable business plan. Interestingly, no forecasting models are used for this application. Instead, historical observations or typical meteorological year data sets are brought into the chessboard under the major assumption that the future will behave as the past did. Sometimes, historical observations are slightly corrected to account for known error trends or expected climate drifts, when such drifts are deemed non-negligible.

Forecast post-processing

At all levels of forecast and with all forecast methods, the forecasts can be post-processed to diminish errors as long as reliable and accurate observations, not yet used in the forecasting chain, are available. This post-processing is particularly beneficial for satellite- and NWP-based forecasts since, unlike ground-based methods, they typically do not make use of such observations to create their forecasts. This data processing is customarily referred to as 'model output statistics' (MOS) and spans a wide spectrum of methods to combine observations and forecasts, from the simple and ubiquitous linear regression to the recent rise of a comprehensive family of skilful methods jointly referred to as machine learning. The improvement achieved by MOS post-processing highly depends on the quality of observations, the ability of the MOS model and the prevailing weather conditions. In addition, and particularly for NWP-based forecasts, the blending of forecasts from various independent NWP models results in enhancement of the forecast performance, as long as the forecast errors of the individual models are not fully correlated.

NWP forecast examples in various climate zones

In order to give a hint about current solar radiation forecast errors, the performance of three of the best-known global NWP models is assessed at three locations in different continents with varying cloud regimes. The models are IFS, GFS and the Global Earth Observing System Version 5 (GEOS-5) of the National Administration Space Agency (NASA) of the United States. The validation is conducted based on the root mean square error (RMSE) score using reference data from the Solargis solar radiation satellite model.

Figure 2 shows the evaluation at the Atacama Desert, in Chile. This location features a study case with prevailing pristine and cloudless conditions (see Fig. 2b; to be compared later to Figs. 3b and 4b) and thus with little cloud variability (see Fig. 2c; to be compared later to Figs. 3c and 4c). The cloud amount is represented by the clearness index parameter, KT, which roughly represents the cloud transmittance of solar radiation (KT is nearly zero for overcast conditions and one for cloudless skies). The validation of models is shown in Fig. 2a for models with both no MOS (thin dashed lines) and MOS (thin solid lines) post-processing, respectively. Roughly,

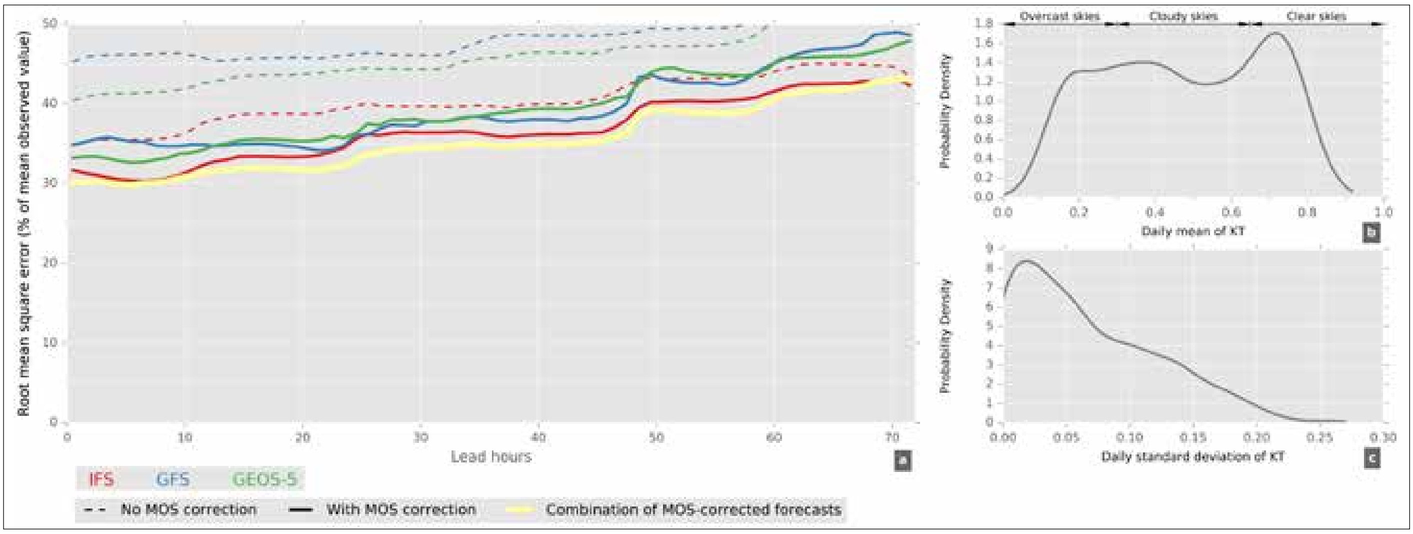


Figure 4. As Fig. 2, but for a location in Bratislava, Slovakia

all models have similar RMSE around 10%. The MOS post-processing does not clearly and systematically improve the initial forecasts. The thick solid line refers to the combined MOS-corrected forecasts, which slightly improve the individual model forecasts.

Figure 3 shows the case of Tokyo, Japan. Now, the relative amount of cloudy days and variability (Figs. 3b and 3c, respectively) increase with respect to the previous location. As a consequence, the overall forecast error of all models increases up to 25% or higher. However, the benefits of the MOS post-processing and the combination of models are now clearer than for the cloudless case. Note also that, unlike for the Atacama Desert, the performance of the forecasts now decreases with forecast lead time, as a consequence of the smaller predictability of cloud-related weather patterns.

Finally, Fig. 4 shows the case of Bratislava, Slovakia, where the relative cloud amount and variability (Figs. 4b and 4c, respectively) is even higher than in Tokyo. Now, the magnitude of forecast errors rises up to 30% or higher, with larger inter-model differences. Again, the MOS post-processing and models blending considerably improve the initial performance, by about 10% on average. The error increase with forecasts lead time is steeper than in Tokyo.

It may be concluded that the predictability of solar radiation decreases with increased occurrence of clouds, although, in parallel, the room for MOS improvements increases. All in all, however, the MOS-corrected forecast RMSE varies from about 10% for prevailing clear and cloudless conditions to more than 30% for locations dominated by cloudy skies where, in addition, the forecast error for three-day forecast horizons may increase by about 10%. The combination of models systematically provides better forecast than any individual forecast model.

Regional forecasting on PV fleets

Thus far, we have focused on pointwise forecasts. However, aggregated forecasts across PV fleets are likewise required in many cases. In general, errors over the aggregated fleet under prevailing stable weather conditions are reduced only marginally, and, to a larger extent, for variable cloud conditions. The rationale is that weather variability produced by passing clouds results in highly uncorrelated solar radiation errors at the different locations of the PV fleet. This leads to cancellation of positive and negative errors when solar radiation is predicted over the entire fleet. Under stable conditions, in contrast, all errors are overall positive or negative, eventually preventing the cancellation of errors. With respect to pointwise forecasts, error reductions of up to 15% have been reported in the scientific literature for locations spread over region scales from 50 to 100 kilometres.

Concluding remarks

Solar radiation forecast errors are the dominating factor in forecasting solar power. The most suitable solar forecasting technique mostly depends on the forecast lead period of interest: i) ground-based methods for sub-hourly time horizons, ii) satellite-based methods up to about five hours ahead, and iii) NWP-based forecasts beyond that period. In general, however, the best results are obtained by intelligently blending forecasts from different approaches and models.

The normal trend is a growth of forecast errors with forecast lead time and cloud occurrence rate. In particular, it has been shown for three state-of-the-art global NWP models that their forecast errors highly depend on the local cloud climatology, varying from about 10% RMSE for prevailing cloudless conditions to more than 30% RMSE for prevailing cloudy conditions. The three-days-ahead solar radiation forecast error may increase by nearly 10% with respect to the intra-day forecast error under heavily cloudy conditions. When the forecast is issued for a PV fleet, the overall error may be broadly reduced by 15% under unstable weather conditions over land scales of about 50 to 100 kilometres. The enhanced capabilities of the satellite and weather observation sensors to come during the next decades are expected to boost the quality of solar radiation forecasts at all timescales.

Author

José A Ruiz-Arias is weather and solar radiation expert in Solargis. He provides support to clients and develops models to assess and forecast solar radiation. Jose has published more than 50 papers in scientific journals as researcher at the University of Jaén, Spain, and the National Center for Atmospheric Research of the United States. He is a member of the IEA PVPS Task 16 on Solar Resource for PV.