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Hedging Risk in Techno-Economic Assessment for CSP Plants Through Synthesis of One-Minute Irradiance Series

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Abstract. For the proper sizing of a solar plant, thorough simulations are performed to obtain the optimum configuration for the optimization objective, such as to minimize the Levelized Cost of Energy. These simulations consider the use of a Typical Meteorological Year, that condenses in a single year the long-term meteorological characteristics. These data sets are often derived from satellite estimates and validated against ground measurements taken over a shorter period of time. One issue with these data sets is concerned with temporal resolution, as they are limited by the capacity of the satellite to resolve phenomena on a temporal scale. This results in a loss of high-frequency detail that could affect the techno-economic design and assessment of a solar plant, creating uncertainty in the expected performance when compared to ground data, thus increasing project risk. This work explores the effect of applying a temporal downscaling technique to generate one-minute estimates of ground radiation from hourly satellite data in the reduction of uncertainty in technical and economic key performance indicators. A Concentrated Solar Power plant of 100MWe and 12 hours of storage is studied and results are compared to determine the extent to which temporal downscaling allows to hedge estimation of performance and in turn, risk. Results show that while the most significant source of uncertainty is the estimation error inherent to the satellite procedure, temporal downscaling allows for a reduction of 2.1% in LCOE estimation, showing that a relatively simple post-processing procedure allows for a measureable reduction in investment risk.

Keywords: Irradiance Downscaling, Satellite Estimation, CSP

1. Introduction

For the proper design and assessment of a solar plant of any nature, accurate solar resource data is required to minimize the uncertainty of the operation's estimated techno-economic performance. Current practices involve the use of satellite estimated data, coupled with on-site ground measurements to either validate the satellite estimate or proceed to site adaptation in order to minimize the differences [1]. Likewise, to assess the lifecycle performance, a Typical Meteorological Year (TMY) is used, which condenses the overall long-term irradiance and meteorological characteristics of a location into a single year [2]. However, these data sources are limited by the temporal resolution on which the inputs for the satellite estimation models are obtained. This constitutes a limitation, as high speed transients in irradiance cannot be captured due to temporal smoothing, which has an effect in the estimation of yields for solar photovoltaic and thermal systems.

Therefore, data post-processing techniques such as interpolation and irradiance synthesis [3] can be applied for those cases in which high temporal resolution data is not available for TMY generation. In this manner, an estimation of these high-speed transients can be created and system design and assessment can consider this data instead, to properly account for how the high-frequency dynamics of the entire system due to variability in solar resource affects the technical and economic performance (and, thus, feasibility) of the operation. Historically, to analyze the impact of the temporal resolution into the design and operation of solar plants, a usual framework is concerned with the integration of one-minute ground irradiance data into lower resolutions. However, this approach presupposes the existence of one-minute ground data, which is not usually the case for potential locations of solar plants. Furthermore, while high temporal resolution data could be available for a validation period of the satellite series, this ground data might not cover the entire period on which the TMY for simulation is constructed, therefore resulting in a lower temporal resolution TMY.

Therefore, this work explores a different approach, in which one-minute synthetic irradiance data is generated from lower temporal resolution satellite estimates. The performance of a Concentrated Solar Plant (CSP) is assessed to determine the extent in which satellite estimation and temporal resolution of input data affect the overall techno-economic performance characteristics of the plant, considering a fixed plant configuration, which constitutes the main contribution of this work.

2. Data sources and methodology

2.1 Data sources and quality control scheme

In this work, satellite estimates and ground measurements for Santiago de Chile (-33.5°N, -70.6°E) are used for the year 2022. Satellite estimates from the National Solar Resource Data Base (NSRDB) are taken, using an hourly resolution. In the case of ground measurements, they were measured using a Rotating Shadowband Irradiometer at one second intervals and stored as one minute averages, with the equivalent hourly values obtained through integration. Measurements were compared and calibrated against a Solys 2-axis tracker fitted with pyranometers and pyrheliometers, but ultimately RSI data was used due to greater availability.

Both data sets were assessed using Quality Control criteria in order to screen for issues such as balance equation violations, extreme irradiance values and inconsistency in irradiance components, following a scheme proposed in [4]. The QC scheme was applied for minute and hourly data, to obtain the valid values for each set and then, only data that was considered valid simultaneously in the ground and satellite data are considered, with the remainder of values (i.e. those that failed QC) being set to zero. Finally, in order to ensure temporal consistency between all data sets, the valid hourly sets (ground and satellite) were interpolated into the equivalent 1-minute resolution, using the same procedure used to generate the low-frequency component for the satellite downscaling, presented in the next section.

2.2 Overview of the temporal scaling methodology

There are several methods available in the literature for irradiance downscaling, such as methods based on statistical generation of synthetic data to match distributions of ground data to physical methods that aim to downscale the inputs for a satellite estimation model [3]. In this work, a recent method based on short-term synthetic variability generation, as a postprocessing step for satellite data is implemented, due to the good results obtained in [4]. In this procedure, a low-frequency one-minute interpolation of the original hourly data is compounded with a high-frequency synthetic data series in order to obtain the downscaled product. First, the Global Horizontal Irradiance (GHI) is downscaled and then its fluctuations are propagated to the remainder of components. Finally, data is adjusted as to comply with QC criteria and avoid generating unfeasible data points.

The low frequency component is obtained through spline interpolation, whereas the high-frequency component is obtained after several stages. First, from the hourly GHI and Diffuse Horizontal Irradiance (DHI) the state of the atmosphere is estimated and an estimation of the short-term intra-hourly variability is made with this information. Then, a Cumulative Distribution Function (CDF) of the possible instantaneous ramps in one-minute GHI is generated so that the resulting variability matches the estimated value using hourly GHI and DHI data.

This yields a potential pool of irradiance ramps on which to construct the downscaled series and random values are taken, with random sings, are integrated, added to the low-frequency component and constrained to comply with enforceable QC limits, generating a pool of candidate downscaled GHI time series. Then, the candidate with the least error in terms of energy and variability with the corresponding hourly value is selected and fluctuations in GHI are propagated into DHI and Direct Normal Irradiance (DNI). Finally, all QC criteria are enforced by clamping to the corresponding limit any exceeding value. The interested reader is referred to [4] for more detailed information.

2.3 Case of study and assessment methodology

A 100MWe net molten salt central receiver CSP plant is considered. This plant is modelled using the NREL's System Advisor Model (2023.12.17), with a default configuration, save for the setting of 12 storage hours and dispatch optimization tailored for the "Generic Duck Curve" dispatch profile, considering a 48-hour dispatch horizon. This plant is assessed in four conditions: hourly satellite data (case 1A), hourly ground data (case 1B), synthesized one-minute data based on the satellite estimate (case 2A) and one-minute ground measurements (case 2B). To isolate the effect of temporal resolution of irradiance, the remainder atmospheric variables are set as constant, equal to the median yearly value of the one-hour satellite estimate.

To assess the effect in performance, solar resource and plant techno-economic performance are assessed. For the solar resource, energy totals and similarity in data distributions are compared. Since the fluctuations in the synthetic one-minute satellite irradiance time series do not necessarily coincide with those in the ground measurement series, and given the randomness in the synthesizing procedure, it is not feasible to compare 1:1 comparison on minute data, as shown in [4]. As for plant performance, some techno-economic indicators are calculated for each case, but also, analysis of data distributions for some key variables that describe the flow of energy from resource to electric output are also considered. The Capacity Factor (CF) and Levelized Cost of Energy (LCOE) are considered as overall techno-economic performance indicators, which are calculated, respectively as the quotient between total yearly energy against the nominal capacity for all hours of the year, and the quotient between plant costs throughout its lifecycle and the corresponding energy produced in the same period.

To analyze the effect of solar resource characteristics on plant operation, the incident power on the receiver, charging and discharging power to the storage system, energy stored in the storage and gross electric output of the power cycle are analyzed. As for the case of solar resource, it is of interest to compare not only value distributions, but also, the variability on each step of the production chain to understand the propagation of variability from resource to production and compare amongst the datasets to evaluate the effect of downscaling. Finally, to quantify the effect of temporal downscaling in improving performance estimates, and thus hedging investment risk, the following analysis is pursued. There are two main sources of uncertainty in the solar resource estimation compared to one-minute ground reference: that inherent to the satellite estimation (energy totals) and that corresponding to high-frequency fluctuations (variability, stemming from differences in temporal resolution). These sources of error are termed SED (difference in solar resource estimation) and TRD (difference due to temporal resolution). The SED can be obtained by comparing the data characteristics of hourly data between satellite and ground data (as the effect of high-frequency variability is not present in these sets due to temporal smoothing) and TRD by comparing the one-minute against the one-hour time series for the satellite and ground sets, separately. From this analysis, the contribution of downscaling can be decoupled from the effect of satellite estimation error.

3. Results and analysis

3.1 Solar resource characteristics

Figure 1 presents the characteristics of GHI and DNI data (top left) as well as its variability (bottom left), and showcases a full day as an example, showing hourly and minute GHI and DHI ground (top) and satellite (bottom) data. An overestimation of solar resource is observed in the satellite series, that shows overall higher values both in GHI and DNI. There is little difference in GHI data distributions between hourly and one-minute cases, while for DNI this is not the case due to short-term variability (even if the hourly data can be comparable, the corresponding one-minute values are not necessarily so). It is of interest to see that the downscaled synthetic series show minimal deviations regarding values for GHI and DNI. As for variability, the bottom subfigures show that while having comparable variability at the hourly scale, the downscaled synthetic series is able to reproduce the dynamic characteristics of fluctuations in GHI and DNI. From the time-series analysis, the downscaler is able to reproduce significant variability during the before noon instances, however since during afternoon the condition of the hourly satellite estimate is consistent with clear sky, the downscaler doesn't add significant variability to this part of the day. This figure showcases the extent on which short-term variability can be added through synthesis to reproduce high-frequency dynamics found in real data.

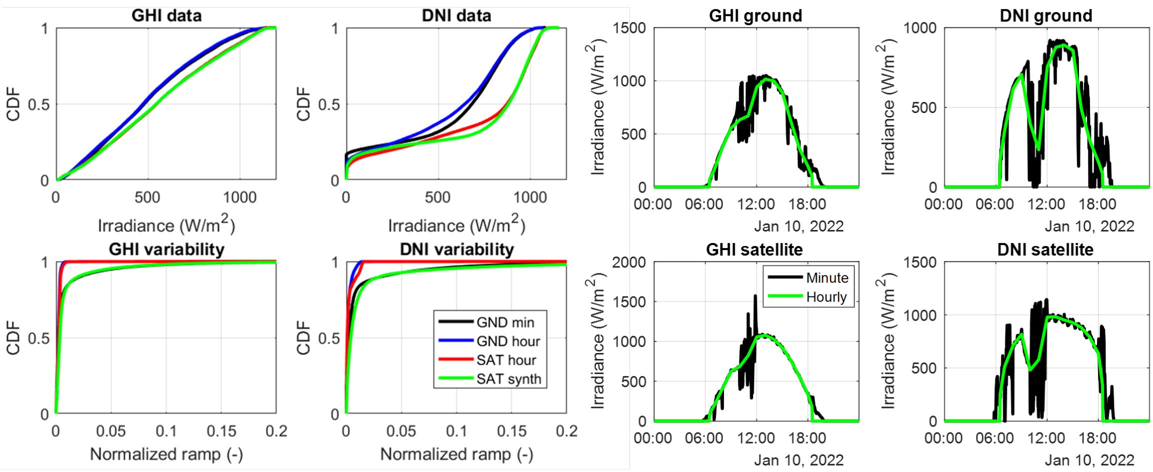

Figure 1. *Data distribution analysis for irradiance (left subfigures) and time series for ground and satellite data at hourly and minute resolutions for a single day.*

3.2 Performance metrics assessment and time series analysis

Figure 2 shows the results for the data distribution analysis for different variables (top row) and their corresponding variability (bottom row). To homogenize the presentation of the results in terms of variability, the reference value for normalization was chosen for each variable as the maximum registered value in the corresponding time series, except for stored energy, in which the normalization factor was chosen as 12 due to the 12 hours of storage.

As for the case of irradiance, there are not significant differences in incident power onto the receiver between the hourly and minute series of each set, but the effect of overestimation in the satellite remains. This results in slightly more power being charged into the thermal storage for the satellite against ground but, since the downscaled satellite can model more instances with very low DNI, it shows less energy charged into the storage. On the discharge power, however, there are more pronounced differences between one-minute and hourly on the satellite series, due to the former being able to store less energy. This is shown when comparing the amount of energy stored into the storage, with the downscaled satellite being much closer to the ground reference. Finally, whilst the power output values are much higher for the satellite estimate than ground reference, this is due to the satellite overestimation, however the downscaled satellite shows slightly less power, due to a better reproduction of high-frequency dynamics that attempt against power generation. For all variables, the variability of the downscaled satellite is comparable to that of one-minute ground case. In the case of power output, the variability is even higher than ground reference by a small margin, which could be attributed to how short-term dynamics are reproduced in the plant model.

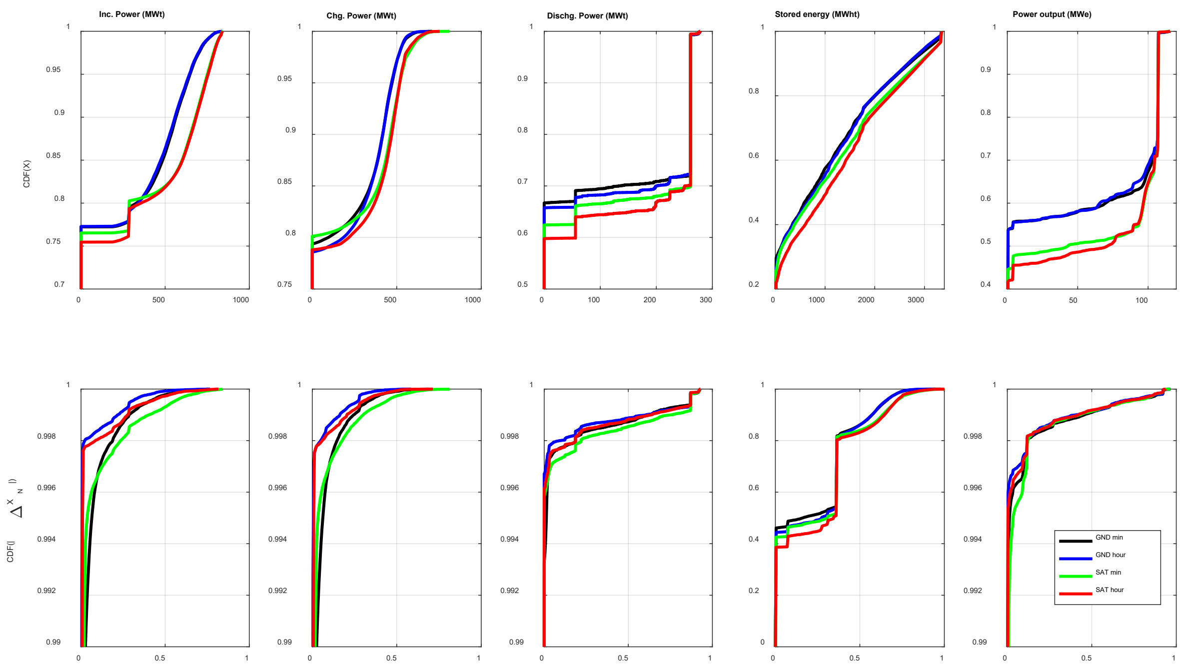

Figure 2. *Data distribution analysis for representative variables of plant's technical performance (top) and the corresponding variability (bottom).*

Figure 3 showcases plant operation in three consecutive days: the first is a clear day and the remainder are highly variable. For the clear day, there are only minor differences, as there is no significant variability and therefore all of the time series are similar, resulting in a charged storage with the ensuing de-focusing to reduce incident power. The second day is a highly variable one and, while there is more electric power output than either of the ground cases, the amount of stored energy is much lower for the downscaled satellite case, which results in a much lower power output compared to the hourly satellite case, and much similar too both ground cases.

For the hourly cases, since ground measurements resulted in lower radiation, the power cycle only delivers power well after the energy storage is fully charged, using the received irradiance to charge it in order to dispatch energy at hours of higher economic value. Since the original satellite involves higher irradiance, it is possible to operate the power cycle without stopping, as there is enough stored energy on the night before and during day, sufficient energy will charge the storage and allow for uninterrupted dispatch. When considering the one-minute cases, the ground measurements overall dynamics are very similar to hourly data, just with slight differences in the rate at which energy is stored. The downscaled satellite, however, differs notoriously from its hourly equivalent and more closely resembles the ground cases. This is due to the fact that, by more accurately capturing DNI transients not as much solar energy can actually be utilized for storing and the power cycle, therefore, less energy is extracted from the storage as the electric output is much lower than the corresponding hourly case. Nevertheless, since the issue of irradiance overestimation remains, overall more energy is available and therefore there is more electric power output in the one-minute satellite than either of the ground cases.

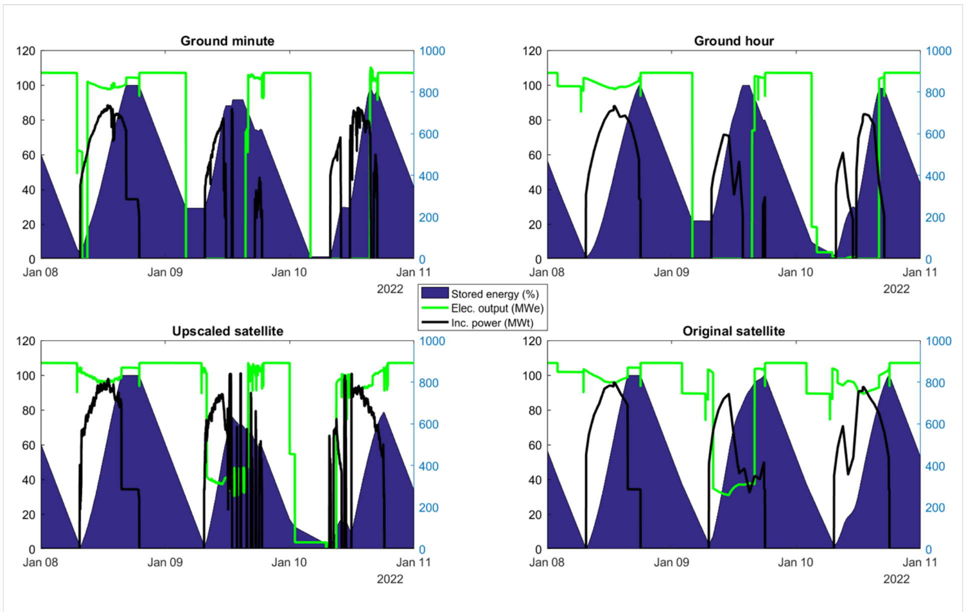

Figure 3. *Performance comparison of hourly and one-minute data for ground and satellite for three consecutive days, showcasing differences in plant operation*

Table 1 summarizes the yearly statistics for several relevant variables, namely total yearly DNI, the incident power on the receiver (INCPOW), charged and discharged energy into/from the thermal storage (TESC and TESD, respectively), annual net energy delivered to the grid (AE), the Capacity Factor (CF) and nominal Levelized Cost of Energy (LCOE). The downscaler showed consistency in yearly energy against the original satellite series, with only 1.3% difference, however in the case of GND data, one-minute data showed a 3.5% increase, which could be attributed mainly to the temporal resolution differences and the effect of interpolation: in high variability scenarios the interpolated data could show only zeros whereas on the one-minute ground series non-zero instances can occur when the solar disc is not entirely covered by clouds. However, the main difference observed is the significant difference in energy totals due to satellite estimation, which propagates into the production chain (incident power, energy storage and energy production). While the CF is comparatively low and LCOE high, this is due to the fact that due to QC, invalid or missing data was flagged as zero resulting in a significant decrease in yearly energy and these values should be taken only as a reference on which to analyze the effect of downscaling in relative terms to the ground truth. Nevertheless, its observed that at higher temporal resolutions, despite showing higher yearly DNI values, for the downscaled series the CF is lower due to the effect of solar resource variability.

Table 1. *Overall performance metrics for each of the analyzed cases*

	SAT (1-min)	SAT (60-min)	GND (1-min)	GND (60-min)
DNI (kWh/m2)	2177.0	2148.5	1745.1	1686.4
INCPOW (GWht)	1244.7	1284.0	1059.9	1048.2
TESC (GWht)	773.8	818.5	703.0	725.4
TESD (GWht)	766.5	811.1	695.7	718.1
AE (GWhe)	444.5	458.5	373.1	369.5
CF (%)	49.9	51.5	41.9	41.5
LCOE (USD/MWh)	13.9	13.6	16.3	16.4

Table 2 presents the results of temporal resolution difference, difference due to satellite estimation, combined effect of SED and TRD for the sixty-minute (1A) and one-minute (2A) satellite data; and the value provided by the downscaling approach (Hedge). These are calculated as follows: SED is obtained as the difference hourly SAT minus GND, normalized against hourly GND; TRD as the difference of one-minute minus hourly, normalized by the corresponding hourly data; the combined effect of SED and TRD (TRD+SED) is calculated as the difference between hourly (1A) and one-minute (2A) satellite minus one-minute GND normalized by the latter and the Hedge is the difference between one-minute and hourly satellite normalized against one-minute ground. In this table AE was omitted as the CF is the normalization of AE against the plant's nominal capacity working all hours of the year.

Table 2. *Differences in performance characteristics due to satellite estimation and temporal resolution differences between satellite and ground data.*

	TRD-SAT	TRD-GND	SED	TRD+SED (1A)	TRD+SED (2A)	Hedge
DNI	1.33%	3.48%	27.40%	23.12%	24.76%	1.64%
INCPOW	-3.06%	1.12%	22.49%	21.14%	17.43%	-3.71%
TESC	-5.46%	-3.09%	12.83%	16.43%	10.08%	-6.35%
TESD	-5.50%	-3.12%	12.95%	16.58%	10.17%	-6.41%
CF	-3.03%	0.96%	24.07%	22.89%	19.17%	-3.73%
LCOE	2.50%	-0.93%	-17.49%	-16.72%	-14.63%	2.09%

From TRD+SED (1A), there are significant differences in the performance estimation when considering satellite hourly data, compared to how the plant would operate under real conditions. These differences stem from estimation error in satellite estimates (SED), but also, due to short term variability of the solar resource and its effect on plant operational decisions: solar field focusing, energy storage charge and discharge and electric dispatch. Additionally, downscaling allowed for the reproduction of high-frequency dynamics that affect electric energy production in a CSP plant in a way in which hourly data is not possible to reproduce, this has a significant effect not only on the incident power on the receiver, but also on stored thermal energy and thus final electric production. While this was also observed for ground data, the differences in yearly energy (and thus CF and LCOE) are much lower, due to the differences in INCPOW being much lower. The reason why there is a significant difference in GND data between DNI and INCPOW might be related with differences occurring in instances where the solar field is de-focused and thus differences in DNI are not translated into differences in INCPOW, while this is not the case for SAT data. Therefore, by using a downscaled version of the satellite estimate, it is possible to reduce the difference in the estimation of critical parameters such as the CF and LCOE, which mitigates investment risk due to a reduction in the uncertainty of the plant's performance. In this case, from temporal downscaling alone, it was possible to reduce the CF estimation error by 3.7% and the LCOE estimation error by 2.1%.

4. Conclusions

This work explores the extent to which irradiance synthesis can be a powerful tool to hedge risk in the techno-economic assessment of solar projects. The results show that even though differences due to satellite estimation are the main source of uncertainty, a non-negligible portion of the risk can be mitigated using synthetic one-minute irradiance estimates. As long as the resulting downscaled irradiance time series exhibits similar data statistical characteristics as ground data would in terms of variability, the effect of transients can be properly captured and will affect the techno-economic assessment of a solar power plant. High-frequency irradiance transients affect not only the amount of energy available for the conversion chain, but also, how effective the control strategy could be under these circumstances. However, the extent to which these transients have a definite effect in plant operations, for the purpose of numerical simulations used for design and assessment, is limited by the ability of the numerical model of the plant to also reproduce the high-frequency dynamics of a CSP plant in an accurate manner and, in particular, start and stop dynamics of the power cycle.

Finally, this work focused on analysing the effect of irradiance downscaling in reducing the risk through more representative assessment of real operational conditions at the one-minute level, than the corresponding hourly data, considering the same plant design in all cases. Naturally, for each data set there will be exist an optimum plant design that minimizes a target metric, such as the LCOE. It is then of interest to assess how the downscaling affects such process and, thus, the resulting plant configurations that emerge from this optimization process. Future studies are needed in this regard, to gather a better understanding of the technical effects of downscaling, but also, to further reduce project risk by designing a plant that will perform as close as possible to the expected performance obtained through the use of high temporal resolution ground data.

Data availability statement

Satellite data used in this work was obtained from the NREL National Solar Resource Database (NSRDB). Ground measurements can be made available upon request for research.

Author contributions

Armando Castillejo-Cuberos: Conceptualization, Methodology, Programming, Formal Analysis, Investigation, Resources, Writing – Original Draft, Visualization, Funding Acquisition. **Ignacio Arias:** Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing – Original Draft, Funding Acquisition. **José Miguel Cardemil:** Conceptualization, Methodology, Resources, Writing – Original Draft, Funding Acquisition. **Rodrigo Escobar:** Conceptualization, Methodology, Resources, Writing – Original Draft, Funding Acquisition.

Competing interests

The authors declare that they have no competing interests.

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