

Reply to anonymous Referee #1

We would like to thank anonymous referee#1 for his/her comments, that helped us improve the manuscript. In the following, analytical replies are provided to each of the reviewer's comments. Reviewer's comments are written in bold font. Line numbers, when provided, refer to the new version with track changes.

The study reflects the lack of adequate reflection on previous work and literature in this area. However, this should be the basis and first step of developments and publications. This lack leads to misleading interpretations of the results and introduction of concepts as novel, which are in contrast well known. I cannot recommend this manuscript for publication in the current form. Please see the detailed comments for further information. I can not recommend the manuscript for publication, see comments below. However, the evaluation results might motivate the publication of the manuscript after a proper major revision.

Thank you for your time and comments, they certainly helped towards a better-quality manuscript.

Major comments/concerns:

L105 and others:

The author uses “~16M combinations of simulated GHI at the earth's surface”. However, several concepts exist with smarter solutions, e.g. with the hybrid eigenvector concept the amount of needed RTM calculations can be reduced to several hundred, also the good old NREL etc. approximations works well, see <https://doi.org/10.1016/j.rse.2009.01.012> or <https://doi.org/10.3390/rs4030622> and references therein for further details. A respective discussion or proof of the benefits of the approach presented in the manuscript is missing. Thus, it is not clear why this algorithm is needed and what the benefits compared to other well established methods are.

Reply

We acknowledge that different concepts exist to reduce the amount of RTM simulations that the LUTs needed to describe the surface solar radiation for different atmospheric/surface conditions and hence reduce the computational time without significantly compromise the accuracy of the retrieval. However, the main concept behind the generation of our clear sky LUT was to have, in addition to total

shortwave, also spectral irradiance outputs in order to be able to integrate different spectral regions according to the targeted application (e.g. erythema, vitamin D, photosynthetically active radiation).

Technically, since the operational set up of the SENSE2 model allows for the computation of the clear sky GHI values from the previous day, the processing time for interpolation to the 7 dimensions of the LUT has no effect in producing timely the real time output of the model every 15 min, while the accuracy of the clear sky output is almost identical with direct RTM simulations, which was investigated in a previous study focusing on clear sky conditions (Papachristopoulou et al., 2022). So, in this case the uncertainties of the clear sky GHI retrievals are related mainly to the uncertainties of the model inputs.

In addition, the 16M simulations were performed only once for building this LUT. This LUT includes various aspects especially for aerosols (aerosol optical depth, single scattering albedo, Ångström Exponent) that can reduce the uncertainty under different aerosol conditions and for broadband solar radiation or specific spectral regions. Especially in the shorter wavelength regions under cloud free conditions and in the presence of different aerosol types.

Finally, we follow similar LUT approach with one that has already published in the previous study by Kosmopoulos et al. (2018), using less combinations. The relevant discussion was added in the manuscript (lines 229 – 247 in the new version of the manuscript with track changes attached) presented previous studies, new concepts along with the proof of the benefits of the approach adopted by the current study.

L 125 “...Wdata (Bhartia, 2012) based climatology) and surface albedo (GOME-2 database (Tilstra et al., 2017, 2021))

Several important aspects are not discussed which affects the accuracy of the product. Is the used SAL consistent with that used for COD ? Further, is the aerosol information used for the COD retrieval identical to those used for SIS ? Are the BRDF corrections for SAL and COT identical ? If not, what does that mean for the consistency of the product. Please note, in particular inconsistent SAL data can lead to a significant bias in SIS, this could be the reason for your bias and not the “sun obscuration”.

Reply

In the revised version of the manuscript more details were including regarding those products, specifically in Lines 221-222 that the directionally dependent

Lambertian-equivalent reflectivity product of GOME-2 was used and in Line 258-259 the relevant references for the cloud retrievals.

Regarding the retrieval algorithm of cloud optical properties for the 2017 dataset used in this study (Météo-France, 2016):

- The surface characteristics are obtained from monthly climatology over land or constant value over sea. Specifically, over land surface reflectances were derived from MODIS white-sky surface albedo monthly climatology available from NASA (<http://modis-atmos.gsfc.nasa.gov/ALBEDO/index.html>). These white sky albedos represent bi-hemispheric reflectances without the direct component which is a good approximation of the surface albedo below a cloud. Over sea, constant values were used: 3% (at 0.6mm) and 1% (at 1.6mm).
- An aerosol free atmosphere is assumed, which might introduce errors under high aerosol plumes (like desert storms and biomass burning events) if a single channel approach used for the retrieval of cloud information (Mueller et al., 2015), but in our case those errors are eliminated (~60% of dust cloud cases are detected) because the retrieval algorithm is based on a multichannel approach and differences in channels according to the cloud features and respective spectral signatures (Météo-France, 2021).
- We used for the GHI retrievals directionally dependent Lambertian-equivalent reflectivity (DLER) of the Earth's surface retrieved from GOME-2 satellite observations (Tilstra et al., 2021). The surface DLER describes Lambertian (isotropic) surface reflection which is extended with a dependence on the satellite viewing geometry. This is a global database of surface reflectivity for 26 wavelength bands between 328 and 772 nm as a function of the satellite viewing angle via a second-degree polynomial parameterization. According to Tilstra et al., (2021) although DLER and BRDF surface reflectances have different properties, they are comparable for wavelengths $\lambda > 500$ nm. Based on their results, the GOME-2 surface DLER is compared with MODIS surface BRDF data from MODIS band 1 (centered around 645 nm) using both case studies and global comparisons and they concluded that the GOME-2 DLER compares well to MODIS BRDF data. So, the surface albedo used in this study is consistent with the dataset used for the retrieval of cloud optical properties.

We also performed a sensitivity for the effect of surface albedo to GHI and for cloudless conditions 10% variation in surface albedo led to <1% variation in GHI, and under cloudy condition (following Fig. 1) it led less than 3 and 5% variation in GHI for COT=2 and 12 respectively.

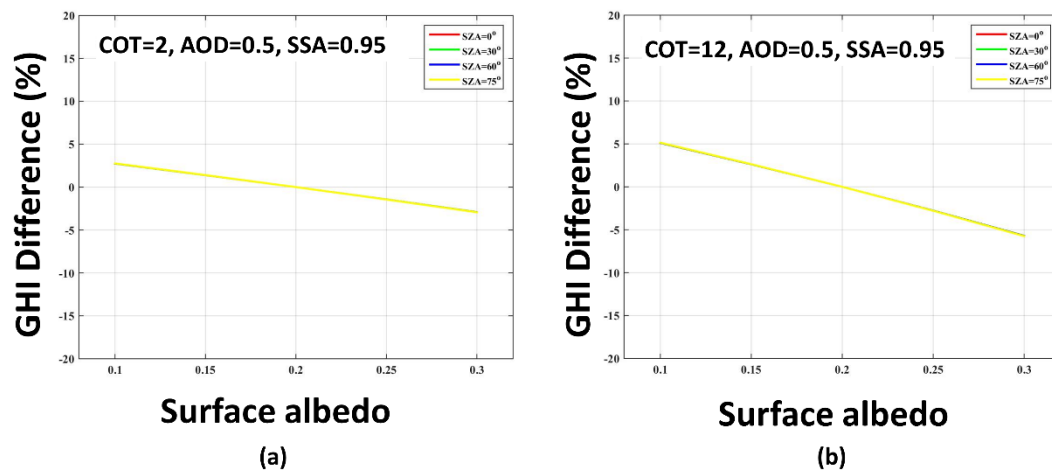


Figure 1. Percentage difference (%) in global horizontal irradiance as a function of surface albedo (using as reference zero value for surface albedo) and solar zenith angle (SZA) under cloudy conditions (cloud optical depth – (a) COT =2 and (b) COT =12) and an atmosphere including aerosols (aerosol optical depth – AOD =0.5 and single scattering albedo- SSA=0.95.)

Additionally, according to our results the error in satellite derived CMF has no correlation pattern with used surface albedo for all stations.

L137, Eq.1

The so called Cloud Modification Factor is the good old clear sky index or cloud coverage index (Cano et al), used in several EU projects and SAFs long ago, ranging from SODA, Satellight to Heliosat-3 and CM SAF. Respective references should be given. Further, by introducing this factor to correct bias resulting from COD they proof that the direct path (see <https://doi.org/10.5194/amt-15-1537-2022> and references therein) is more favorable. It is not clear why the authors have chosen the indirect path.

Reply

The Heliosat method and the semi-empirical models using the combination of the clear sky index (derived by cloud coverage index from satellite data) and a clear sky model is a well-established method, and it is used by all the projects mentioned by the reviewer and according to the suggestion all the respective references have been included in the manuscript by adding in the introduction 1 paragraph (lines 52-56 from the old version of the manuscript were replaced by lines 75 -98 in the new version of the manuscript).

To justify the choice of the fully physical approach and the use of cloud optical properties retrievals instead of the direct path, 2 additional paragraphs were included in the introduction (lines 99 -125) and the paragraph 3 of the previous version of the manuscript (Lines 65-74) has been changed accordingly (Lines 126-146 in the new version of the manuscript).

The main rationale for this choice is that the original SENSE was designed as a fully physical model taking advantage of the NWCSAF cloud product generated operationally in house using MSG data and up to then, as far as we know, hasn't used before from other solar energy nowcasting application. We decided to retain this fully physical approach at SENSE2 and at the same time improve the scheme that uses that specific cloud input to retrieve surface solar irradiance.

L189:

Optical flow method “We apply Farneback”. Is Farneback still state of the art for SSI nowcasting ? In Urbich et al 2018 (<https://doi.org/10.3390/rs10060955>) evidence is given that TV-L1 outperforms Farneback. This finding is supported by other studies and the maths. TV-L1 is more robust concerning changes of the intensities. It is part of OpenCV and thus free software as well. Further, it is not enough to compare your nowcasting method to persistence. It should be compared with other methods as well, including state of the art NWP (see respective publications of the IEA framework). Within this scope the effect of changing intensities on the quality of the forecasts should be discussed. One of the first works in the area of solar surface irradiance (SSI) nowcasting can be traced back to Lorenz et al. (University of Oldenburg, now ISE) and others. These works should be cited and discussed as well.

Reply

The current study is a follow-up study of Kosmopoulos et al. (2020). In this study both methods Farneback and TV-L1 used to forecast clouds (in terms of COT and CMF) and compared against persistence approach (clouds at the same position) for 3 (pan-European) case study days with different cloud movement patterns. Both methods performed equally well, with Farneback showing slightly better results for the selected test days, highlighting the strong dependence of the accuracy of both methods to the specific characteristics of the cloud patterns. It was pointed out that the selection of Farneback after the optimization of the model parameters it wasn't a generalization, and further analysis was needed in terms of comparing irradiances (forecasted against ground-based measurements) for at least one full year of forecasts for more robust conclusions. For more information for the reader

Lines 320-323 have been added in the new version of the manuscript. We would like to follow up this comment and during a future study to evaluate both optical flow methods in a larger spatiotemporal timeframe using SENSE2. However, it is a difficult task to isolate optical flow uncertainties, as such analysis has to isolate first other uncertainties based on cloud properties retrievals and assumptions and also to take into account regional to local aspects linked with e.g. cloud formation and flow above various terrains and prevailing atmospheric conditions (e.g. different cloud types and levels).

The discussion regarding the comparison of our short-term forecasting method with other methods beyond persistence, including state of the art NWP and the effect of changing intensities on the quality of the forecasts has been added at section 3.2 Lines 742-764 of the new version of the manuscript.

According to the suggestion of the reviewer the works in the area of solar surface irradiance (SSI) short-term forecasting have been cited and discussed. We introduce a new paragraph in the introduction (Lines 56-63 of the previous version of the manuscript were replaced by Lines 146-165 in the new version of the manuscript).

L 315 “The interesting part is that the same case stands for the whole range of measured GHI, indicating that it is a general limitation of satellite that it cannot take into account clouds.” as well as L 334. “Cases with partial cloudiness and the sun obscured as seen from the ground sensor (almost total attenuation of direct irradiance) will be associated with low measured irradiance that cannot be captured by the model. This is the main reason of the overall model overestimation.”

Misleading discussion and interpretation. The satellite can of course take into account clouds that obscure the sun. Else, all values would be clear sky values, or ? Let us assume a partly cloudy pixel with 50 % clear sky and 50 % cloudy sky, leading to an average cloudiness of 0.5. If only the sun obscured regions (100% cloud sky) are investigated you surely will find a bias, namely, an overestimation of SSI by the SAT retrieval, because the area average seen by the satellite is partly cloudy (50%). But statistically, there are also situation where the ground based station sees the sun (100% clear sky), but the satellite is partly cloudy sky (50%). On average there is an “error” cancelation of these effects. No figure or statistics are shown for situations where ground measurements see the sun, but the pixels are partly cloudy. Hence, there is no proof that the overall bias results from the “sun obscured” effect. In several studies bias values are reported for algorithms without sun obscuration correction, which are not significant or depending on the method positive or negative (see e.g. validation

reports and publications of CM SAF, e.g. Uccarra et al, <https://doi.org/10.1016/j.rse.2017.07.013>). Thus, the cancellation of the “errors” induced by different viewing geometries seems to work well and they are several other reasons for the bias. Thus, your conclusion seems a bit hasty and misleading. You should check SAL, it is likely a source for your bias.

In addition, there already exists a lot of publications dealing with broken clouds, 3-D cloud effects or the uncertainties arising from the comparison between ground based and satellite based SSI. Please read them, discuss and cite them and clarify what your work adds to existing works. In my opinion currently not much, beside misleading conclusions. Of course, for slant geometries the cloudiness is overestimated, but that is another story, which is not taken into account in your study. You will find respective articles, e.g. in the CM SAF publication list.

Reply

Probably it was not clearly written but of course using the satellite-based inputs here is the reason to take clouds into account, so of course satellite data can take into account clouds. It is just some limitations that are discussed here. The main problem comparing instantaneous measurements is exactly that under cloudy conditions satellite pixel and ground-based point measurements have differences mainly attributed to the sun visibility or not. The discussion on this point is clearer in the new text.

What is meant here is that satellite-based cloud retrievals cannot distinguish between cases that the sun is obscured and cases that it is not over the ground-based station. This combined with the facts that direct sun attenuation from clouds: a. is completely different from GHI, b. it is not linearly decreasing with cloudiness or cloud optical thickness and finally c. its contribution to GHI depends on various parameters (mainly solar elevation), introduces an issue in any instantaneous comparison between satellite based and measured GHI. So, it is mainly a spatial representativeness issue that affects the model evaluation statistics.

About the example and the statement of the 50% of the pixel covered lead to a an “error cancelation”. Yes, it does spatially lead to a possible error cancelation, but it does not statistically when we use a single point measurement to evaluate the instantaneous (15 min) satellite pixel-based retrieval. Exactly due to the nonlinear behavior of direct sun irradiance to cloud coverage. In a very simplistic way for a 50% cloudiness with a calculation of a $COT = X$: The average GHI of the cases that the clouds obscure the sun and the ones that is not obscured, is not equal with the case of half cloudiness or using 50% of X (it is less due to the $Direct \sim \exp(-\mu COT)$ dependence (μ is the air mass)). So yes, in this case there is a 50% chance statistically that the sun is obscured and 50% that is not. But errors in GHIs for all

these cases are not cancelled out. Things are more complex with cloudiness of more or less than 50% and also depends on the solar elevation ranges (which in addition are location dependent e.g. higher latitudes - less range). However, as said the purpose of satellite-based use models is to represent the whole pixel that for a lot of cases is not represented by a single point station. So, the main meaning of this sun obscure or not analysis is to discuss on possible systematic biases due to this representativeness issue.

Here is an example of 2 and a half years of 1-minute pyranometer (CMF) and camera images (cloud fraction) and pyr heliometer (sun-visibility) measurements at Davos, Switzerland.

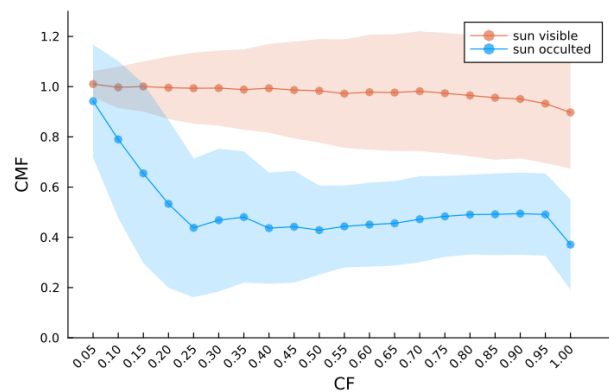


Figure 2 Cloud modification factor (CFM) based on 1-minute pyranometer data as a function of cloud fraction (CF) derived from sky camera image, for sun visible and sun obscured conditions over the ground-based station (based on pyr heliometer data).

Blue and orange are "two different worlds" to estimate using satellite data, and for e.g. 50% CF, probably having a number of pyranometers in a satellite pixel would capture the mean pixel irradiance as retrieved based on the satellite cloudiness. However, for instantaneous comparisons, a 50% cloudiness as seen from the satellite will lead to a reflectance or COT retrieval that will not lead to the calculation of a mean (of the blue and orange curve) CMF. So, satellite-based CMF will never be either orange (given that $COT > 0$) or blue. In our opinion it will be systematically lower than the blue and orange average CMF as in the case of visible sun a 50% cloud covered pixel COT will underestimate more GHI (through direct sun large underestimation) than the obscured sun case overestimation. It is still a representativeness comparison issue and not a satellite "problem", but maybe it is interesting to mention it here. The respective discussion has been added in Lines 524-531 of the new version of the manuscript to complete the discussion regarding the sun visibility analysis over the ground-based stations.

However, we agree that the whole section needs clearer writing, and we thank the reviewer for the comments that help on this direction. The statement "satellite cannot take into account clouds that obscure the sun" may lead to misleading impression since it was incomplete. It just meant that for a partial cloudiness the

satellite does not “know” in which one of the above Figure 2 curves, the pyranometer instant measurement belongs.

Both sentences that reviewer is mentioning in his comment have been changed accordingly, along with the whole Section 3.1.3 major changes in conjunction with the comments of referee 2 (the reason for GHI bias and the discussion of the results moved to the end of 3.1.3, at the CMFmsg analysis).

With the sentence of L315 we would like to say that due to the satellite spatial resolution, small broken clouds maybe cannot be resolved, resulting to COT=0 value, but those clouds may have a significant impact in ground based measured irradiance in case that they are obscuring the sun (almost total attenuation of direct irradiance) (new Fig. 8 d points above the identity line). In case that they do not obscure the sun is the clear sky case, but for GB measurements enhancement maybe occur. So, we replaced the sentence in L315 of the previous version of the manuscript with the following in Lines 497 -499 in the new version of the manuscript:

“Most of the cases are on the 1:1 line, with few ones being higher, especially, for measured $GHI < 250 \text{ W/m}^2$, meaning that there are clouds over the ground-based station that haven’t been resolved by the satellite pixel (COT=0).”

We agree with referee’s example of partially cloud pixels and the 1s case, and actually this is the main source of overestimation of our GHI retrieval, depicted in new Fig.8 e, f in combination with new Fig.8 b, c and new Fig. 9.

Of course, there are also cases with the opposite, partially cloudy pixels where the ground-based station sees the sun, which are depicted in new Fig. 8e for Sun visible situations as points below the 1:1 line.

But in our case, it is not evident the “error” cancellation (Fig. 4a and new Fig. 8) for the reasons that we discussed in the first part (paragraphs 1-5) of this answer regarding the instantaneous comparisons and due to COT product and how it treats the partially cloudy cases directly related to the satellite spatial resolution (the size of the clouds can be resolved).

To our opinion new Fig. 8e for Sun visible situations is the figure showing situations where ground measurements see the sun (as actual ground-based measurements have been used to define this) and the fact that the pixel is partially cloudy demonstrated by points below 1:1 line also possibly related with cloud enhancement. Meanwhile the Sun obscured situations at new Fig 8f are associated with high overestimation. At this point we would like to clarify that we didn't perform sun obscurity correction.

We included and discussed the proposed studies and the reported biases along with the reasons for the bias in the introduction (Lines 116 -125) and at the Section 3.1.4 where we compared our results of satellite GHI retrievals with other studies (Lines 634 -663).

The effect of SAL on the GHI bias has been investigated in the Major comment L125 of reviewer 1.

The relevant discussion and respective publications dealing with the uncertainties of the comparison between point ground-based measurements and satellite retrievals (Lines 570 -573), broken clouds (Lines 573 -585) and 3d effects (Lines 560 -569) have been added in the revised version of the manuscript.

In addition, old Fig. 8 now Fig. 9 has been updated to include the distributions of CMFmsg and measured CMF and their differences also for the classification of the cases for the sun obscurity to support the discussion in section 3.1.3.

The aerosol study is well done, but also this part lacks a bit on discussion and citations concerning former works

Reply

According to referees comment the respective discussion was added at 3.1.2 at Lines 456 -472 of the new version of the manuscript, as follows:

“An overestimation of the CAMS forecasted AOD at 550nm is also reported for 2017 over Europe (average modified normalized mean bias ranging from ~10 to 30%) from the continuous quarterly evaluation of the AOD forecasts against daily AERONET cloud-screened (i.e. Version 3 level 1.5) sun photometer data (Basart et al., 2023; Eskes et al., 2021). While this is the case on average, in contrast during high aerosol loads, CAMS forecasted AOD is underestimated, especially in desert regions and during dust events (Basart et al., 2023; Papachristopoulou et al., 2022) which might explain the almost zero bias for Tamanrasset station (the overestimation of small AODs masked out by the frequent underestimation of large AODs) compared to the greater values of bias (>0.01) found for most of the rest stations. Qu et al. (2017) analysed case studies at Tamanrasset and found that the CAMS (MACC) AOD at 550nm is frequently underestimated against AERONET data during summer dust events, explaining the strong positive bias they found for their modelled direct irradiance (using Heliosat-4 method and the McClear clear sky model). In contrast to the CAMS AOD underestimation during dust events, in the same study (Qu et al., 2017) a systematic overestimation of AOD was found during periods free of those events for the two examined desert stations (Sede Boqer and Tamanrasset), to which they associated the underestimation of their modelled direct irradiance. The updated McClear v3 clear sky model used in study by Schroedter-Homscheidt et al. (2022) and for their GHI estimates under clear-sky conditions a negative bias was found for most of the station especially

for those located in dust affected regions, which is in line to our results although not directly comparable since they compared directly with the BRSN measured irradiances. Our results demonstrate the good performance of the clear sky model using CAMS forecasts, highlighting that AOD product forecasted by CAMS is suitable for GHI nowcasting applications.”

Minor comments:

L54 ,”..considered as big data”. Please delete, it is not really big data compared to other fields....

Reply

It has been deleted in the context of major revisions of the introduction for the major comment 3 of the reviewer.

L 47 “The availability of solar resources is primarily affected by clouds and aerosols (e.g., Fountoulakis et al., 2021; Papachristopoulou et al., 2022).”

This is misleading. In areas with low aerosol variability water vapor is much more important than AOD (as a climatology value works well there). Please add H2O as important variable.

Reply

Water vapor was also added as an important variable, by changing the previous sentence, now Lines 51-54, as follows:

“Under all-skies the availability of solar resources is primarily affected by clouds (e.g., Fountoulakis et al. 2021) and for clear-sky conditions it depends on the atmospheric composition with the most important variables being aerosols (e.g., Papachristopoulou et al., 2022) and water vapor (Yu et al., 2021).”

L95 “SENSE2 is an operational system that produces fast estimates of GHI in real time every 15min, for a wide area including Europe and Middle East-North Africa (MENA)”

Please mention how the user can get these data.

Reply

The following sentence has been added in Lines 194-195:

“The new version of the SENSE2 system is available as a webservice via https://solar.beyond-eocenter.eu/#solar_short (last access: 2023-12-15).”

L113: The aerosol model of Shettle is used, but no discussion of the limitation induced by the assumption of spherical aerosols is given.

Reply

Aerosol assumptions in any real time forecasting model with no real time measurement inputs are uncertainty sources. There are different “levels” of uncertainties concerning aerosols as inputs on solar forecasting models. Trying to keep this discussion short:

The profile: Shettle assumes a nearly exponential decrease in the extinction coefficient with altitude, which is not always realistic, but does not practically affect the GHI at the surface (e.g., Fountoulakis et al., 2022).

Shape and size: According to Song et al., 2022, Kok et al., 2017 and Fountoulakis et al. 2023 under review) this can be important above mineral dust related areas and in this case the size plays a much more important role than the shape. In the latest and references therein, in the case of spheroid dust particles the effect was found negligible, while for very large particles differences at the surface for GHI shortwave were found less than 1% over ocean and less than 5% over desert for solar zenith angles 0 to 30 degrees.

AOD: All the above can be clearly masked by the moderately high uncertainty of the AOD forecast in case of variable aerosol cases/locations.

Other than AOD properties: Any model has to use some kind of assumption on the aerosol type at the particular time and location. Here, as reported, we directly consider optical properties (SSA, Angstrom exponent) from a monthly climatology dataset. There are uncertainties related to the use of climatological optical properties which are minor relative to the uncertainty in the forecasted AOD, for the usual AOD levels over Europe. For higher AOD values (e.g., AOD (at 500 nm) > 0.3 - 0.4) uncertainties in aerosol optical properties (SSA) play a more significant role. Angstrom exponent can play a role on the GHI model calculation uncertainty in cases of locations with variable aerosol types and sizes, as most GHI estimation models do not use spectral AOD as an initial input.

In a few words in a GHI reanalysis study (using as model inputs aerosol measured optical properties) maybe aerosol size information, especially in dust aerosol areas,

could slightly improve the results. However, in a real time forecast model with AOD forecasts and other optical properties climatology, any aerosol shape correction is statistically meaningless.

L 140: Use of NWC SAF products: I did not understand the sense of this approach, why do you need NWC-SAF ?

Reply

The use of the cloud product of NWC SAF is explained in the introduction in Lines 132-139 of the new version of the manuscript.

"It is a combination of geophysical input parameters from satellite-based and model data sources and a neural network (NN) technique, trained on precalculated surface solar radiation simulations (look up table – LUT) using RTM. It uses the cloud optical thickness (COT) retrievals produced by the Application Facilities Support to Nowcasting and Very Short Range Forecasting (NWC-SAF) algorithm based on the MSG satellite data and aerosol optical depth (AOD) forecasts from the Copernicus Atmospheric Monitoring Service (CAMS) as inputs to the NN to derive the surface solar radiation in real time. More details about the previous version of the SENSE service can be found in Kosmopoulos et al. (2018)."

L 145: Typical values for the effective radius ($Reff = 10 \mu m$) and the liquid water path ($LWP = 1 g/m^3$ 145) were used, given the unavailability of those data and their small impact on GHI"

This phrase is quite misleading. First of all there are algorithms available to derive $Reff$ and LWP , further I would not say that the impact is small, in particular when considering ice clouds.

Reply

We thank the referee for his comment, it is true that the sentence gives a wrong impression. A more analytical description is given in the new version of the manuscript (Line 264-274), clarifying that the unavailability of the cloud information referred to the exact position and extent of the clouds inside the atmosphere. Also, the respective discussion and references are given regarding the impact of different cloud parameters on simulating surface solar radiation.

"The design of the cloud model was a trade -off between the relevance of the cloud property and the operational implementation of the model. It has been shown in previous studies (Qu et al. 2017) that for most of the cases (except for high surface

albedo values >0.9), the cloud vertical position and extent has a small or negligible influence for the RTM simulations of surface solar irradiance. Under cloudy conditions, COT is the variable that has the greatest impact on simulating surface solar radiation (Qu et al., 2017, Oumbe et al., 2014, Taylor et al., 2016). In our simulations, spherical droplets were assumed, with typical values for the effective radius ($R_{\text{eff}} = 10 \mu\text{m}$) and typical climatological mean heights (base at 2 km, 3 km height) (Taylor et al. 2016, Kosmopoulos et al., 2018), given the unavailability of height descriptors in the operational mode and the negligible influence of changes in droplet effective radius with respect to COT on simulating surface solar radiation (Oumbe, 2009) and towards simplify the cloud model. The COT of the cloud layer is additionally specified at 550 nm, which leads to an adjustment of the liquid water content default value of 1 g/cm^3 , using the parameterization by Hu and Stamnes (1993).”

L 195: "Smart persistence": I find the term irritating, please delete it. Please clarify that this kind of persistence is typically used for SIS nowcast comparisons. Add some discussion and references of former works here as well.

Reply

The title of Section 2.3 changed to Persistence forecast and a more detailed discussion has been included in Lines 329-333 of the new version of the manuscript as follows:

"2.3 Persistence forecast

It is not easy to evaluate the quality of different forecasting methods of surface solar radiation using only statistical metrics, since the study period, the geographical area and other factors are affecting their forecasting accuracy. That's why it is a typical practice of evaluation to benchmark the different forecasts against some simple forecast methods (Pelland et al., 2013). We used the persistence forecast to benchmark the CMV forecasted GHI of NextSENSE2 system which is a commonly used reference in solar forecasting (e.g. Kosmopoulos et al., 2020; Kallio-Myers et al., 2020)."

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Effects of clouds and aerosols on downwelling surface solar irradiance nowcasting and short-term forecasting

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Abstract. Solar irradiance nowcasting and short-term forecasting are important tools for the integration of solar plants into the electricity grid. Understanding the role of clouds and aerosols in those techniques is essential for improving their accuracy. In this study, we introduce the improvements in the existing nowcasting/short-term forecasting operational systems SENSE/NextSENSE, based on a new configuration and by the upgrading of cloud and aerosol inputs ~~methods~~ and ~~also~~, we also investigate the limitations of such model evaluation with surface-based sensors due to cloud effects. We assess the real-time estimates of surface global horizontal irradiance (GHI) produced by the improved SENSE2 operational system at high spatial and temporal resolution (~5 km, 15 min) for a domain including Europe and Middle East-North Africa (MENA) region and the short-term forecasts of GHI up to 3 hours ahead by the NextSENSE2 system, against ground-based measurements from 10 stations across the models' domain, for a whole year (2017).

Results for instantaneous (every 15 minutes) comparisons show that the GHI estimates are within +/-50 W/m² (or +/-10%) of the measured GHI for 61% of the cases, after the new model configuration and a proposed bias correction. The bias ranges between -12 W/m² to 23 W/m² (or -2% to 6.129%) with mean value 11.3 W/m² (2.3%). The correlation coefficient is between 0.83 to 0.96 with mean value 0.93. Statistics are significantly improved ~~improved a lot~~ when integrating in daily and monthly scales (mean bias ~~6.6-3.3~~ W/m² and ~~25.7~~ W/m², respectively). We demonstrate that the main overestimation of the SENSE2 GHI is linked with the ~~uncertainties of the cloud related information within the satellite pixel~~ ~~underestimation of cloud optical thickness from the Meteosat Second Generation (MSG) satellites~~, while the relatively low overestimation linked with aerosol optical depth (AOD) forecasts (derived from Copernicus Atmospheric Monitoring Service - CAMS) ~~results in low overestimation of~~ ~~is reported for~~ cloudless sky GHI. The highest deviations for instantaneous comparisons are associated

with cloudy atmospheric conditions with clouds obscuring the sun over the ground-based station. Thus, they are much more linked with satellite/ground-based comparison limitations than the actual model performance. The NextSENSE2 GHI forecasts based on the cloud motion vector (CMV) model, outperform the ~~smart~~-persistence forecasting method, which assumes the same cloud conditions for the future time steps. The forecasting skill (FS) of the CMV based model compared to the persistence approach increases with cloudiness (FS up to ~20%), linked mostly to periods with changes in cloudiness, that persistence, by definition, fails to predict. Our results can be useful for further studies on satellite-based solar model evaluations and, in general, for the operational implementation of solar energy nowcasting and short-term forecasting, supporting solar energy production and management.

1 Introduction

Climate change mitigation along with energy production in a sustainable manner could be addressed with the deployment of renewable energy technologies (Edenhofer et al., 2011; Pörtner et al., 2022). Diverse technologies of renewable energy are investigated worldwide, and their deployment has been increasing, with solar energy markets growing rapidly, with a prospect to be the major source of energy supply in next decades (Arvizu et al., 2011; IEA, 2022). Since solar energy resources are strongly affected by atmospheric conditions, they are highly variable in space and time. **Therefore, there is a need for operational nowcasting and short-term solar forecasting for real time energy production, to better integrate solar energy exploitation technologies with national and international power systems.** ~~Under all-skies t~~The availability of solar resources is primarily affected by clouds (e.g., Fountoulakis et al. 2021) and for clear-sky conditions it depends on the atmospheric composition with the most important variables being aerosols (e.g., Fountoulakis et al., 2021; Papachristopoulou et al., 2022) and water vapor (Yu et al., 2021). Among those variables, clouds and aerosols are characterized by large temporal and spatial variability which constitutes them as key variables for solar energy applications. ~~Therefore, there is a need for operational nowcasting and short term solar forecasting for real time energy production, to better integrate solar energy exploitation technologies with national and international power systems.~~ The continuously improved earth observation (EO) data (satellite-based and atmospheric models) are exploited to produce in real time (nowcasting) accurate estimates of spectral surface solar radiation, with numerous applications apart from the solar energy sector (e.g., Qu et al., 2014; Thomas et al. 2016; Kosmopoulos et al., 2018) in different fields like human health (e.g., Kosmopoulos et al., 2021; Schenziger et al., 2023). To increase the accuracy of those nowcasting and forecasting tools, it is imperative to understand the spatiotemporal variability ~~role~~ of clouds and aerosols properties in their implementation.

~~The continued development and improvement of earth observation (EO) techniques in the last two decades constitute a big source of new atmospheric information. Satellite-based information and atmospheric models provide high quality data of atmospheric composition and state at high spatial and temporal resolution, considered as big data. By exploiting that multiplatform information, accurate estimates of surface solar radiation can be produced in real time (nowcasting), with numerous applications in different fields like solar energy and health (e.g., Kosmopoulos et al., 2018, 2021). The operational~~

solar energy forecasting methods are categorized into three base methods (Sengupta et al., 2021; Yang et al., 2022) with the time horizon (few seconds to few days) and the exogenous data, i.e., sky cameras, satellite data and numerical weather predictions (NWP). Additionally, there are many statistical and machine learning methods, which are often combined with NWP data to improve their outputs (post-processing or blending). The use of cloud motion vector (CMV) technique on satellite data is commonly used for solar forecasting of few hours ahead (e.g., Garniwa et al., 2023; Kallio-Myers et al., 2020), giving better results than the persistence solar forecasting approach, a method that assumes constant cloudy conditions for the future time steps.

Solar resources assessment at a particular location is important for planning and management of solar energy technologies. The use of ground-based measurements of surface solar radiation is only available in a few locations with possible gaps in time. Those spatial and temporal gaps are filled by modelled estimates of surface solar radiation. Of particular importance are gridded surface solar radiation estimates with high spatial and temporal resolution and a large coverage (up to global scale), provided by satellite-based models or atmospheric models (e.g., an overview of those techniques in Sengupta et al., 2021).

Geostationary satellite data due to their large area coverage and high temporal resolution are used to produce estimates of surface solar radiation both at real time as an operational service and to generate historical archives based on long term satellite measurements. Several methods exist for satellite estimates of surface solar irradiance. A well-established method considers cloud extinction through the cloud coverage index (Cano et al., 1986) or cloud index, calculated by normalized satellite reflectances. Using the cloud index, the transmission factor or the clear sky index (also called cloud modification factor - CMF hereafter) is calculated, which finally multiplied with the results of a clear sky model to retrieve solar irradiance at the earth surface (Hammer et al., 2003). This is the general idea behind the HELIOSAT method (Cano et al., 1986; Hammer et al. 2003), widely used in various European research projects and applications. The derivative Heliosat-2 method (Rigollier et al., 2004) is launched in real time by the SoDa service to produce the HelioClim-3 database (Qu et al., 2014), a real time solar radiation database from February 2004 onwards. The more recent and most advanced version 5 (HC3v5) of the HelioClim-3 database (Thomas et al. 2016) combines the McClear clear-sky model (Lefevre et al., 2013; Gschwind et al., 2019) with cloud index values extracted from Meteosat Second Generation (MSG) satellite images. The Satellite Application Facility on Climate Monitoring (CM SAF) provide satellite-based estimates of surface solar radiation using data from Meteosat geostationary satellites. Currently, the third edition of the Surface Solar Radiation Data Set - Heliosat (SARAH-3, Pfeifroth et al. 2023a) covers the period 1983 - 2020 as climate data record (CDR) and is operationally extended as interim climate data record (ICDR) to the present with a delay of a few days. The retrieval algorithm MAGIC SOL (Pfeifroth and Trentmann, 2023; Müller et al., 2015) is a combination of a modified Heliosat method to derive the effective cloud albedo (CAL) and the SPECMAGIC clear-sky model (Mueller et al., 2012). More available open access satellite-based surface solar radiation climatological datasets based on the cloud index method can be found in Müller and Pfeifroth (2022).

There are also fully physical models, that directly estimate surface solar radiation using radiative transfer models (RTM) and geophysical parameters as inputs for given atmospheric state including clouds (cloud and aerosol optical properties, total column values for water vapor and ozone content) and surface conditions. The combination of multi-channel information from

105 geostationary satellites with cloud retrieval schemes provides cloud optical properties that can be explicitly used in RTM to account for cloud extinction and finally calculate surface solar radiation. Parameterizations or look-up-tables based on RTM simulations are used instead of direct radiative transfer calculations, to optimize the computational time for operational use of the models. This is the case for the Heliosat-4 method (Qu et al., 2017) which is used in Copernicus Radiation Service (CAMS Radiation Service) estimates of surface solar irradiance. Their Heliosat-4 method is composed of two models considering independently the clear sky and cloudy conditions. Specifically, the McClear model (Lefevre et al., 2013; Gschwind, et al., 2019) is used for calculations of cloud free irradiances and the McCloud model for calculating the extinction of irradiance by clouds (through the clear sky index), both based on look-up tables (LUTs) to speed up calculations. The input cloud properties

110 of the current CAMS Radiation Service v4 are retrieved by the adapted APOLLO Next Generation scheme to the MSG/SEVIRI satellite images (Schroedter-Homscheidt et al., 2022). The most recent version of the U.S. National Renewable Energy Laboratory's (NREL's) gridded National Solar Radiation Data Base (NSRDB 1998-2016, Sengupta et al., 2018) is also based on a fully physical model. This is the Physical Solar Model (PSM) which was developed by NREL and produces gridded surface solar irradiance estimates using satellite retrievals for clouds and other atmospheric properties from GOES data as

115 input to the radiative transfer model.

The continued developments and improvements since 80s in satellite estimates of surface solar radiation resulted to accurate climatological and real time datasets (Qu et al., 2014; Urraca et al., 2017; Pfeifroth et al., 2023b; Qu et al., 2017; Schroedter-Homscheidt et al., 2022; Sengupta et al., 2018; Habte et al., 2017) although certain sources of biases and common factors that increase the uncertainty have been reported: the increase of the distance from the subsatellite point, the more frequent

120 occurrence of clouds (especially fragmented cloud cover), complex terrain and bright surfaces (snow, desert). In addition, it is a challenge per se and increases the evaluation uncertainties when any model is validated at an instantaneous time scale. Gridded satellite-estimates with ground-based point measurements of surface solar radiation differ not only due to model uncertainties but also due to different spatio-temporal scales involved (satellite pixels representative of a large area and large time intervals of few minutes, ground-based measurements representative of the area exactly over the station and for smaller

125 time intervals).

Motivated by the recent advances in satellite-based retrievals of surface solar radiation and building upon the knowledge of the already existing and well-established methodologies, an upgrade has been performed to an existing service that provides satellite estimates of surface solar radiation in real time, with the aim the improved nowcasting system to be the basis of the new forecasting system. The Solar Energy Nowcasting System (SENSE) is a nowcasting system of surface solar radiation was

130 developed under the EU project Geo Cradle, as a collaboration of by the Beyond centre of EO research and satellite remote sensing at the National Observatory of Athens, Greece, in collaboration with the ~~Physical Physies~~ and Meteorological Observatory of Davos, of the World Radiation Center, Switzerland (Kosmopoulos et al., 2018). It is a combination of geophysical input parameters from satellite-based and model data sources and a neural network (NN) technique, trained on precalculated surface solar radiation simulations (look up table – LUT) ~~using RTM by radiative transfer modelling~~. It uses the

135 cloud optical thickness (COT) ~~retrievals product~~ produced by the Application Facilities Support to Nowcasting and Very Short

~~Range Forecasting (NWC-SAF) algorithm based on from the Meteosat Second Generation (MSG) satellite data and aerosol optical depth (AOD) forecasts from from the Copernicus Atmospheric Monitoring Service (CAMS) as inputs to the NN to derive the surface solar radiation in real time. More details about the previous version of the SENSE service can be found in Kosmopoulos et al. (2018). In the same publication the validation of this method showed a good agreement on daily and monthly levels; however, various sources of uncertainties have been identified, concerning mainly the use of the NN especially during under high irradiance values atmospheric conditions, the COT input, and the structure/density of atmospheric parameters in the LUTs. The reason for the development In of the new version of the model, called SENSE2, that has been used in the present study, the model configuration changed, and was to minimize those uncertainties were limited, before use it for the new forecasting system. For the new version of the model, it was decided to retain the fully physical approach of the model that benefits from the MSG satellites cloud optical properties monitoring and recent advances in EO and improve the scheme that replace the direct radiative transfer calculations.~~

~~The solar energy forecasting methods are categorized into three base methods (Sengupta et al., 2021; Yang et al., 2022) with the time horizon (few seconds to few days) and the exogenous data, i.e., sky cameras, satellite data and numerical weather predictions (NWP). Additionally, there are many statistical and machine-learning methods, which are often combined with NWP data to improve their outputs (post-processing or blending). Each method fits the specific needs of different applications. The use of cloud motion vector (CMV) technique on satellite data is commonly used for solar forecasting of few hours ahead (up to 6 h). Using consecutive satellite images, the CMVs are calculated, and assuming constant cloud speed, the future cloud positions are derived by applying the CMV field to the latest cloud image. The early stages of the use of CMV for short term forecasting of surface solar radiation based on satellite data start almost twenty years ago (Hammer et al. 1999; Hammer et al. 2003; Lorenz et al. 2004). In the last decade, the interest in using optical flow techniques from the computer vision community in satellite images for cloud motion estimation in the context of solar forecasting has been increased. One of the first works was by Urbich et al. (2018), where for the European domain two optical flow methods were used and compared in forecasting MSG satellite derived effective cloud albedo. Those forecasted values of effective cloud albedo combined with SPECMAGIC NOW delivers surface solar irradiance short-term forecasts (SESORA -seamless solar radiation, Urbich et al., 2019). An optical flow method to effective cloud albedo maps based on SEVIRI images used by Kallio-Myers et al. (2020) to forecasted global horizontal irradiance up to 4 h ahead with 15 min time resolution for southern Finland, by applying the Heliosat method to forecasted effective cloud albedo maps in combination with the Pvlb Solis clear sky model (Solis-Heliosat forecasting model). In the same study, they also found that their forecasting model mostly outperforms persistence, especially under changes in cloudiness. It is a common practice to benchmark forecasts of surface solar radiation with the persistence approach (e.g. Kallio-Myers et al., 2020; Garniwa et al., 2023), a method that assumes constant cloudy conditions for the future time steps.~~

~~The NextSENSE system was developed as a continuation of SENSE, during the EU project E-shape and by the same research groups. The NextSENSE system was first introduced in the study of Kosmopoulos et al. (2020), as a novel short-term solar energy forecasting system (3 h ahead, every 15 min), based on forecasts of satellite derived COT using a CMV technique, with solar irradiance estimated by the SENSE model. The NextSENSE system was developed as a continuation of SENSE, during~~

170 ~~the EU project E-shape and by the same research groups previously mentioned.~~ The employed CMV technique is based on
state-of-the-art image processing technologies (dense optical flow). ~~In the same study, a first-~~The evaluation of the CMV
forecasts ~~accuracy~~ was performed ~~by Kosmopoulos et al. (2020) for selected test days with different cloud movement patterns,~~
against the real MSG COT and ~~in term of irradiance estimates using both forecasted and real COT. They found that~~ the
175 deviations of forecasted irradiances compared with nowcasting outputs ranged from 18% to 34% under changing cloudy
conditions, outperforming the persistence method for certain conditions. ~~However, this first evaluation was based on the~~
~~satellite-derived COT, so-~~The aim of the current study is to ~~compare the~~ validate the NextSENSE model for one full year of
irradiance forecasts with ground-based measurements, ~~for more robust conclusions.~~ Additionally, as NextSENSE is based on
the same hierarchy of SENSE with only addition the CMV analysis, all improvements of SENSE2 are inherited in the new
NextSENSE2 system too.

180 The present study aims to investigate the role of clouds and aerosols in nowcasting and short-term forecasting of global
horizontal irradiance (GHI), using ground-based measurements, by:

- Introducing the SENSE2 and NextSENSE2 upgrades of SENSE and NextSENSE systems, respectively.
- Validating the improved nowcasted GHI using ground based pyranometer measurements for 1 year (2017).
- Investigating cloud and aerosol effects on GHI estimates.

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- Proposing a possible correction for GHI estimation based on MSG COT real time information.
- Validating CMV forecasted GHI and benchmarking the results with those by the persistence method.

2 Data and methods

2.1 SENSE2

SENSE2 is an operational system that produces fast estimates of GHI in real time every 15_min, for a wide area including
190 Europe and Middle East-North Africa (MENA) region at high spatial resolution (~5_km), calculated from earth observation
(EO) data and look-up-tables (LUTs) derived from radiative transfer model (RTM) simulations. The SENSE2 presented in this
study (Fig. 1) is an improved system, compared to the previous SENSE version, in terms of the parameterizations for radiative
transfer calculations and, mainly, the improvement of aerosol and cloud representation in the model using a more detailed
look up table (LUT) and multiparametric equations for different aerosol and cloud scenes, respectively. The new version of
195 the SENSE2 system is available as a webservice via https://solar.beyond-eocenter.eu/#solar_short (last access: 2023-12-15).

The first improvements of the SENSE2 system are that:

- the computations of clear-sky GHI are performed in the previous day, for the whole domain (1.5M pixels), every 15 min and, for the current day, the real-time cloud information is applied to provide all skies GHI in real time (no NN is used).

200 • the computations of clear-sky GHI are based on a new, more detailed LUT of ~16M combinations of simulated GHI at the earth's surface, that was generated using the GRNET High Performance Computing Services and the computational resources of ARIS/GRNET infrastructure. The RTM simulations were performed using the libRadtran package (Emde et al., 2016; Mayer & Kylling, 2005) and Table 1 summarizes the input variables and their resolution resulted to the ~16M runs.

205 RTM simulations were performed spectrally from 280 to 3000 nm, with 1 nm spectral resolution using the DISORT radiative transfer solver in pseudo-spherical mode (Buras et al., 2011). The molecular absorption parameterization of representative wavelength approach – REPTRAN was used in the solar range (Gasteiger et al., 2014) to account for the absorption of atmospheric gases for the whole solar spectrum. The Kurucz 1.0 nm (Kurucz, 1994) extraterrestrial solar spectrum and the U.S. Standard Atmosphere (Anderson et al., 1986) were used as inputs. The default aerosol model of Shettle (1989) was used
210 as the basis with modified aerosol optical properties of AOD, single scattering albedo (SSA) and Ångström Ångström exponent (AE) varied according to Table 1. The spectral global irradiances were integrated over the spectral range of the simulations to derive the GHI.

The clear-sky GHI ~~modelled values estimates~~ by SENSE2 (Fig. 1) are calculated in the previous day, by linear interpolation in the 7 dimensions (7D) of the precalculated GHI LUT using the corresponding inputs. Specifically, the solar zenith angle
215 (SZA) values are precalculated for every grid cell of the domain (1.5M in total), for the 15 min time step. The main input parameter for the clear-sky computations is the forecasted AOD at 550nm from CAMS (CAMS AOD hereafter). The forecasts for the day of interest are values from the CAMS run of the previous day initialized at 00:00 UTC (e.g., the AOD used to simulate the GHI for the 24th of a month, has been derived from the CAMS run that started on the 23rd at 00:00 UTC). Climatological values are used for the interpolation in the 7D LUT for the additional aerosol optical properties of SSA and AE
220 (MAcV2 climatology, Kinne, 2019), for the water vapor (WV) (CAMS reanalysis (Inness et al., 2019)), the total ozone column (TOC) (OMI TOC data (Bhartia, 2012) based climatology) and surface albedo (GOME-2 database of directionally dependent Lambertian-equivalent reflectivity (Tilstra et al., 2017, 2021)). It should be mentioned that the interpolation procedure in the 7D LUT was added in the new SENSE2 to further improve the accuracy of the GHI estimations. Finally, since the results of the RTM runs are at sea level and for the mean earth-sun distance, a post correction of the clear-sky GHI values from the LUT
225 is performed for the surface elevation following the methodology described in Fountoulakis et al., (2021) and the actual earth-sun distance for the particular day of the year (DOY). Based on simulations for various atmospheric and surface albedo conditions, Fountoulakis et al. (2021) estimated an average increase of the GHI by 2% per km, which has been also applied to the model output to correct the surface GHI for sites at higher altitudes than sea level.

The use of LUTs at operational surface solar radiation retrievals instead of direct RTM calculations is well established (e.g.,
230 Qu et al. 2017; Mueller et al., 2009). From a technical point of view, various concepts exist which can reduce by several orders of magnitude the number of RTM simulations needed for a LUT generation. Mueller et al. (2009) developed a flexible, fast, and accurate scheme to retrieve the broadband surface solar irradiance (CM-CAF datasets) using the hybrid eigenvector approach, resulting in a combination of basis LUTs with optimized interpolation grid and parameterizations, using only almost

one thousand RTM calculations. This approach was extended by Mueller et al., (2012) to wavelength bands for spectrally
235 resolved surface solar irradiance retrievals from spaceborne data. This optimization of the computing performance is of
paramount importance for the reprocessing of a large amount of satellite data (up to a few decades). In this work, the main
concept behind the generation of our clear sky LUT was to have spectral irradiance outputs (1nm spectral resolution). The
choice to calculate spectral solar data and not directly shortwave radiation is based on the fact that the SENSE2 output could
be used for other (health, agriculture, other) applications, based on the irradiance weighting of a relevant spectral range with
240 an action spectrum (function) defined for each of the effects. So, a large number of RTM runs had to be performed (once) for
spectral surface solar irradiance covering all possible combinations of atmospheric and surface states. Technically, since the
operational set up of the SENSE2 model allows for the computation of the clear sky GHI values from the previous day, the
processing time for interpolation to the 7 dimensions of the LUT has no effect in producing timely the real time output of the
model every 15 min, while the accuracy of the clear sky output is almost identical with direct RTM simulations
245 (Papachristopoulou et al., 2022) and the uncertainties of the clear sky GHI retrievals are related only to the uncertainties of the
model inputs. In addition, this LUT includes various aspects especially for aerosols (AOD, SSA, AE) that can reduce the
uncertainty under different aerosol conditions, for broadband solar radiation or specific spectral regions.

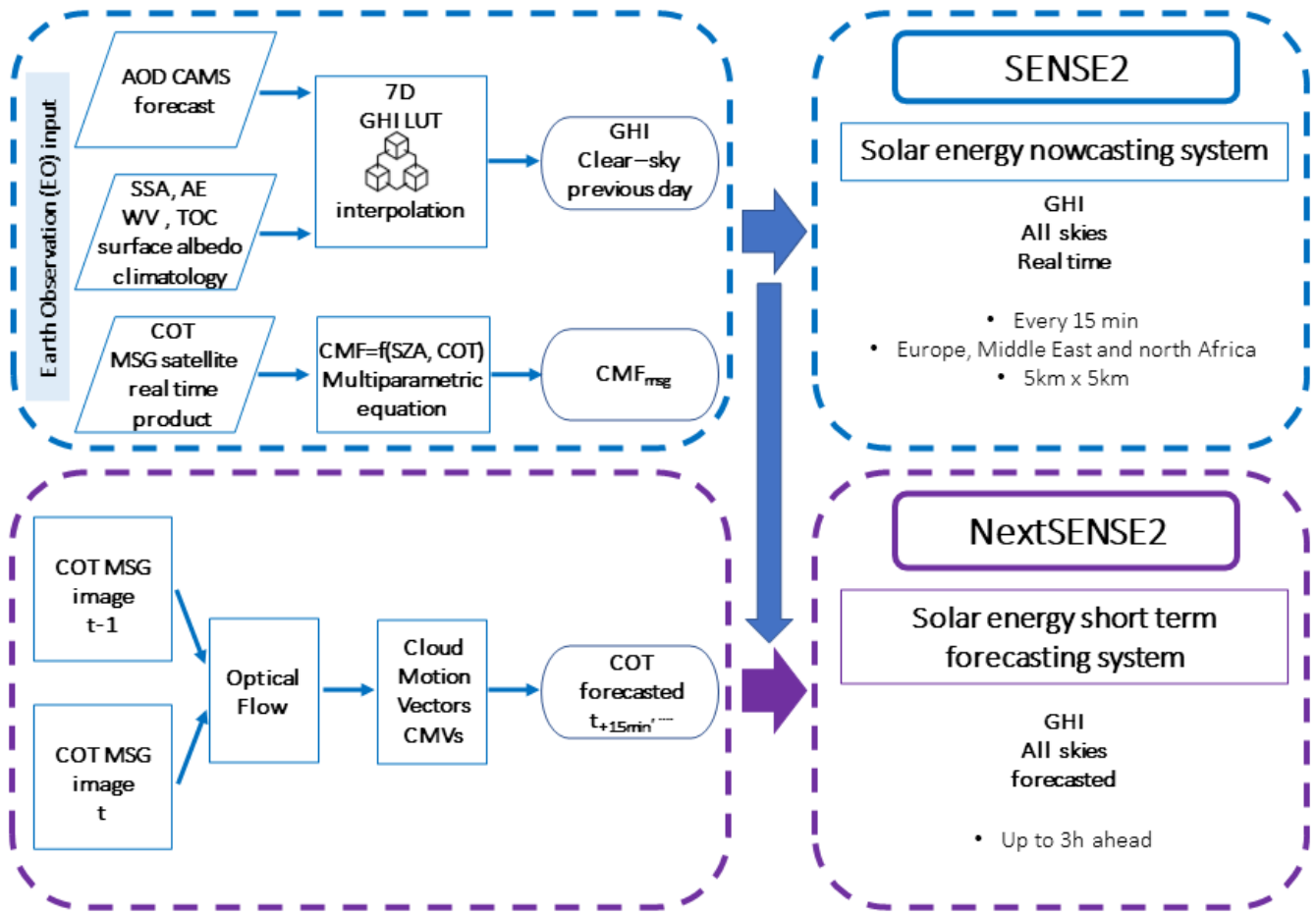


Figure 1 Schematic overview of solar energy nowcasting system (SENSE2) and short-term forecasting (NextSENSE2) up to 3h ahead.

250 Table 1 Input parameters to radiative transfer simulations performed at the ARIS GRNET supercomputer resulted to the 7D GHI LUT.

Parameter	Range	Resolution
Solar zenith angle (SZA in deg)	1 to 89	1
Aerosol optical depth at 550nm (AOD)	0 to 2, 2.5,3.0	0.05
Single Scattering Albedo (SSA)	0.6 to 1	0.1
Angstrom exponent (AE)	0 to 2	0.4
Total Ozone Column (TOC in DU)	200 to 500	100
Water Vapor (WV in cm)	0.5 to 3	0.5
Surface albedo	0.05 to 0.8	0.15

Another improvement is related to the cloud representation in real time, using multi-parametric equations for different cloud scenes, based on the Cloud Modification Factor (CMF) concept, instead of using the COT as an input parameter in direct the RTM calculations. The computation of the all-skies GHI in real time, every 15_min, is based on the COT product we extract operationally in real time using broadcasted MSG satellite data and the software package provided by EUMETSAT Satellite Application Facilities of Nowcasting and Very Short Range Forecasting, NWC SAF (Meteo France, 2016; Derrien & LeGLEau, 2005). To provide timely the all skies GHI SENSE2 product for 1.5M pixels, neither the running-of-direct radiative transfer simulations nor the multi-dimension interpolations would be sufficiently fast. Instead, a multi-parametric equation was constructed, fitted on libRadtran simulations for a wide range of COT values for different SZAs (points in Fig.2a). ~~In our simulations, spherical droplets were assumed having typical climatological mean heights (base at 2km, 3km height) and microphysical properties. Typical values for the effective radius ($R_{eff} = 10 \mu m$) and the liquid water path ($LWP = 1 g/m^3$) were used, given the unavailability of those data and their small impact on GHI (Oumbe et al., 2014; Qu et al., 2017).~~ The design of the cloud model was a trade -off between the relevance of the cloud property and the operational implementation of the model. It has been shown in previous studies (Qu et al. 2017) that for most of the cases (except for high surface albedo values >0.9), the cloud vertical position and extent has a small or negligible influence for the RTM simulations of surface solar irradiance. Under cloudy conditions, COT is the variable that has the greatest impact on simulating surface solar radiation (Qu et al., 2017, Oumbe et al., 2014, Taylor et al., 2016). In our simulations, spherical droplets were assumed, with typical values for the effective radius ($R_{eff} = 10 \mu m$) and typical climatological mean heights (base at 2 km, 3 km height) (Taylor et al. 2016, Kosmopoulos et al., 2018), given the unavailability of height descriptors in the operational mode and the negligible influence of changes in droplet effective radius with respect to COT on simulating surface solar radiation (Oumbe, 2009) and towards simplify the cloud model. The COT of the cloud layer is additionally specified at 550 nm, which leads to an adjustment of the liquid water content default value of $1 g/cm^3$, using the parameterization by Hu and Stamnes (1993). Finally, for the libRadtran simulations homogeneous layer clouds were used, meaning cloud cover fraction value of 100%, which is one of model limitations, since assuming totally cloudy pixels is not always correct for low values of COT (Mueller et al. 2009). The simulated GHI for each COT was divided by the GHI for COT=0 (clear sky) for the same SZA to derive the CMF (Eq. 1). The CMF ranges from zero (overcast conditions) to 1 (clear sky) and it is easy to use to provide all skies GHI by simply multiplying clear-sky GHI with CMF (Eq. 3). The libRadtran-derived CMF for each SZA were fitted against COT using the hyperbolic tangent function. The resulting fits are shown as solid lines in Fig.2a and are mathematically expressed by the multi-parametric Eq. 2.

$$CMF = \frac{GHI}{GHI_{clr}} \quad (1)$$

$$CMF = 1 - \tanh^b(COT^a) \quad (2)$$

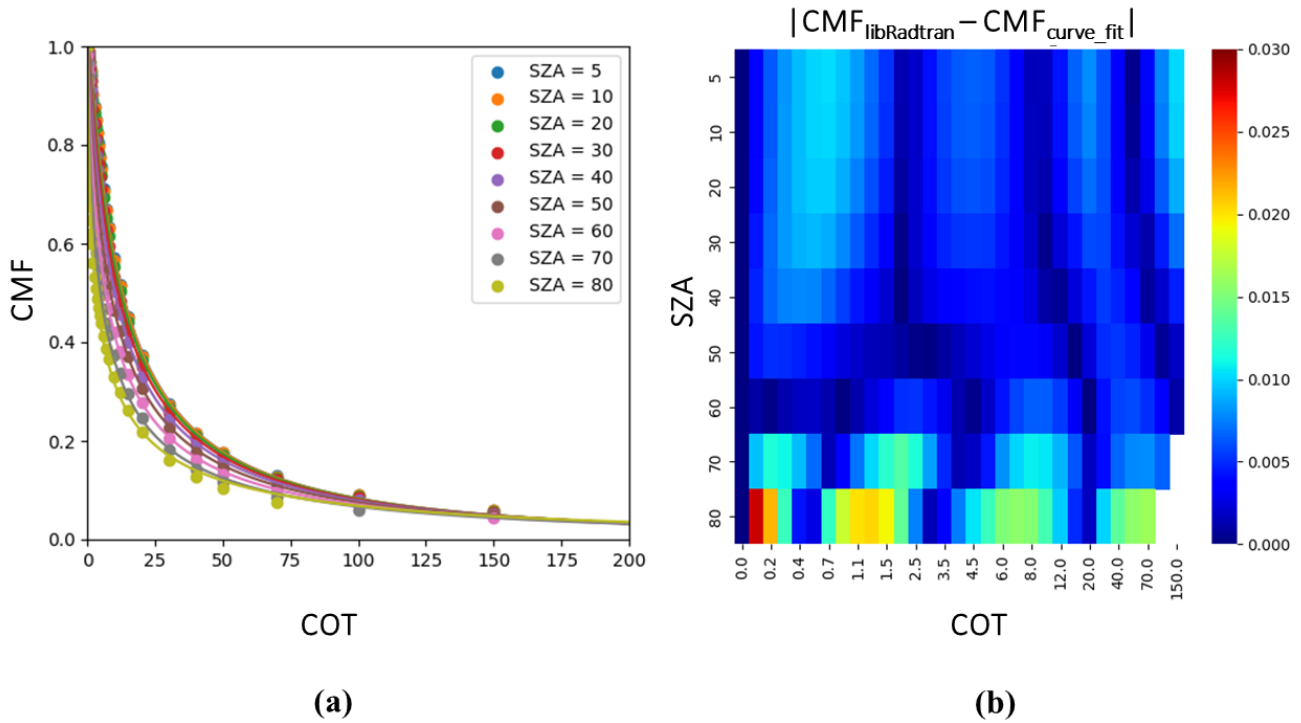
where a and b are polynomials of SZA

$$a = 2.24 \cdot 10^{-1} + 2.81 \cdot 10^{-4} \cdot SZA - 2.18 \cdot 10^{-5} \cdot SZA^2 + 3.71 \cdot 10^{-7} \cdot SZA^3 - 2.65 \cdot 10^{-9} \cdot SZA^4 \quad (2a)$$

$$b = 12.2 + 5.27 \cdot 10^{-3} \cdot SZA - 2.24 \cdot 10^{-3} \cdot SZA^2 + 8.33 \cdot 10^{-6} \cdot SZA^3 + 3.94 \cdot 10^{-8} \cdot SZA^4 \quad (2b)$$

The real time MSG COT is used as input in Eq. 2 every 15 min, along with SZA, for ~1.5M pixels, to calculate the CMF (CMF_{msg} hereafter). Apart from being very fast, the use of this formula to calculate CMF_{msg} is also accurate, as it can be seen by the comparison of the CMF values derived by Eq. 2 against those of libRadtran runs (Fig. 2b). CMF differences are less than 0.015 (or 1.5%) for SZA lower than 70 degrees, while they are up to 0.03 (3%) for SZAs between 80 and 90 degrees, showing the very good representation of the CMF as a function of COT with Eq. 2. In terms of accuracy this means that using Eq. 2 is almost the same as running RTM simulations, but in terms of computational time is by far more efficient in the operational mode. Finally, by multiplying CMF_{msg} with clear-sky GHI, the all-skies GHI product is provided (Eq. 3), in less than 1 min for 1.5M pixels.

295
$$GHI = GHI_{clr} * CMF_{msg} \quad (3)$$



300 **Figure 2 (a) Cloud modification factor (CMF) versus cloud optical thickness (COT) and solar zenith angle (SZA) based on radiative transfer simulations of global irradiances using the libRadtran package. CMF is the ratio of global horizontal irradiance (GHI) values to those under cloudless conditions (COT=0). (b) Differences between the CMF directly derived from libRadtran simulations against those derived from Eq. 2, as a function of COT and SZA.**

The new SENSE2 configuration was built for the improvement GHI nowcasting on the 15 min time scale. Additionally, it allows a greater flexibility for the system to:

- include reanalysis or measured data of AOD and other optical properties e.g., CAMS reanalysis or AERONET measurements.

- 305 - extent to other output products. Apart from GHI, direct normal irradiance (DNI) or total irradiance on tilted surface could be also produced. By introducing spectral information and making the appropriate modifications, products related to specific spectral regions could be also derived (e.g., UV Index by using real time input for TOC, photosynthetically active radiation (PAR) etc).
- run a past time series of one or few locations, autonomously, using as input actual measurements. In this case, if there is
310 no time constrain, model runs could be performed without the parametrizations (LUT and multiparametric functions).

2.2 NextSENSE2

NextSENSE2 is the operational system that provides forecasts of GHI up to 3-hours ahead with a 15-min time step by applying a CMV technique to the MSG COT product (Fig. 1). In this section, we describe the method employed to produce forecasted COT, which is the main input to derive the operational forecasts of GHI. All the other EO inputs and the radiative transfer
315 parameterizations for fast estimates of forecasted GHI are the same as those described in the previous section for the SENSE2 model.

We use CMVs to predict the motions of the clouds and project their future positions. The CMVs in NextSENSE2 are calculated by applying a state-of-the-art optical flow algorithm from the computer vision community. Optical flow is the apparent motion of objects between consecutive frames, caused by the relative movement between the object and a camera. We apply the
320 Farnebäck (2003) two-frame motion estimation technique to images of COT product (Kosmopoulos et al., 2020). Several other optical flow algorithms like TV-L1 are available as free software (OpenCV) and are used for cloud motion estimation in solar energy short-term forecasting systems (Urbich et al., 2019). In this study we used Farnebäck based on the results of the previous study by Kosmopoulos et al. (2020). By applying the algorithm to two consecutive images of satellite derived COT the optical flow displacement vectors are calculated. This CMV field is applied to the later COT image (real) to get the next COT image
325 (forecasted COT). This procedure is repeated for 12 times resulting to the 3h forecasting horizon. Main assumptions are the brightness constancy and that the cloud's displacements are only two dimensional (image plane). More details regarding the CMV model and forecasted COT can be found in Kosmopoulos et al. (2020).

2.3 ~~Smart-p~~Persistence forecast

It is not easy to evaluate the quality of different forecasting methods of surface solar radiation using only statistical metrics, since the study period, the geographical area and other factors are affecting their forecasting accuracy. That's why it is a typical practice of evaluation to benchmark the different forecasts against some simple forecast methods (Pelland et al., 2013). We
330 used the persistence forecast to benchmarked the CMV forecasted GHI of NextSENSE2 system which is a commonly used reference in solar forecasting (e.g. Kosmopoulos et al., 2020; Kallio-Myers et al., 2020). with the so-called smart-persistence approach, which- This method assumes that the state of the clouds remains constant for future time steps, while all other
335 variables like SZA etc. dynamically change. Hence, it uses the same COT values from the later satellite information as input to the next 12 time-steps in order to forecast GHI up to 3h ahead.

2.4 Ground based irradiance measurements

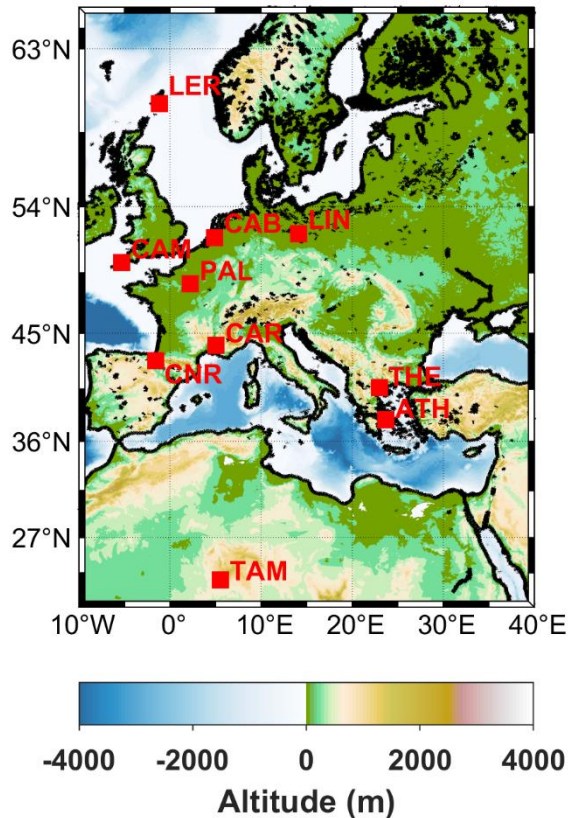
To validate the modelled GHI, ground-based measurements from pyranometers were utilized. The 1-min GHI ground based measurements were collected from stations of the Baseline Surface Radiation Network (BSRN; Driemel et al., 2018) that are within the study area and have data throughout 2017, and from two additional stations at Athens (ASNOA: NOA's Actinometric Station) and Thessaloniki. Table 2 summarizes the information of the 10 in total stations utilized and Fig. 3 depicts their geographical locations.

BSRN station-to-archive files were accessed and manipulated using the SolarData v1.1 R package (Yang, 2019). The function that reads the data from the station-to-archive files also computes several auxiliary variables such as solar zenith angle, clear sky irradiances using the Ineichen-Perez clear sky model (Ineichen & Perez, 2002) and extraterrestrial GHI. Using the same methodology, the Ineichen-Perez clear sky model values were also computed for the non BSRN station data, [by adjusting the functions of the SolarData v1.1 R package for the non-BSRN stations](#).

The BSRN recommended Quality Check (QC) tests (Long & Dutton, 2010) ~~where~~ performed to the collected measurements, to ensure the best quality of the measurements. Measurements that were not respecting the above QC tests, were flagged, and set to as a missing value. [The GHI records that are available at the two Greek stations \(1951 – present in Athens, 1993 – present in Thessaloniki\) are among the longest continuous high quality GHI records at the Eastern Mediterranean Basin, an area where BSRN data are not available for the period of this study. The pyranometers in Athens and Thessaloniki are calibrated regularly and the GHI measurements have been subjected to quality control before being used in the study. More information for the GHI datasets at the two stations can be found in Bais et al., \(2013\) for Thessaloniki, and Kazadzis et al., \(2018\) for Athens.](#)

Table 2 Detailed information about the ground-based stations used in this study.

Name	Ground based pyranometer network			location	AERONET station
		Lat. (°N)	Lon. (°E)		
ATH - Athens	-	37.9	23.7	Europe/Greece	Co – located
CAB – Cabauw	BSRN	51.9711	4.9267	Europe/Amsterdam	Co – located
CAM – Camborne	BSRN	50.2167	-5.3167	Europe/London	Co – located
CAR – Carpentras	BSRN	44.083	5.059	Europe/Paris	Co – located
CNR – Cener	BSRN	42.816	-1.601	Europe/Madrid	Co – located
LER – Lerwick	BSRN	60.1389	-1.1847	Europe/London	Co – located
LIN – Lindenberg	BSRN	52.21	14.122	Europe/Berlin	Co – located (metObs LIN)
PAL – Palaiseau, SIRTAs Obser	BSRN	48.713	2.208	Europe/Paris	Co – located
TAM – Tamanrasset	BSRN	22.7903	5.5292	Africa/Algiers	Co – located
THE -Thessaloniki	-	40.63	22.96	Europe/Greece	Co – located



360 **Figure 3** Locations of the ground-based stations measuring global horizontal irradiance (GHI) that are used in the current study. These are eight BSRN stations, plus Athens, and Thessaloniki, Greece.

2.5 Ground based aerosol information

To assess the CAMS AOD forecasts used as input to the model, ground-based measurements of AOD from the AERONET network (Holben et al., 1998) were used. All the ground-based stations with pyranometer data (BSRN, Athens and Thessaloniki) have a collocated AERONET station (see Table 2). The level 2, version 3 direct sun (Giles et al., 2019) AOD data at 500nm were collected and using the Ångström exponent for 440-675nm, the AOD values at 550nm were derived. Only for Cabauw, measurements of AOD at 500 nm weren't available, therefore AOD at 440 nm was used instead and converted to 550 nm using the Ångström exponent for 440-675 nm.

2.6 Evaluation metrics

370 For the validation of the SENSE2/NextSENSE2 derived GHI values against ground-based measurements, common statistical metrics have been adopted. Given that the error is defined as the difference between modelled values ($x_{m,i}$) and observed values ($x_{o,i}$), we have the following common metrics:

Mean Bias error:

$$MBE = \frac{1}{N} \sum_{i=1}^N (x_{m_i} - x_{o_i}) \quad (4)$$

Root mean square error:

375

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_{m_i} - x_{o_i})^2} \quad (5)$$

And Pearson correlation coefficient R. The relative values of those metrics rMBE and rRMSE were obtained with respect to the mean of the observed values of GHI.

380 An additional metric the forecast skill (FS) was used to assess the performance of CMV forecasted GHI using persistence model as a benchmark model:

$$FS = 1 - \frac{rRMSE_{CMV}}{rRMSE_{pers.}} \quad (6)$$

where rRMSE_{CMV} and rRMSE_{pers.} are the relative RMSE of the CMV and persistence forecasting models, respectively.

3 Results and Discussion

385 The results are discussed separately for the evaluation of nowcasted GHI (Section 3.1) related to SENSE2 outputs (modelled GHI hereafter) and the evaluation of the short-term forecasted GHI (Section 3.2), namely the NextSENSE2 product (forecasted GHI, hereafter). The comparisons between ground based and estimated GHI where restricted to SZAs below 75° (i.e., for solar height above 215° from the local horizon), because for higher SZAs the accuracy of the satellite cloud retrievals degrades due to the limitations in the field of view of the satellite.

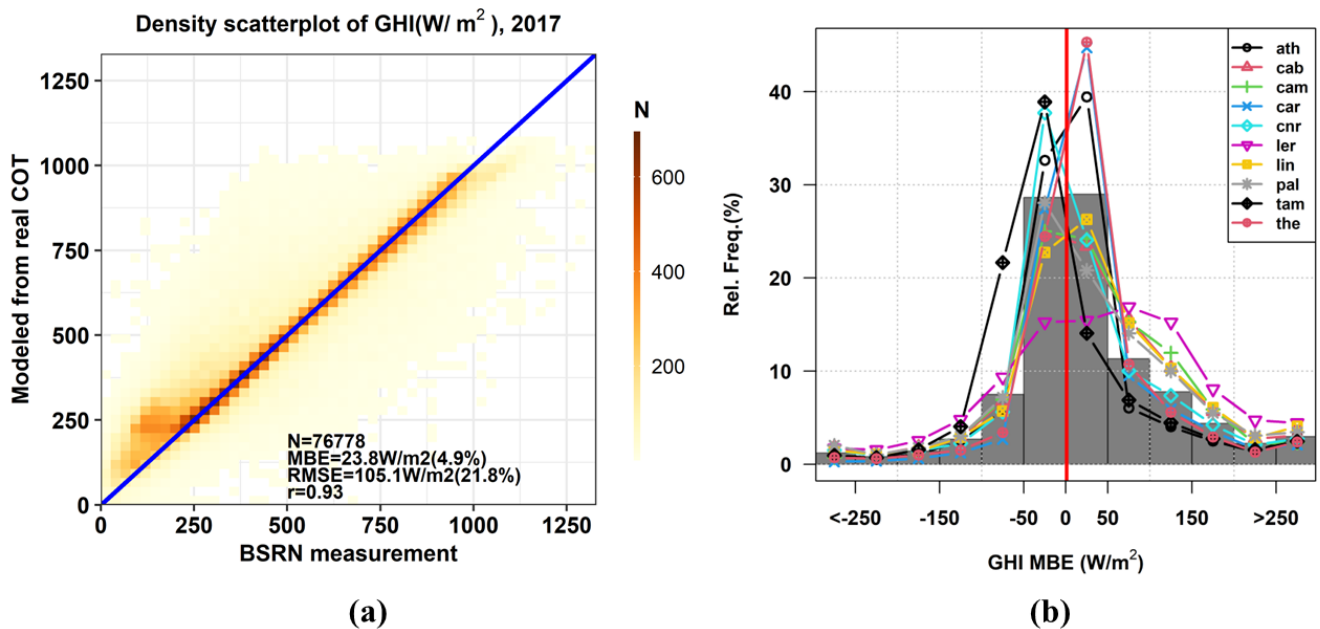
390 The CMF derived from the ground-based measurements of GHI was used in our analysis to evaluate CMFmsg and to categorize the cloudiness conditions. Specifically, the CMF was calculated as the ratio (Eq. 7) of measured GHI to the clear sky irradiance calculated by the Ineichen-Perez clear-sky model (Ineichen & Perez, 2002) (See Section 2.4).

$$CMF = \frac{GHI_{measured}}{GHI_{clr}} \quad (7)$$

Three categories according to CMF are used in the following: CMF ≥ 0.9 for clear sky conditions, $0.4 < CMF < 0.9$ for partially cloudy conditions and CMF ≤ 0.4 for overcast conditions.

3.1.1 Overall performance

Figure 4 presents the overall performance of the SENSE2 system at the (instantaneous) 15_min time scale, by comparing the modelled GHI values against ground-based measurements, for all stations, for a whole year (2017). We can see that most of the points (Fig. 4a, number of cases $N > 600$) fall on the 1:1 line (blue line) which indicates the overall good performance of the system, with a correlation coefficient of 0.93. For 58 % of the cases, the absolute differences between modelled and ground-based measurements of GHI are within $\pm 50 \text{ W/m}^2$ or $\pm 10 \%$ (Fig. 4b). The SENSE2 system mostly overestimates the GHI, which corresponds to points above identity line (Fig. 4a), with MBE 23.8 W/m^2 (4.9%). ~~This overestimation is attributed to the underestimation of cloud related information from satellite (MSG-COT), when we compare point measurements with a pixel in satellite images corresponding to a wide area of almost $5 \text{ km} \times 5 \text{ km}$. This overestimation, which~~ is more pronounced for low irradiances (low left corner of Fig. 4a with $\text{GHI} < 250 \text{ W/m}^2$), ~~indicating the challenging task of accurately modelling GHI based on satellite data for stations with enhanced cloudiness. Especially at high latitudes, measurements with clouds and at large SZAs are more frequent.~~ Lerwick is the most northern station and at the same time the station with the greatest MBE (Fig. 4b and Fig A1,2 in Appendix A). ~~There are also points below the identity line, which indicate that the measured GHI is greater than the modelled. This is attributed partly to the irradiance enhancement by clouds that occurs often when the sky above the ground station is partially cloudy, and the sun is visible. In this case, the reflection of solar radiation by clouds increases the diffuse component, and hence the GHI, at the ground, even though the satellite “sees” a cloudy pixel. The cloud effect on GHI estimates is investigated in more detail in Section 3.1.3.~~



415 **Figure 4 (a) Comparison of the global horizontal irradiance (GHI) modeled versus measured for all ground based stations, for 2017. (b) Relative frequency of GHI MBE for all stations (grey bars) and for each station (lines with different symbols and colors).**

420 We investigated the influence of the mean cloudiness (CMF) of every station along with its latitude and the mean measured GHI to the GHI MBE and is presented in Fig. 5. The GHI MBE increases with an increase in cloudiness (decrease in mean CMF). At the same time the cloudiness increases with latitude, where lower values of mean measured GHI are observed as well. Those results are in line with previous studies (Qu et al., 2014; Qu et al., 2017). According to Qu et al., (2014) the error of the satellite estimates of surface solar radiation increases with an increase of the distance from the subsatellite point (lat=0°, lon=0° for Meteosat) and in occurrence of fragmented cloud cover. Qu et al (2017) found lower accuracy of their retrievals for the northernmost stations which was attributed to the more frequent cloud occurrence over those stations and the more erroneous satellite retrievals of clouds properties for large SZAs and satellite viewing angles. One of those stations was Lerwick, which is close to the edge of the field of view of Meteosat satellite, where errors due to parallax becomes important

425 [\(Marie-Joseph et al., 2013; Schroedter-Homscheidt et al., 2022\)](#). The cloud effect on GHI estimates is investigated in more detail in Section 3.1.3.

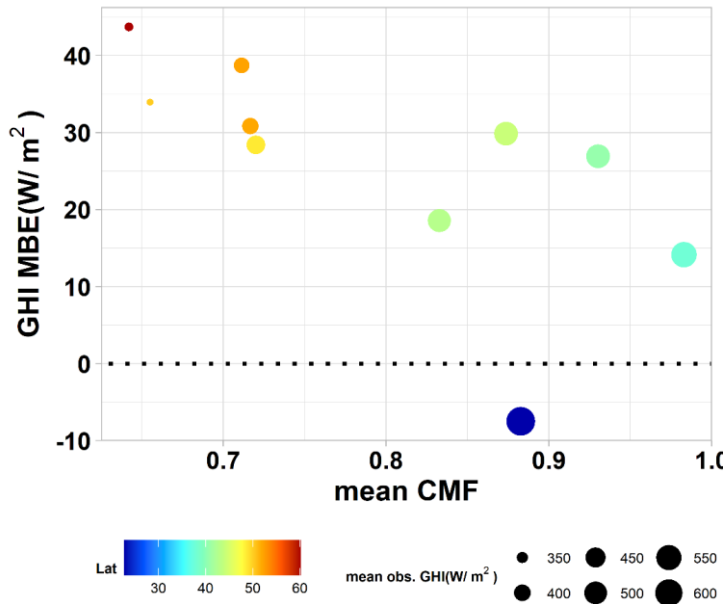
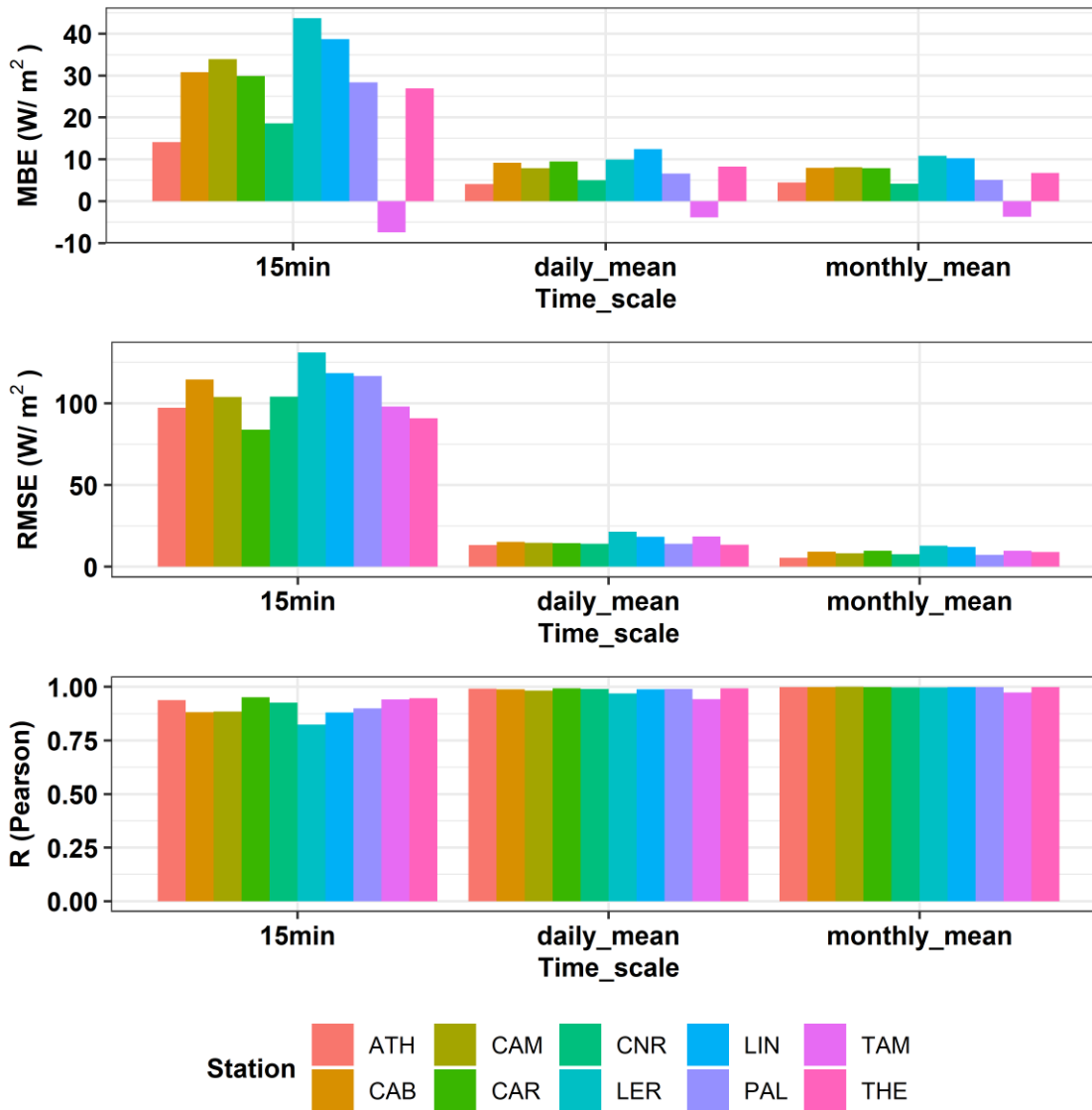


Figure 5 GHI MBE dependence on the mean CMF for all stations. The colour of the points indicates the latitude of the station and their size the magnitude of the mean GHI observed at the ground-based stations.

430 All the statistical metrics are drastically improved with increasing time scale for all stations (Fig. 65). Stations with similar results are the northern most stations CAB, CAM, LER, LIN, and PAL. At the 15 min time scale their MBE, RMSE and correlation coefficient range 29-43 W/m², 104-131 W/m² and 0.82-0.90, respectively. Those statistics are improved for the monthly means to 5-10 W/m² for MBE, to 7-13 W/m² for RMSE and to r~1. Similar results were found for the rest southernmost stations (MBE, RMSE and correlation coefficient range from -7 to 30 W/m², from 84 to 104 W/m² and from 0.93 to 0.95, respectively, for 15 min time scale and from -4 to 8 W/m², from 6 to 10 W/m² and r~1, respectively, for monthly means). The overall MBE and RMSE is reduced to 6.6 W/m² (3.3%) and 15.4 W/m² (7.7%) for the daily mean GHI and to 5.7 W/m² (3.2%) and 9.2 W/m² (5.2%) for the monthly means, while correlation coefficient reaches values up to almost 1, which was anticipated since the cloud effect is smoothed out for larger time scales.



440

Figure 65 Comparison of the global horizontal irradiance (GHI) modeled versus measured per ground based station, for 2017, for different time scales (15 min, daily mean and monthly mean).

3.1.2 Aerosol effect on retrieved solar irradiance

445 The CAMS AOD forecasts used as input to the operational model were assessed against ground-based measurements from the AERONET network, and the related uncertainty introduced to modelled GHI has been calculated. The AERONET AOD direct sun measurements were matched with CAMS AOD forecasts (1h time resolution) interpolated to the 15 min time steps of the model. The closest AERONET measurement +/- 10 minutes around the 15 min time steps were matched (or the mean value if more than one measurements were available). To estimate the model uncertainties due to forecasted AOD, the clear sky GHI

was calculated using as input first the forecasted CAMS AOD and second, the synchronized AERONET AOD measurements.

450 The comparison for AOD and modelled GHI is presented in Fig. 76 per station in terms of MBE.

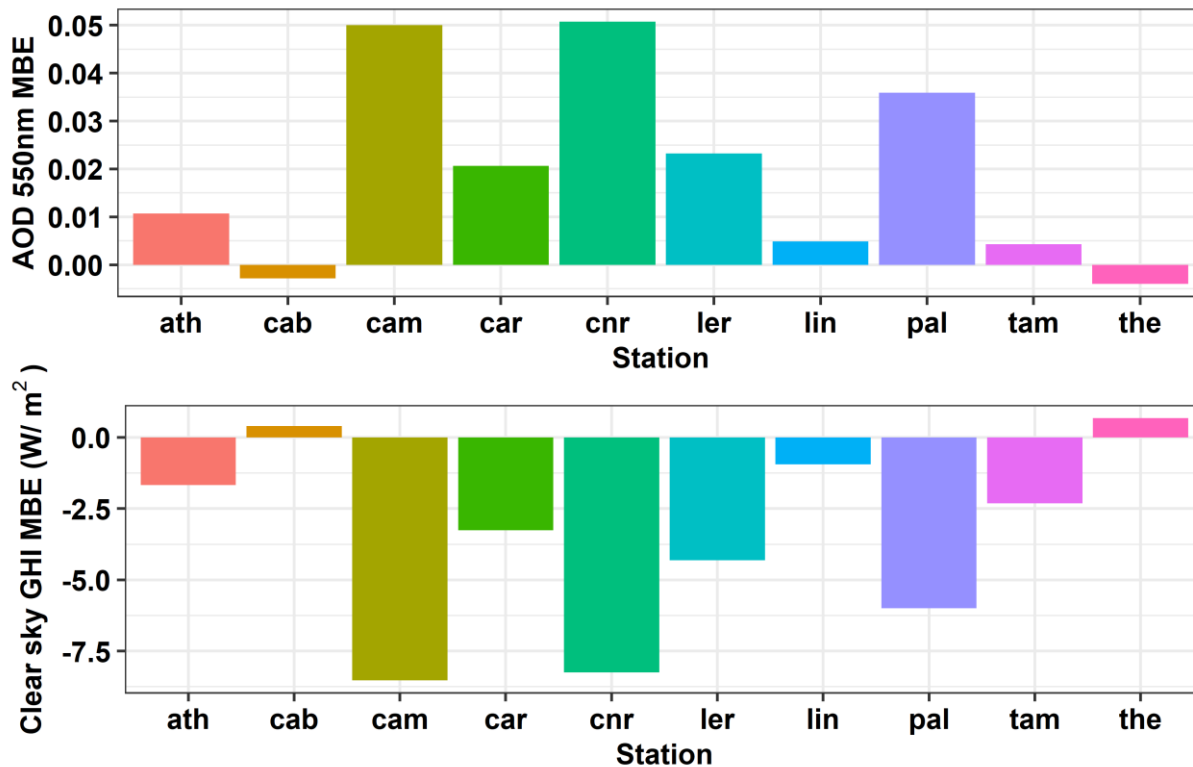
CAMS forecasts mostly overestimate AOD with MBE 0.015 (10%) for all stations which results to an underestimation of modelled clear sky GHI -2.7 W/m^2 (-0.4%). The greatest overestimation 0.05 (~50%) was found for CAM and CNR which resulted to the greatest underestimation of clear sky modelled irradiances -8.5 W/m^2 (-1.4%). Underestimation of AOD was found for CAB and THE, with $\text{MBE} < 0.01$ (<3%), resulting in negligible overestimation of modelled irradiances ($\text{MBE} < 1 \text{ W/m}^2$ or 1%).

455 An overestimation of the CAMS forecasted AOD at 550nm is also reported for 2017 over Europe (average modified normalized mean bias ranging from ~10 to 30%) from the continuous quarterly evaluation of the AOD forecasts against daily AERONET cloud-screened (i.e. Version 3 level 1.5) sun photometer data (Basart et al., 2023; Eskes et al., 2021). While this is the case on average, in contrast during high aerosol loads, CAMS forecasted AOD is underestimated, especially in desert regions and during dust events (Basart et al., 2023; Papachristopoulou et al., 2022) which might explain the almost zero bias for Tamanrasset station (the overestimation of small AODs masked out by the frequent underestimation of large AODs) compared to the greater values of bias (>0.01) found for most of the rest stations. Qu et al. (2017) analysed case studies at Tamanrasset and found that the CAMS (MACC) AOD at 550nm is frequently underestimated against AERONET data during summer dust events, explaining the strong positive bias they found for their modelled direct irradiance (using Heliosat-4 method and the McClear clear sky model). In contrast to the CAMS AOD underestimation during dust events, in the same study (Qu et al., 2017) a systematic overestimation of AOD was found during periods free of those events for the two examined desert stations (Sede Boqer and Tamanrasset), to which they associated the underestimation of their modelled direct irradiance. The updated McClear v3 clear sky model used in study by Schroedter-Homscheidt et al. (2022) and for their GHI estimates under clear-sky conditions a negative bias was found for most of the station especially for those located in dust affected regions, which is in line to our results although not directly comparable since they compared directly with the BRSN measured irradiances. Our results demonstrate the good performance of the clear sky model using CAMS forecasts, highlighting that AOD product forecasted by CAMS is suitable for GHI nowcasting applications.

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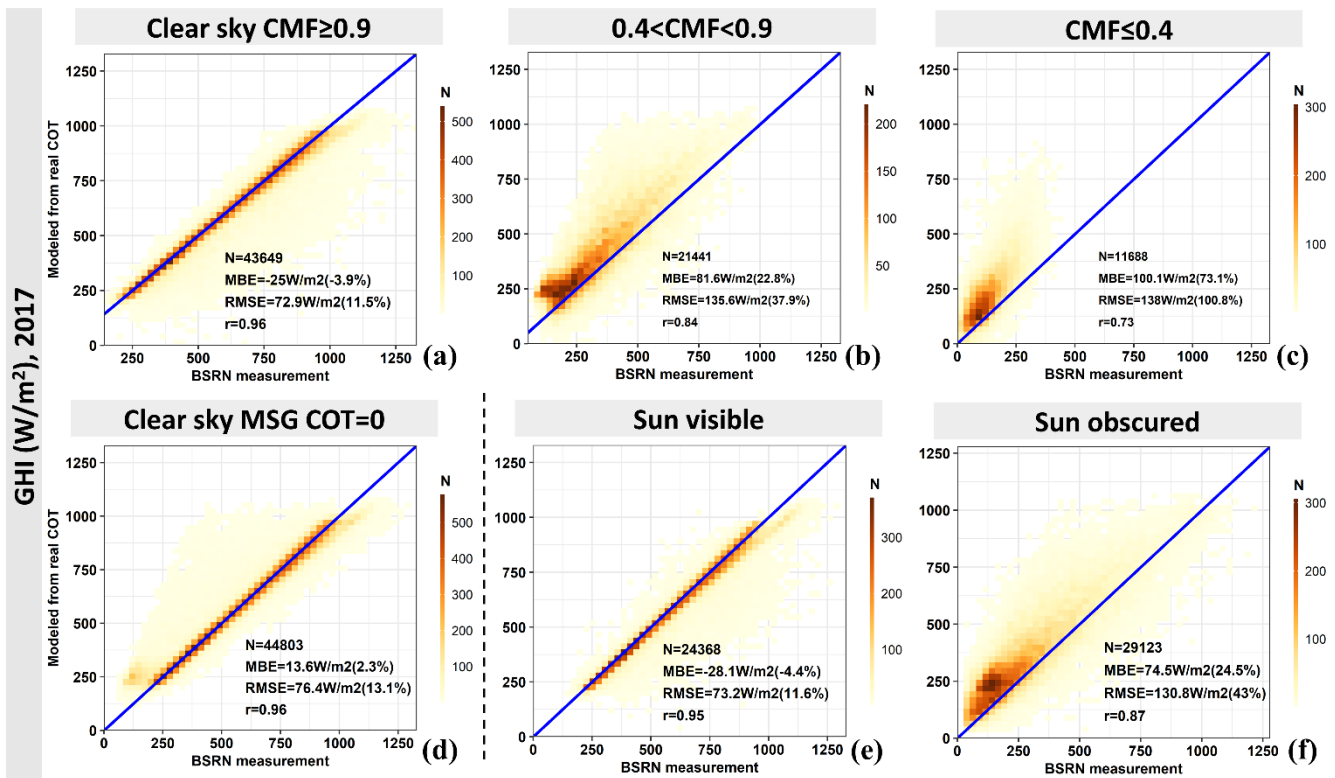
475 | **Figure 76** Upper panel: Mean bias error (MBE) of aerosol optical depth (AOD) at 550nm forecasted by CAMS (1 day ahead forecast) compared to AOD measured by ground based sun photometers of the AERONET network. Lower panel: MBE of global horizontal irradiance (GHI) modeled under clear sky conditions using as input CAMS forecasted AOD at 550nm versus measured values (AERONET).

3.1.3 Cloud effects on retrieved solar irradiance

480 Overall, the model relatively overestimates GHI, as we saw in Section 3.1.1, ~~which~~ The improvement of the statistics going from instantaneous comparison to integrated time scales (e.g. daily) points to the direction that such overestimation can be attributed both to the uncertainties related to the underestimation of cloud information from satellite retrievals, but also to satellite/ground-based evaluation representativity issues. (MSG-COT). To In order to investigate this more, we decomposed the error in modelled GHI for different conditions in cloudiness induced due to satellite cloud information,

485 Initially, we classified the cloudiness conditions using ground-based CMF (Fig 87a, b, c). We can see that the According to the results, GHI is overestimated by the model under cloudy conditions (CMF < 0.9), while for clear sky conditions (CMF ≥ 0.9, Fig. 8a) the model closely resembles the measured GHI. ~~The category of CMF > 0.9 contains apart from the conditions with actual clear sky, also the CMF > 1 which exists due to the cloud enhancement of solar irradiance, responsible for the underestimation of modeled GHI in this category (see Section 3.1.1).~~ For partially cloudy conditions (0.4 < CMF < 0.9, Fig. 8b and > 0.4), the MBE is 81.6 W/m² (22.8%) and the greatest error in GHI occurs for the low CMF values (CMF ≤ 0.4, Fig.

490 8c) (MBE=100.1 W/m² or 73.1%). In theis latest category, the largest occurrence of high deviations at low measured GHI
values lowest values of measured GHI are found (<250 W/m²) is found. The high modeled GHI values could be attributed to
the underestimation of MSG COT product due to complex geometries related to high latitudes and large SZAs. Additionally,
there are also situations when the low measured GHI values are related to partially cloudy sky, with clouds blocking the sun,
a situation that cannot be resolved by the satellite COT retrieval. To demonstrate this last situation, w
495 We compared also the modelled and measured GHI values for clear sky conditions according to the satellite data, MSG namely
COT=0 (Fig. 8d7b, clear sky from the satellite point of view). In this case, the model overestimates GHI with MBE 13.6 W/m²
(2.3%). Most of the cases are on the 1:1 line, with few ones being higher ~~Most of the points are above the 1:1 line~~, especially,
for measured GHI<250 W/m², -meaning that there are clouds over the ground-based station that haven't been resolved by the
satellite pixel (COT=0). A positive bias was also found for all stations examined by Qu et al. (2017) for cases of clear sky
500 pixels as defined by APOLLO/SEV cloud properties retrieval scheme which contributes to the overall overestimation for the
all sky conditions, and it was attributed to small broken clouds causing large variability in surface GHI, and due to a false
detection by the cloud retrieval algorithm being treated as clear sky cases. The interesting part is that the same case stands for
the whole range of measured GHI, indicating that it is a general limitation of satellite that it cannot take into account clouds
that obscure the sun.

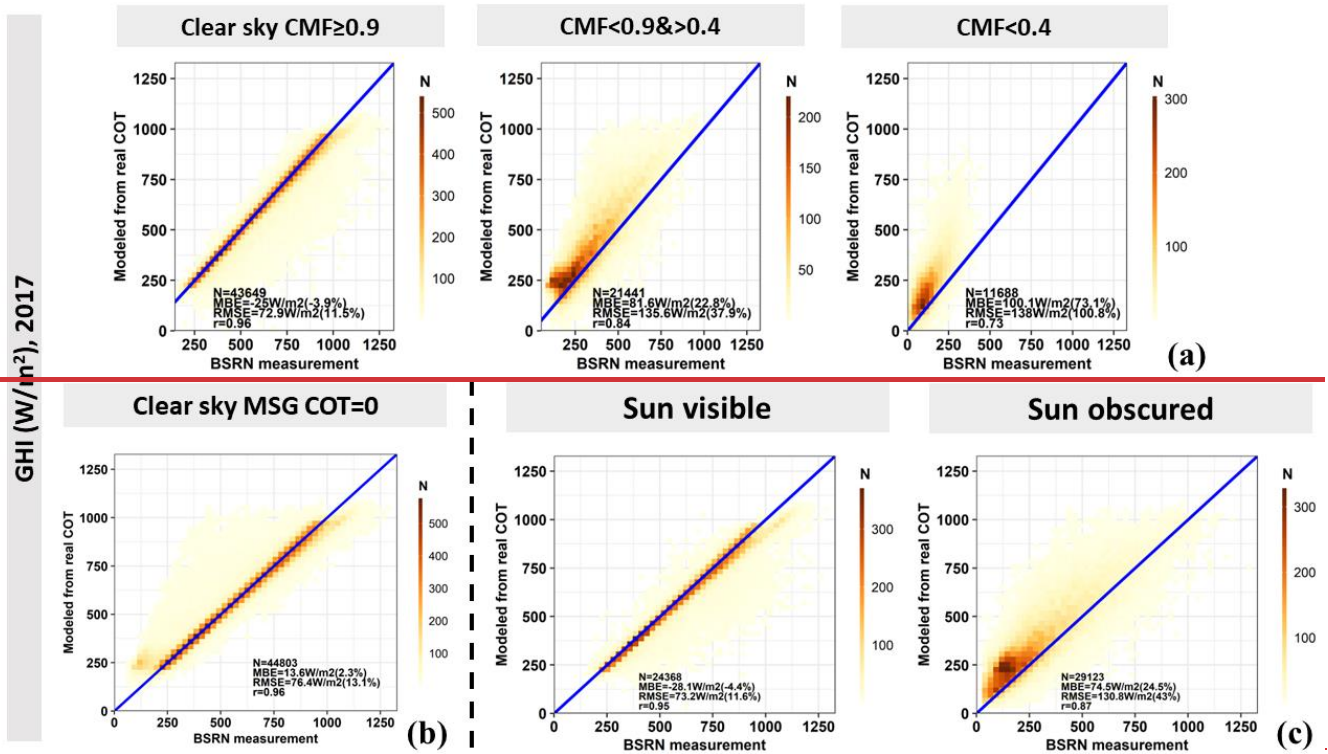


505 **Figure 8 Comparison of the global horizontal irradiance (GHI) measured versus modeled for all ground based stations (a, b, c) for different cloudiness conditions based on the cloud modification factor (CMF) derived by the ratio of GHI ground based**

measurements divided by clear-sky GHI (clear-sky model) (d) for clear-sky conditions as determined by MSG satellite product by zero values of cloud optical thickness (COT=0) (e, f) for conditions characterized as sun visible or obscured.

510 ~~To verify that the sun visibility is the main reason for the overestimation~~To demonstrate the effect of sun visibility over the
ground-based stations to the GHI error, we tried to separate those instances by using the pyrheliometer measurements of direct
irradiance (DNI – direct normal irradiance) available by the BSRN network. The DNI measurements (1_min) were divided
with the clear-sky DNI, again from the Ineichen-Perez clear sky model (Ineichen & Perez, 2002). ~~According to this ratio~~
~~values,~~We classified as sun visible the situations with ratio of actual to clear sky model DNI >0.8. This threshold was
515 selected to account for the strong effect of aerosols in DNI, given that a monthly mean climatological value for aerosol
attenuation factor is used by DNI clear-sky model (Ineichen & Perez, 2002). We classified as sun obscured situations with
ratio <0.6, and we omitted as unclassified situations those with ratio values between 0.6 and 0.8, to be confident that direct
irradiance is blocked by clouds by more than 40%. The results of the GHI comparison between modeled and measured values
were grouped based on the sun visibility classification and are presented in Fig. ~~78e,fe~~. We can see that the sun visible situations
520 give quite good results (points close to the 1:1 line, with MBE -28.1 W/m² or -4.4%). ~~In addition, several cloud enhancement~~
~~events (points below 1:1 line), cannot be captured by the model.~~

In contrast, the model overestimates GHI (MBE 74.5 W/m² or 24.5%) when the sun is obscured over the ground-based station.
Comparing Fig. 8b and Fig. 8c with Fig 8f we can see that most of the above the 1:1 line cases happen when the sun is obscured.
This is caused by the fact that the satellite-based cloud retrieval is representative of the whole pixel, while the information if
525 the sun is obscured over the ground-based station is representative for the (point) station, and it cannot be inferred from the
satellite cloud retrievals. This combined with the facts that the direct irradiance attenuation from clouds is completely different
from GHI, it is not linearly decreasing with cloudiness or cloud optical thickness and finally its contribution to GHI depends
on various parameters (mainly solar elevation), introduces an issue in any instantaneous comparison between satellite based
GHI retrieval representing the whole pixel and single point measured GHI. So, the main result of this sun visibility over the
530 station analysis is to discuss on possible systematic biases due to satellite pixel versus station evaluation representativeness
issue. This issue makes the instantaneous model output evaluation difficult, especially in partly cloudy situations, ~~–a situation~~
~~that cannot be inferred from satellite information. Comparing station (point) data with model derived, based on satellite pixel-~~
~~based cloud retrievals, introduces deviations linked with the cloud features within this pixel. Even if the satellite imager can~~
~~resolve a cloud within the pixel, the COT product for this pixel is a constant value, namely a spatially homogeneous cloud~~
535 ~~optical property for the corresponding area. In this atmospheric scene, GHI measured at the ground level, with the sun obscured~~
~~or not, will affect the comparison dramatically. Cases with partial cloudiness and the sun obscured as seen from the ground~~
~~sensor (almost total attenuation of direct irradiance) will be associated with low measured irradiance that cannot be captured~~
~~by the model. This is the main reason of the overall model overestimation.~~



540 **Figure 7 Comparison of the global horizontal irradiance (GHI) measured versus modeled for all ground based stations (a) for different cloudiness conditions based on the cloud modification factor (CMF) derived by the ratio of GHI ground based measurements divided by clear sky GHI (clear sky model) (b) for clear sky conditions as determined by MSG satellite product by zero values of cloud optical thickness (COT=0) (c) for conditions characterized as sun visible or obscured.**

Since the main source of errors in this analysis is associated with clouds, we further investigate assess the satellite derived
 545 cloud input in the model from satellite data. The MSG COT is transformed to CMF_{msg} using Eq. (2) and this is the cloud related input in the SENSE2 model. Since it cannot directly be evaluated with ground-based measurements, we compared indirectly evaluated the CMF_{msg} with the CMF derived from GHI measurements (Eq. 7) and the results are presented in Fig. 98, as relative frequency distributions of CMF_{msg}, CMF and their difference (CMF_{msg} – CMF), for all cases and different cloudiness conditions. In Fig. 8a and b, for all situations, we can see the overall, the CMF_{msg} is overestimation of CMF
 550 (0.17, Fig. 9a and b) by satellite (underestimation of MSG-COT), which is the reason for the overall overestimation of SENSE2 modelled GHI. This CMF_{msg} overestimation is linked to the partially cloudy (CMF < 0.9 and > 0.4 , comes mainly from situations that are characterized as cloudy (Fig. 98g, and h,) and the overcast (CMF < 0.4 , Fig. 8i and j) conditions and at the same time when the sun is obscured over the ground based station (Fig. 9m and n). The large relative frequencies of CMF_{msg}=1 in Fig. 8i are situations when the satellite cannot resolve any clouds giving COT=0 or CMF_{msg}=1, but the measurements demonstrate the presence of clouds. There is also a large fraction of enhancement events (CMF > 1) which is not captured by the CMF_{msg} (Fig. 8a). During those events satellite cloud product gives mostly no clouds (CMF_{msg}=1, Fig. 8c and e).

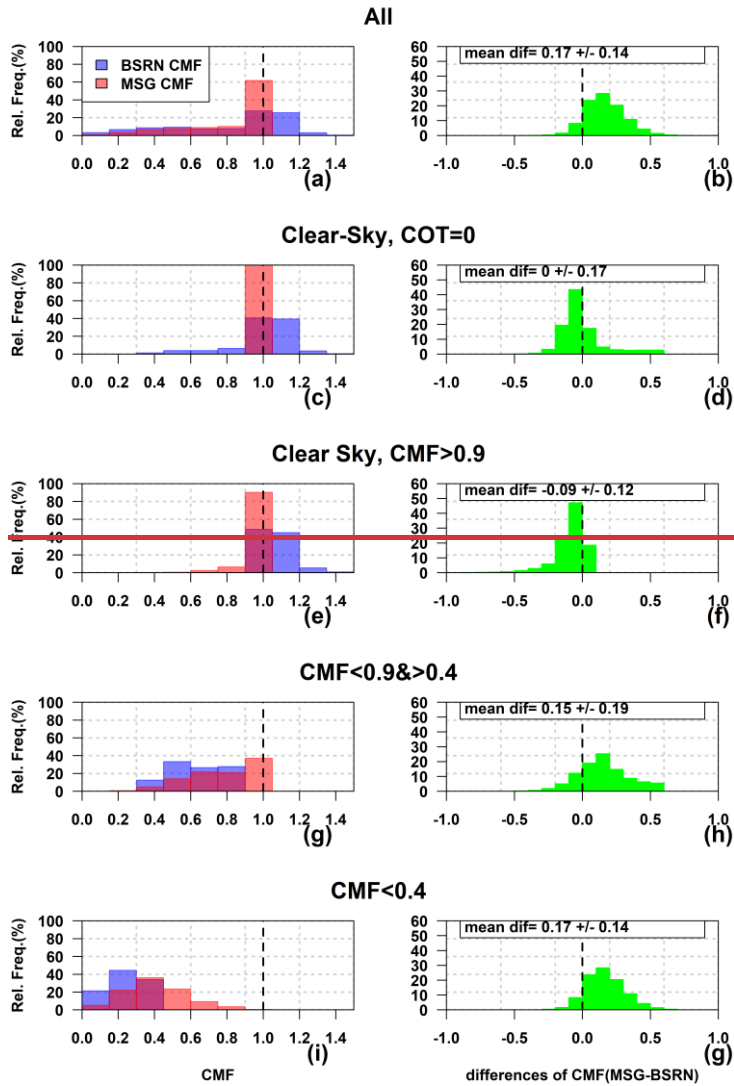
560 There are also cases of CMFmsg underestimation (differences of CMF <0 in Fig. 9b), which come mostly from situations characterized as cloudless (CMF>0.9, Fig. 9e and f) and explains the points below the 1:1 line in Fig. 4a and 8, indicating that the measured GHI is greater than the modelled. The first reason for this is a cloudy satellite pixel, namely CMFmsg<1 in Fig. 9e, but the ground-based CMF=1 indicates that no clouds are over the station. There is also a large fraction of CMF > 1 (Fig. 9e) that is attributed to the irradiance enhancement by clouds, that occurs often when the sky above the ground station is partially cloudy, and the sun is visible (see also Fig. 9k and l and Fig. 8e). In this case, the reflection of solar radiation by clouds increases the diffuse component from directions relatively close to the sun, and hence the ground based measured GHI. This is a 3-dimensional effect of clouds that cannot be reproduced using 1 dimensional radiative transfer modelling that used in this study. This is a limitation of the SENSE2 model that does not include 3-dimensional cloud effects (enhancement of GHI or parallax) which can be reproduced using 3D RT simulations (e.g. Mayer 2009). However, the 3-dimesional cloud structure information is not available for an operational solar energy nowcasting model from geostationary satellites (Qu et al., 2017; Schroedter-Homscheidt et al., 2022) and on the other hand the introduction of parameterizations and techniques to improve the computational time (Tijhuis et al., 2023) is essential.

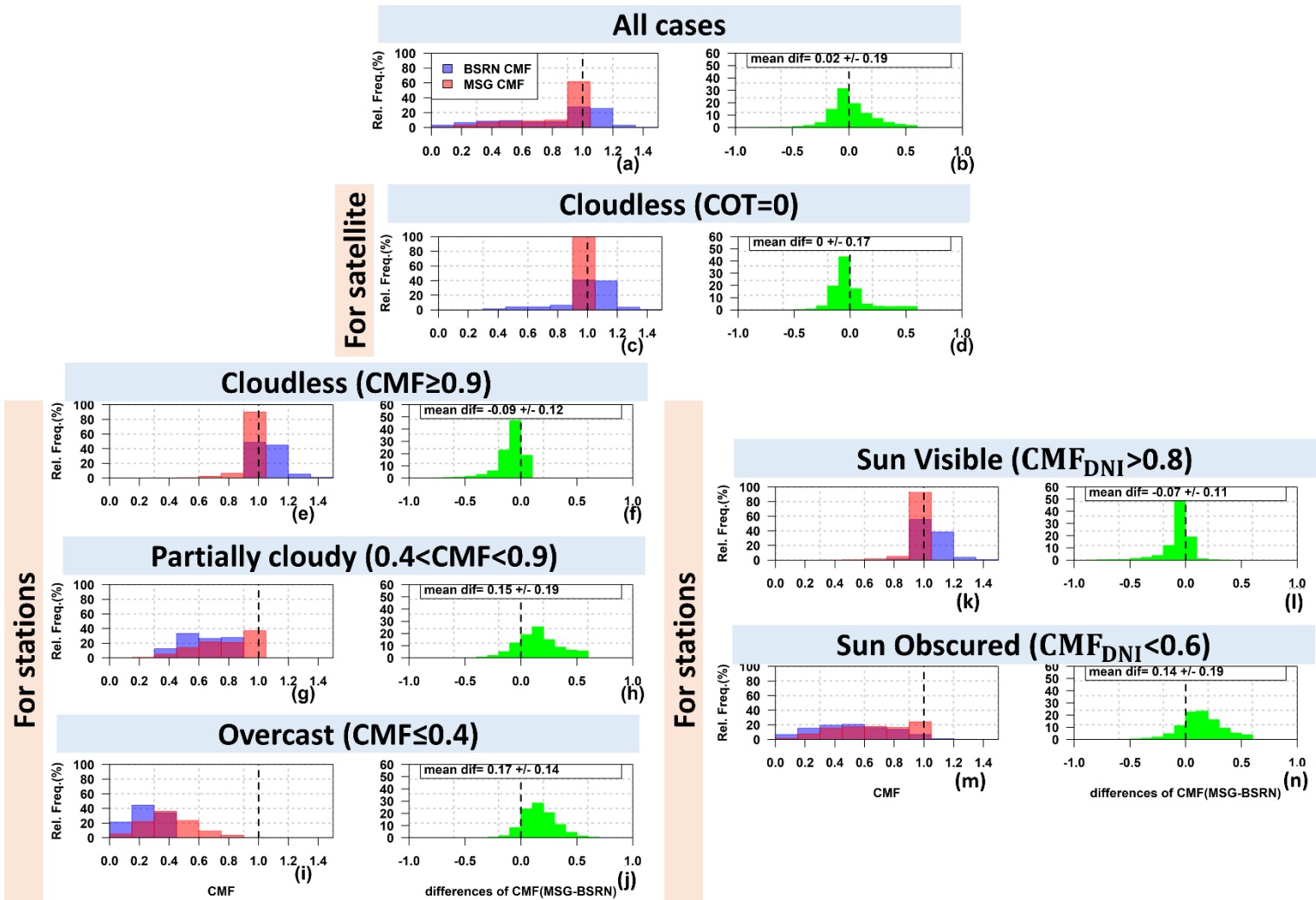
570 Summarizing, to explain the overestimation of SENSE2 GHI retrievals, we have to consider that the direct comparison between point measurements of solar radiation at the ground and of satellite estimates representative of a pixel, introduces deviations (e.g., Kazadzis et al., 2009; Schenziger et al., AMT; Carpentieri et al., 2023) linked with the cloud features within this pixel and the limitations of cloud monitoring using satellite data (e.g. spatial resolution). We investigated both CMFs' distribution and their differences separately again for clear sky conditions according to the satellite (namely COT=0, Fig.9 c and d).

575 Regardless the unique value of CMFmsg=1 meaning no clouds resolved by the satellite, there are cloudy cases for the ground-based station with CMF<1 (Fig.9 c). Due to the satellite spatial resolution, at some cases, small scale broken clouds cannot be resolved (e.g., Schenziger et al., 2023, Marie-Joseph et al., 2013; Qu et al., 2017), but those clouds may have a significant impact in ground based measured irradiance in case that they are obscuring the sun (almost total attenuation of direct irradiance). In case that they do not obscure the sun is the clear sky case also for the ground-based station, without excluding the effect of cloud enhancement of measured GHI (CMF=1 and CMF>1 in Fig.9 c, respectively). In a recent study by Schenziger et al. (AMT) using sky camera images, the limitation of MSG satellite based modelled CMF is demonstrated for small scale clouds. For two different stations inside the same satellite pixel that was characterized as cloud free different results were found. For one station that was cloud free the model agreed with measurements, while for the station that was covered by localized cumulus clouds that couldn't resolved by the satellite, lead to discrepancies between ground based and satellite based modelled values. Nevertheless, even for the cases that the satellite imager can resolve clouds within a partially cloudy pixel, the COT product for this pixel is a constant value, namely a spatially homogeneous cloud optical property for the corresponding area. In this atmospheric scene with high spatial variability of clouds, GHI measured at the ground level, with the sun obscured or not, will affect the comparison dramatically.

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Figure 98 Left panels (a, c, e, g, i, k, m): Distribution of cloud modification factor (CMF) from measurements of global horizontal irradiance (GHI) (blue bars) and from MSG cloud optical thickness (COT) (red bars), under all cases and under different cloudiness conditions. Right panels (b, d, f, h, j, l, n): Distribution of the CMF differences between those derived from measurements of GHI and those derived from MSG satellite COT.

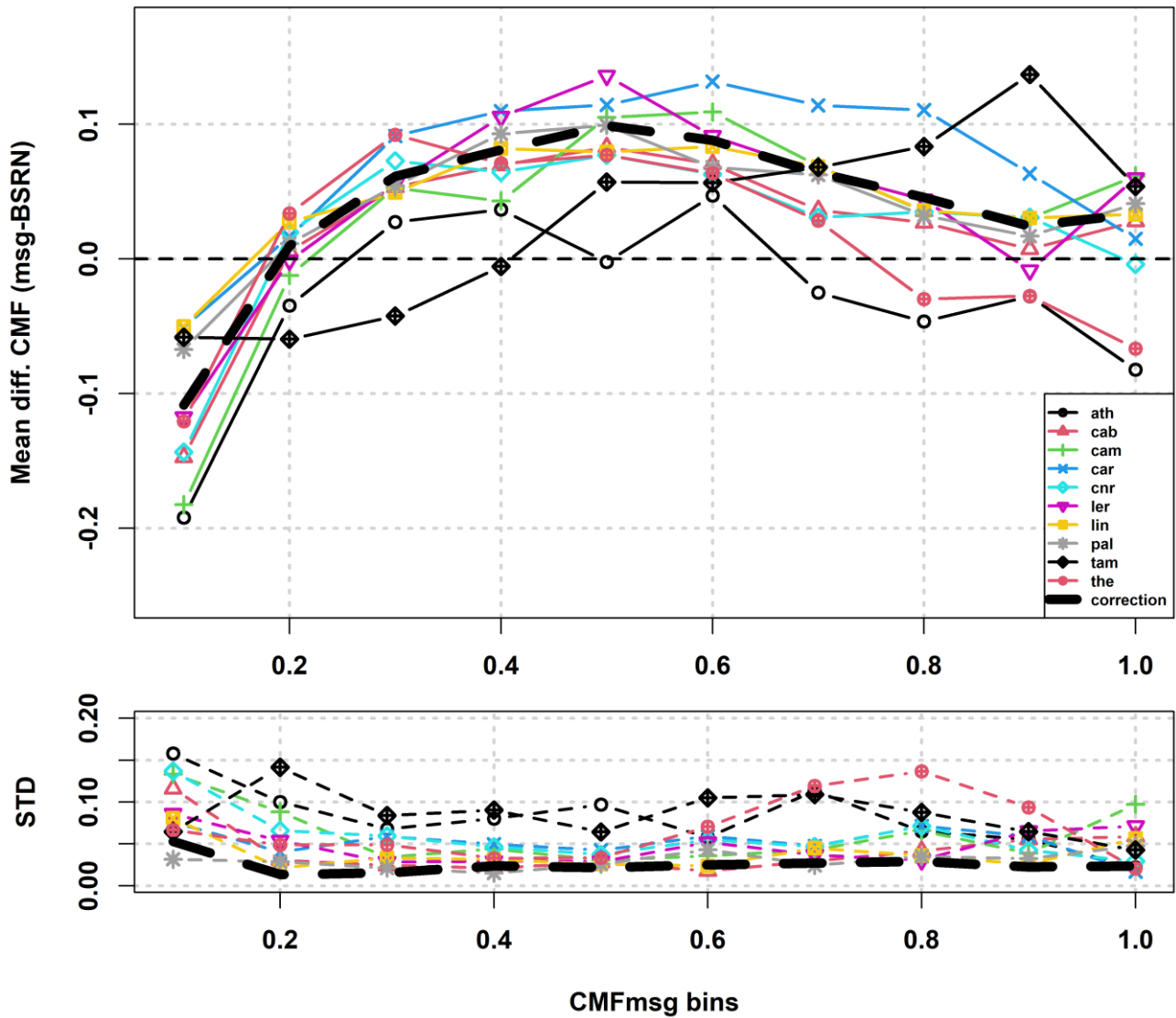
3.1.4 Bias correction based on cloud input

595 The model overall relatively overestimates GHI, which is attributed to the CMFmsg overestimation ~~(COT underestimation)~~
~~under cloudy conditions~~. Based on the main conclusions from CMF differences from the previous section, we tried to find if
there is any common pattern for all stations, in those CMF differences (modelled against measured) as a function of CMFmsg,
since the latest is the only operationally available input, every 15min. Additionally, we found that those differences hardly
change with SZA (Fig. BA1 in the Appendix B), so we will investigate their relation only with CMFmsg.

600 We calculated the mean CMF difference and their standard deviation per CMFmsg bins for every station and the results are
presented in Fig. 910. A pattern of mean CMF differences was found for almost all station (apart from TAM, ATH and THE)
with CFMmsg overestimation up to almost 0.1 starting from CMFmsg bin 0.3 up to 0.8, related also with low standard
deviations over those bins.

As we discussed in the previous section, this CFMmsg overestimation (up to ~0.1) is mostly related ~~with~~ to partial cloudiness
605 and the sun obscured conditions over the station. Nevertheless, the sun's visibility is information that couldn't be provided by
satellites. Consequently, we tried to correct CMFmsg (the operational input) with those CMF differences (modelled against
measured). We used the mean of the of CMF differences per CMFmsg bin from seven out of ten stations (excluding TAM,
ATH and THE) to derive the correction factor (the correction hereafter), which is depicted as the thick black dashed line in
Fig. 109. The correction was applied to CMFmsg values falling in the bins 0.3-0.8 only. The correction was applied to all
610 stations, including TAM, ATH and THE, which act as a test bed (low frequency of cloudy cases) for the general correction
derived from the rest seven stations.

Table 3 summarizes the statistics of corrected modeled GHI against ground-based measurements. The MBE and RMSE are
improved after the correction. ~~We can see that the correction was successful for all stations.~~ LER and CAM are the two stations
with the greatest improvement in their statistics, following CAB and LIN, which was anticipated since those are stations at
615 higher latitudes associated with high cloudiness. Even ATH and THE stations, that were independent from the correction factor
derivation-construction procedure, exhibit better results after applying the correction. TAM is the only station where statistics
weren't improved. Due to its rare cloudiness, this station's statistics were already good, indicating that probably a hybrid
approach of the correction according to the area's cloudiness would be better. Overall, after the correction for 61% of the cases
the GHI differences (modeled against measured) were within +/-50 W/m² (or +/-10%). The MBE for all stations was also
620 improved to 11.3 W/m² (2.3%), compared to the uncorrected values (23.8 W/m² or 4.9%). For the daily mean GHI the overall
MBE and RMSE was improved to 3.3 W/m² (1.7%) and 13.1 W/m² (6.6%), compared to the uncorrected values of 6.6 W/m²
(3.3%) and 15.4 W/m² (7.7%), respectively. For monthly means, the MBE improved to 2.7 W/m² (1.6%) compared to 5.7
W/m² (3.2%) before correction and the RMSE to 6.3 W/m² or 3.6% (before correction 9.2 W/m² or 5.2%).



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Figure 109 Upper panel: Mean cloud modification factor (CMF) difference between modeled (from MSG satellite cloud optical thickness) values CMF_{msg} and those derived from global horizontal irradiance (GHI) measurements per modeled CMF_{msg} bins. Lower panel: The corresponding standard deviation (STD) of CMF differences per modeled CMF bins. The different colors in lines and different symbols correspond to different stations.

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Table 3 Performance of nowcasted irradiances before and after correction with CMFmsg.

		<u>15min</u>						<u>daily</u>						<u>monthly</u>					
		<u>MBE W/m² (%)</u>		<u>RMSE W/m² (%)</u>		<u>R</u>		<u>MBE W/m² (%)</u>		<u>RMSE W/m² (%)</u>		<u>R</u>		<u>MBE W/m² (%)</u>		<u>RMSE W/m² (%)</u>		<u>R</u>	
<u>station</u>	<u>N</u>	<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>		<u>cor.</u>	
<u>ATH</u>	<u>9472</u>	<u>14 (2.5)</u>	<u>8 (1.4)</u>	<u>97 (17.5)</u>	<u>97 (17.5)</u>	<u>0.94</u>	<u>0.94</u>	<u>4.1 (1.9)</u>	<u>2.1 (0.9)</u>	<u>13.2 (5.9)</u>	<u>12.3 (5.5)</u>	<u>0.99</u>	<u>0.99</u>	<u>4.5 (2.3)</u>	<u>1.8 (0.9)</u>	<u>5.6 (2.8)</u>	<u>3.3 (1.7)</u>	<u>~1</u>	<u>~1</u>
<u>CAB</u>	<u>7749</u>	<u>31 (7.8)</u>	<u>11 (2.9)</u>	<u>115 (29.0)</u>	<u>110 (28.0)</u>	<u>0.88</u>	<u>0.88</u>	<u>9.2 (5.5)</u>	<u>3.3 (2.0)</u>	<u>15.2 (9.2)</u>	<u>11.4 (6.9)</u>	<u>0.99</u>	<u>0.99</u>	<u>8.0 (6.0)</u>	<u>3.2 (2.4)</u>	<u>9.3 (7.0)</u>	<u>4.2 (3.2)</u>	<u>~1</u>	<u>~1</u>
<u>CAM</u>	<u>2376</u>	<u>34 (10.1)</u>	<u>13 (3.7)</u>	<u>104 (30.8)</u>	<u>98 (29.0)</u>	<u>0.89</u>	<u>0.89</u>	<u>7.9 (5.8)</u>	<u>3.6 (3.2)</u>	<u>14.7 (10.8)</u>	<u>11.5 (10.0)</u>	<u>0.98</u>	<u>0.99</u>	<u>8.1 (6.6)</u>	<u>3.7 (3.4)</u>	<u>8.2 (6.7)</u>	<u>4.5 (4.1)</u>	<u>~1</u>	<u>~1</u>
<u>CAR</u>	<u>8985</u>	<u>30 (5.8)</u>	<u>23 (4.5)</u>	<u>84 (16.2)</u>	<u>80 (15.4)</u>	<u>0.95</u>	<u>0.96</u>	<u>9.5 (4.5)</u>	<u>8.0 (3.8)</u>	<u>14.5 (7.0)</u>	<u>12.5 (6.0)</u>	<u>0.99</u>	<u>0.99</u>	<u>7.9 (4.2)</u>	<u>6.6 (3.5)</u>	<u>9.9 (5.3)</u>	<u>8.5 (4.5)</u>	<u>~1</u>	<u>~1</u>
<u>CNR</u>	<u>8806</u>	<u>19 (3.7)</u>	<u>6 (1.2)</u>	<u>104 (20.6)</u>	<u>102 (20.1)</u>	<u>0.93</u>	<u>0.93</u>	<u>5.0 (2.5)</u>	<u>2.1 (1.1)</u>	<u>14.0 (6.9)</u>	<u>11.1 (5.7)</u>	<u>0.99</u>	<u>0.99</u>	<u>4.2 (2.3)</u>	<u>1.8 (1.0)</u>	<u>7.6 (4.2)</u>	<u>4.7 (2.7)</u>	<u>~1</u>	<u>~1</u>
<u>LER</u>	<u>5191</u>	<u>44 (12.9)</u>	<u>21 (6.1)</u>	<u>131 (38.6)</u>	<u>124 (36.5)</u>	<u>0.82</u>	<u>0.83</u>	<u>9.9 (7.0)</u>	<u>3.6 (2.6)</u>	<u>21.6 (15.3)</u>	<u>17.9 (12.7)</u>	<u>0.97</u>	<u>0.97</u>	<u>10.9 (7.6)</u>	<u>4.1 (2.9)</u>	<u>12.9 (9.0)</u>	<u>5.4 (3.8)</u>	<u>~1</u>	<u>~1</u>
<u>LIN</u>	<u>7989</u>	<u>39 (10.0)</u>	<u>21 (5.3)</u>	<u>119 (30.8)</u>	<u>114 (29.6)</u>	<u>0.88</u>	<u>0.88</u>	<u>12.4 (7.3)</u>	<u>7.1 (4.2)</u>	<u>18.4 (10.8)</u>	<u>13.7 (8.1)</u>	<u>0.99</u>	<u>0.99</u>	<u>10.3 (7.6)</u>	<u>6.0 (4.5)</u>	<u>12.2 (9.0)</u>	<u>7.5 (5.5)</u>	<u>~1</u>	<u>~1</u>
<u>PAL</u>	<u>8011</u>	<u>28 (6.7)</u>	<u>11 (2.5)</u>	<u>117 (27.4)</u>	<u>113 (26.5)</u>	<u>0.90</u>	<u>0.91</u>	<u>6.6 (3.5)</u>	<u>1.9 (1.0)</u>	<u>14.1 (7.4)</u>	<u>11.6 (6.1)</u>	<u>0.99</u>	<u>0.99</u>	<u>5.1 (3.4)</u>	<u>1.4 (1.0)</u>	<u>7.4 (5.0)</u>	<u>4.9 (3.3)</u>	<u>~1</u>	<u>~1</u>
<u>TAM</u>	<u>9011</u>	<u>-8 (-1.2)</u>	<u>-12 (-2.0)</u>	<u>98 (15.4)</u>	<u>98 (15.4)</u>	<u>0.94</u>	<u>0.94</u>	<u>-3.9 (-1.5)</u>	<u>-4.1 (-1.6)</u>	<u>18.5 (7.2)</u>	<u>18.2 (7.2)</u>	<u>0.94</u>	<u>0.94</u>	<u>-3.7 (-1.5)</u>	<u>-4.5 (-1.8)</u>	<u>9.8 (3.8)</u>	<u>8.8 (3.5)</u>	<u>0.97</u>	<u>0.97</u>
<u>THE</u>	<u>9188</u>	<u>27 (5.2)</u>	<u>18 (3.6)</u>	<u>91 (17.6)</u>	<u>88 (16.9)</u>	<u>0.95</u>	<u>0.95</u>	<u>8.2 (3.8)</u>	<u>6.0 (2.8)</u>	<u>13.6 (6.3)</u>	<u>11.2 (5.2)</u>	<u>0.99</u>	<u>0.99</u>	<u>6.7 (3.5)</u>	<u>4.8 (2.5)</u>	<u>9.1 (4.7)</u>	<u>7.2 (3.7)</u>	<u>~1</u>	<u>~1</u>

Table 3 Performance of nowcasted irradiances before and after correction with CMFmsg.

BSRN							
station	N	MBE (W/m ²)	MBE-cor. (W/m ²)	RSME	RSME-cor.	r	r-cor.
ATH	9472	14	8	97	97	0.94	0.94
CAB	7749	31	11	115	110	0.88	0.88
CAM	2376	34	13	104	98	0.89	0.89
CAR	8985	30	23	84	80	0.95	0.96
CNR	8806	19	6	104	102	0.93	0.93
LER	5191	44	21	131	124	0.82	0.83
LIN	7989	39	21	119	114	0.88	0.88
PAL	8011	28	11	117	113	0.90	0.91
TAM	9011	-8	-12	98	98	0.94	0.94
THE	9188	27	18	91	88	0.95	0.95

After the improvements in the configuration of the SENSE2 model and by correcting the bias in CMFmsg for partially cloudy conditions (for CMFmsg bins between 0.3 to 0.8, the “bell-shaped curved” that has been also reported in other studies e.g. Marie Joseph et al. (2013)), more accurate estimates of GHI have been produced, in line with the results from similar models (Qu et al., 2014; Thomas et al., 2016; Qu et al., 2017). These SENSE2 GHI estimates will be the basis for the new forecasting system NextSENSE2, evaluated in the next Section (3.2).

Comparing our results with other studies, for HC3v3 database of surface solar irradiation (Qu et al., 2014), for the 15 min time scale, correlation coefficient values greater than 0.92 and relative RMSE between 14-38% were found. In the same study, for daily irradiation correlation coefficient values greater than 0.97 were found with relative RMSE between 6 and 20 %. For the latest version 5 of HelioClim-3 database (HC3v5) the validation against 14 BSRN stations (Thomas et al., 2016) resulted bias between -4 to 5% and rRMSE between 14.1 and 37.2% for GHI. Both studies highlight the good performance of the clear sky irradiation values from the McClear clear-sky model (which uses advanced inputs for aerosol, water vapor and ozone, instead of climatological values). The comparison of 15 min means of global irradiance estimated by the fully physical Heliosat-4 method (combination of McClear and McCloud models) against ground-based measurements from 13 stations of the BSRN network (Qu et al. 2017) showed large correlation coefficients for all stations (0.91-0.97), and bias and RMSE of GHI that ranged between 2-32 W/m² and 74-94 W/m² respectively. In the same study, the greatest values of relative RMSE of the mean irradiances were found for stations with rainy climates and mild winters (26% to 43%, the greatest value for the northernmost station), while for stations in desert and Mediterranean climates values ranged between 15% and 20%, which are in line with our finding for the northernmost and southernmost stations in this study. The previously observed positive biases using APOLLO cloud retrieval in Heliosat-4 (Qu et al. 2017) for CAMS Radiation Service, have been significantly reduced and balanced after applying the new cloud retrieval scheme of APOLLO NG (new cloud mask with cloud probability threshold to 1% among other improvements, more details in Schroedter-Homscheidt et al., 2022). After the improvements, a relative RMSE

655 of hourly GHI between 10.3 and 25.5% with a mean of 13.7% has been reported for 2015 (Schroedter-Homscheidt et al.,
2022). An extensive validation (Urraca et al., 2017) of the operational product (ICDR) of the CM SAF over Europe for 2008-
2015 period gave for daily means of the product a MBE 4.5 W/m² (4%) and RMSE 18.1 W/m² (15.1%) and it was reported
that it was overestimated at high latitudes in contrast to the climate data records (CDR). For the new SARAH-3 CDR SIS
660 product for the period 1983-2020 the validation (Pfeifroth et al., 2023) showed for the 30-min instantaneous data, daily mean,
and monthly mean biases of 4.2 W/m², 2.18 W/m² and 2.25 W/m² respectively. The validation of the operational product
(ICDR) with respect to the SARAH-3 CDR for the year 2020 showed that it consistently extent the SARAH-3 CDR in time.
The reasons for differences between these two products were the different auxiliary data (like water vapor, etc.) and time range
used for driving effective cloud albedo and daily snow cover.

3.2 Short term forecasting

665 3.2.1 Overall performance - Benchmark with Persistence method

Figure 119 summarizes the performance of the CMV method (green points) in predicted GHI as function of forecasting horizon, by providing main statistics, after comparison with GHI ground based measurements, from all ten stations, for a whole year (2017). Detailed results per station, for representative statistics and selected time steps (+60, +120, +180 mins) can be found in Table 4. As a benchmark, the results of the commonly used persistence forecasting method are presented also in Fig. 670 119 (black points). We can see that the CMV model systematically outperforms persistence for all time steps. It is interesting that the first time step (+15 min) is not the one with the maximum difference between the CMV and persistence statistics (or the maximum of CMV FS%), indicating that for such short time interval the probability of changing cloudiness is low, which favours the persistence method. The second time step is the one with the maximum of CMV FS% (best performance) compared to persistence up to ~10%. As the forecasting horizon increases all metrics deteriorate for both methods, while, at the same 675 time, persistence is systematically worse than CMV.

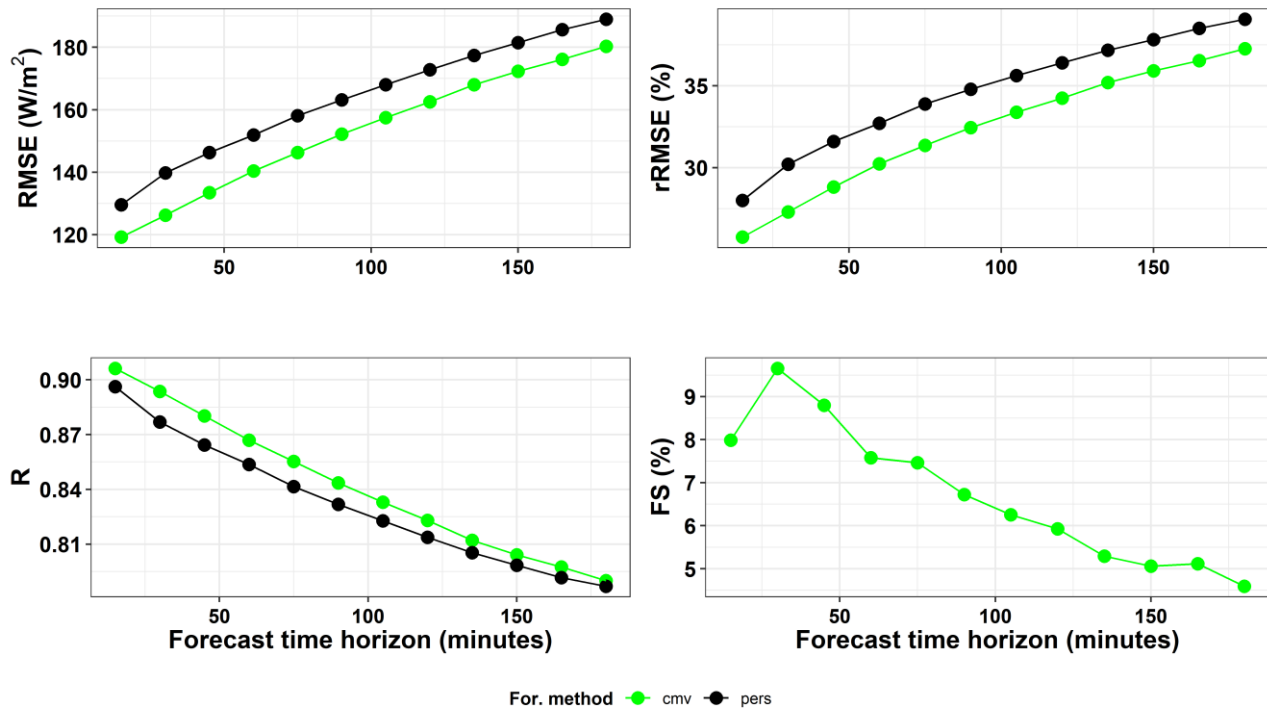


Figure 1140 Performance statistics of CMV modeled (green points) and persistence method (black points) forecasted global horizontal irradiance (GHI) for every 15_min time step up to 3_h ahead.

Table 4 Performance statistics of CMV modeled forecasted global horizontal irradiance (GHI) for the 60_min, 120_min and 180_min time steps.

station	Mean CMF	rRSME (%)			R			FS (%)		
		time step (min)			time step (min)			time step (min)		
		+60	+120	+180	+60	+120	+180	+60	+120	+180
ATH	0.97	22.0	24.5	25.3	0.90	0.87	0.86	0	1.7	3.2
CAB	0.68	39.7	45.6	49.6	0.80	0.73	0.68	10.5	7.5	5.8
CAM	0.63	54.1	62.0	68.9	0.66	0.58	0.50	2.7	3.4	1.5
CAR	0.85	22.8	26.3	29.6	0.90	0.86	0.82	8.1	5.6	3.1
CNR	0.81	31.0	34.8	37.4	0.85	0.79	0.75	2.4	2.9	2.6
LER	0.61	50.8	56.0	59.6	0.73	0.67	0.62	10.4	9.5	9.4
LIN	0.68	39.7	45.9	51.2	0.81	0.74	0.69	13.9	10.9	8.8
PAL	0.68	38.9	44.9	48.8	0.82	0.75	0.71	11.6	7.6	6.0
TAM	0.87	21.4	23.1	24.7	0.89	0.86	0.82	2.2	1.0	-1.3
THE	0.91	23.9	27.2	29.2	0.89	0.86	0.84	6.8	5.1	2.4

An interesting grouping of stations resulted by comparing main statistics (rRMSE and FS) for both forecasting methods with stations' mean CMF, representing their mean cloudiness (Fig.124). Three time-steps were selected (+60, +120, +180 min) and are depicted with increasing transparency. Two groups of stations are evident. Those with high mean cloudiness (LER, CAM, PAL, LIN, and CAB), which show worse rRMSE than those of lower cloudiness (ATH, THE, TAM, CAR and CNR), independently of the method. Again, the CMV model (green symbols) outperforms the persistence method (black symbols) for all stations for these time steps (except of TAM for +240_min). The interesting finding is that the FS (%) of the CMV method increases with decreasing CMF, namely the forecasting skill of CMV model is higher compared to persistence for stations with higher cloudiness, demonstrating the applicability of the CMV forecasting method on GHI under cloudy conditions.

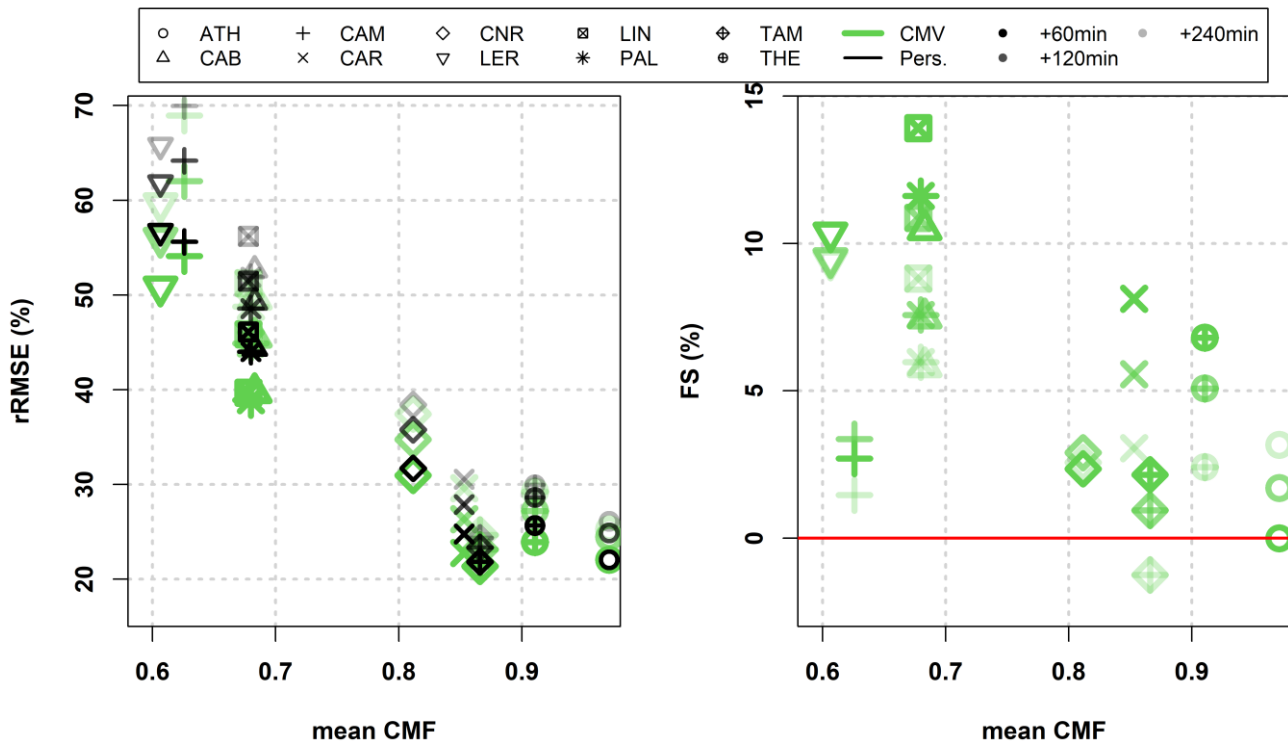


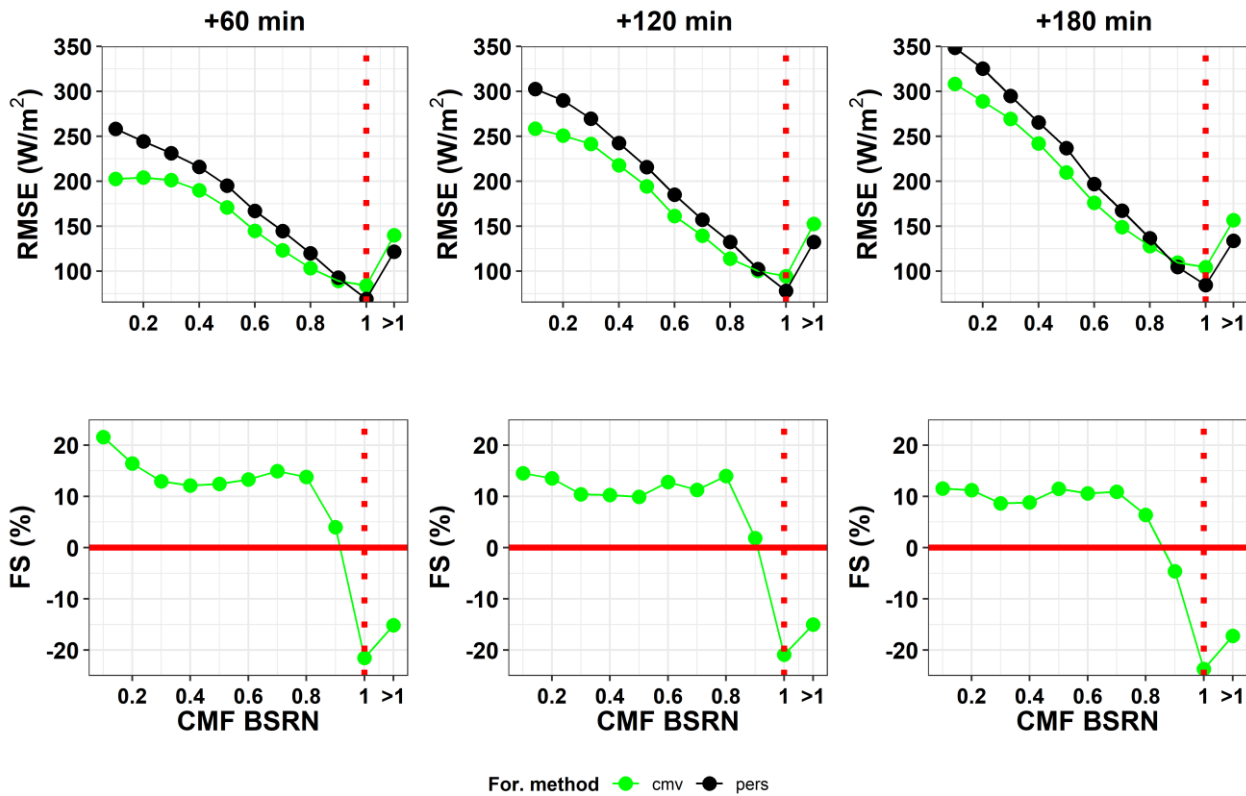
Figure 124 Mean bias error (MBE) and its relative values (rMBE%), relative root mean square error (rRMSE%) and forecasting skill expressed in percentage (FS%) of CMV model (green symbols) and persistence method (black symbols) forecasted global horizontal irradiance (GHI) versus the average cloudiness of stations (mean CMF) for the time steps +60, +120 and +240_min (increasing transparency of symbols).

700 **3.2.2 Performance for different cloudy conditions**

To demonstrate the value of the CMV model against the persistence method that assumes the same cloudy conditions for all future time steps, we compare their performance under different cloudy conditions and transitions in cloudiness. Figure 132 presents the RMSE for both models (CMV green points and persistence black points) and the CMV model FS% as a function of CMF, for three time-steps (+60, +120 and +180 min). Persistence performs better than CMV model under clear sky conditions, namely CMF=1, for all times steps (as expected, as there is no change in cloudiness). This is also true for the CMF bin 0.9 only for time step +180 min and for CMF bin >1 for all time steps, a bin which contains mainly clear sky cases. For cloudy conditions, namely CMF<0.9, the CMV model outperforms persistence for all time steps (apart from +180 min time step and CMF bin 0.9). The cloudier the conditions (the smaller the CMF), the better the performance of CMV model and the greater the CMV FS% (up to ~ 20% for time step +60 min). The FS of CMV model decreases slightly with forecasting horizon, however, for the maximum of the forecasting horizon (+180 min) remains quite high ~+10% for CMF bins <0.7.

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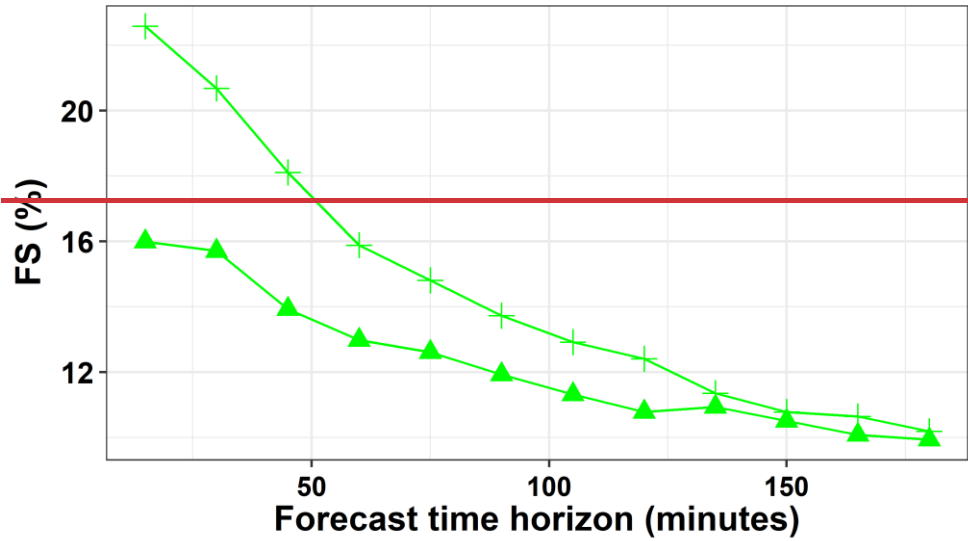
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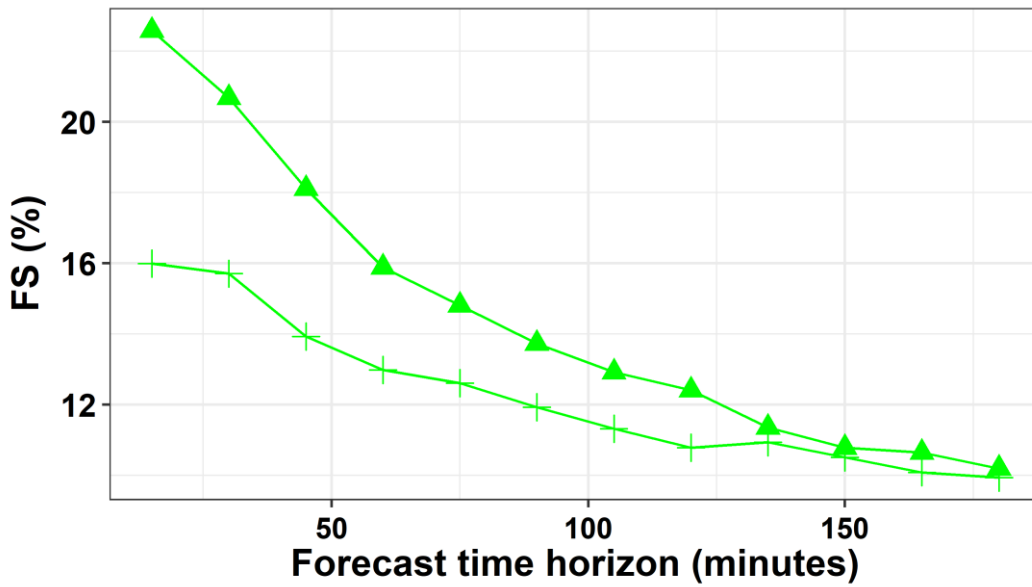
715 **Figure 1312** Upper panel: Root mean square error (RMSE) of forecasted global horizontal irradiances (GHI) for all stations with the CMV model (green symbols) and with the persistence method (black symbols) versus cloud modification factor (CMF) derived from GHI measurements, for 3 time steps (+60, +120 and +180 min). Lower panel: The CMV model forecasting skill against CMF classes for the same time steps with upper panel.

To demonstrate the better performance of CMV method compared to the persistence for all time steps under cloudy conditions, we calculated CMV FS% for partially cloudy conditions ($0.4 < \text{CMF} < 0.9$ and > 0.4) and overcast conditions ($\text{CMF} \leq 0.4$) and the results are presented in Fig. 143. We can see again that the FS of CMV model decreases with time, however, the minimum value is ~10% for both categories. The maximum of FS is for both categories at +15 min time step at ~16% and ~22% for $0.4 < \text{CMF} < 0.9$ (cross triangle-symbols) and $\text{CMF} \leq 0.4$ (triangle cross-symbols), respectively.

CMF Classes + cmf<0.4 ▲ cmf>0.4&<0.9



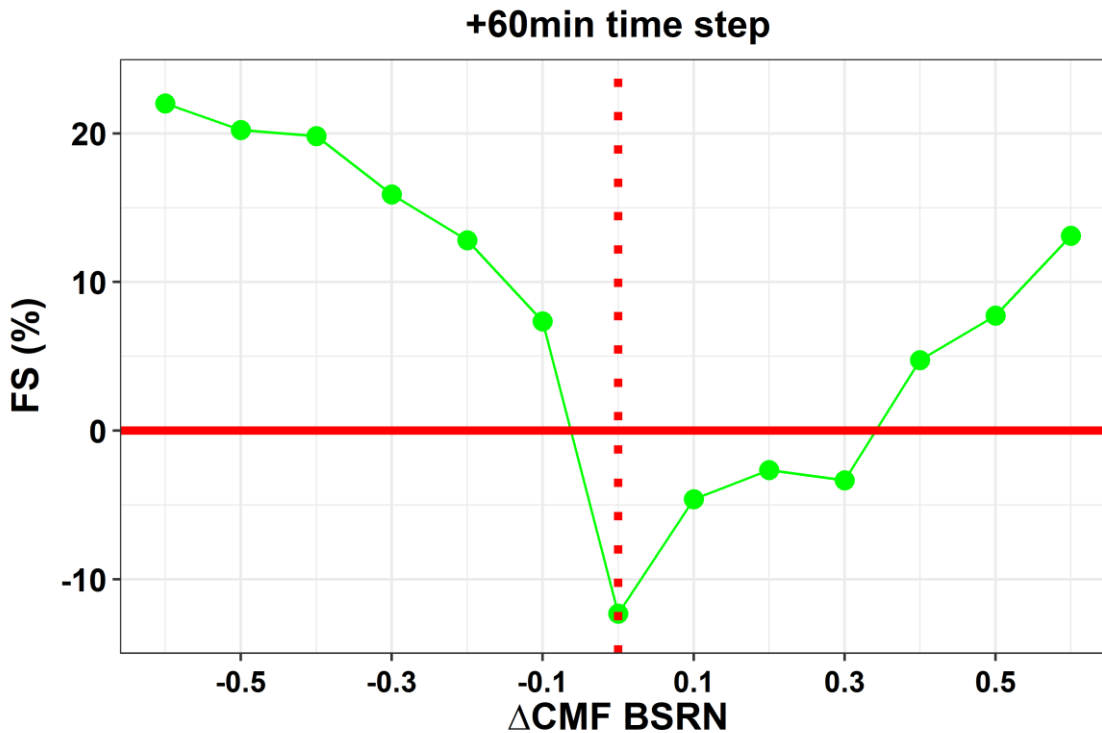
CMF Classes + 0.4<CMF<0.9 ▲ CMF<=0.4



725 **Figure 1413** Forecasting skill (FS) expressed in percentages of CMV model against the persistence method as a function of time horizon, from all stations, for two different cloudiness conditions: $0.4 < \text{CMF} < 0.9$ and $\text{CMF} \leq 0.4$ (trianglescrosses) and $\text{CMF} \leq 0.4$ (trianglecrosses).

The performance of the CMV model against the persistence method was assessed also for changing cloudiness, in terms of CMF changes (from ground-based measurements). The CMF changes were calculated for a time interval of 60_min (as $\Delta\text{CMF} = \text{CMF}_{t+60} - \text{CMF}_t$), and the results of the CMV model FS (%) are presented for the +60_min time step, as a function of CMF changes in Fig. 154. The high negative value of FS for zero CMF changes bin indicates that the persistence method is better for that bin, which was anticipated, since we have zero or almost zero changes of CMF, which practically is the persistence method definition. Persistence is still better than CMV for CMF changes from cloudy to clearer conditions, up to the +0.3 CMF change bin, but the FS is less negative than the zero bin. For CMF changes with higher magnitudes (bins > 0.4) from cloudy to clearer conditions, CMV is better than persistence, with FS values 15% for the CMF change bin +0.6. Consistent results were found for the opposite situation, namely from clearer to cloudy conditions, with CMV model always being better that persistence, with FS values up to ~20%.

Our analysis for different cloudiness conditions, highlights the limited ability of the persistence method compared to the CMV based NextSENSE2 to accurately forecast GHI under cloudy conditions (CMF values < 0.9) and to follow the transitions in cloudiness (especially from clearer to cloudy conditions).



740 **Figure 1514** Forecasting skill (FS) expressed in percentages of CMV model against the persistence method from all stations as a function of CMF changes within 60 min time interval (from time 0 to +60 min time step).

A direct comparison of the results of the present study for the NextSENSE2 short-term forecasting model with other studies is not straightforward, as the study period, the geographical area and the validation methods are different. Kallio-Myers et al. (2020) validated their Solis-Heliosat satellite-based GHI forecast modelled over southern Finland and they found that the rRMSE reached 50% at 4h time step. Urbich et al. (2019) validated SESORA short-term forecast of solar surface irradiance over Germany and parts of Europe for seventeen different cases with different weather patterns for the period August to October 2017, with all forecasts initiated at 9:15 UTC and reported for the validation against the SARA-2 data by CM SAF a RMSE of 59 W/m² after 15 min which reaches its maximum (142 W/m²) after 165 min.

One of the limitations and source of error for the NextSENSE2 is related to the satellite based optical flow method for the short-term forecasting and it is that it cannot reproduce cloud formation or dissipation. One example is the convective clouds that form very fast, violating the criterion of the optical flow of constant intensity of the pixels between two consecutive images (e.g., Urbich et al., 2018; 2019). Urbich et al. (2018) applied the common approach of the separation into subscales for the optimization process, which eventually didn't improve the forecast, while increased at the same time the complexity of the implementation. As has already been discussed in the introduction, satellite based short term forecasting is the best choice for the time horizon up to 6h ahead, since it is available in real time and at high spatial resolution. However, its merge with NWP models it is a solution for increasing the time horizon and the quality of forecasts (Lorenz et al., 2012; Wolf et al., 2016) compensating for the effect of changes in intensities (during convection or cloud dissipation) that cannot be captured by CMV models (Müller and Pfeifroth, 2022). A comparison has been presented by Urbich et al. (2019) between a short-term forecasting model of surface solar radiation (the SESORA model) with different NWP models (apart with the persistence model) and found that the intersection point that the NWP model delivers better results depends on the model and it is beyond 3-4h, which is also in line with the finding of other studies (e.g., Lorenz et al., 2012; Wolf et al., 2016). The merge of our short-term forecasting model with NWP model is out of the scope of the present study. After the elaborative benchmark analysis of the NextSENSE2 system with persistence approach, its applicability as an operational tool for the time horizon up to 3h ahead has been demonstrated.

4 Summary and conclusions

Our motivation is the continuous improvement of the EO based estimates and the accuracy of short-term forecasts of available solar resources to support solar energy exploitation systems on a regional scale (Europe and MENA region). In this study, we improved the SENSE/NextSENSE nowcasting/short-term forecasting operational systems, and analyzed in detail the cloud related uncertainties, discriminating also situations based on sun visibility, using ground-based measurements.

In terms of the aerosol related inputs, the slight overestimation of CAMS AOD that was found against the AERONET retrievals (<10%) resulted to SENSE2 clear-sky GHI underestimation lower than 1%, highlighting the applicability of CAMS forecasts as EO inputs for operational solar resources nowcasting. In terms of modeled all skies GHI, it was found that ~~clouds are the main source of uncertainty. The~~ SENSE2 mostly overestimates GHI with MBE 23.8 W/m² (4.9%) for instantaneous

comparisons, which was attributed to the uncertainties related to satellite cloud retrievals~~MSG cloud underestimation~~ (overestimation of CMFmsg by ~0.17) and also to the spatial representativeness between satellite based retrievals and ground-based measurements. We demonstrated that the most difficult situations to be modeled are related to high spatial variability of solar radiation within the satellite pixel due to clouds (e.g., small broken clouds and the sun obscurity over the ground station, an information not possible to be derived from satellite data). Based on our cloud related analysis using ground-based data, a correction for the modelled GHI was used, resulting to an overall improvement of the SENSE2 modelled GHI with 61% of the cases within +/-50 W/m² (+/-10%) of measured GHI and a final MBE of SENSE2 11.3 W/m² (2.3%). Our main analysis was based on the 15 min time scale, however based on the application hourly, daily or monthly data could be used. The daily and monthly SENSE2 GHI showed much better statistics (MBE ~~3.36-6~~ W/m² and ~~25.7~~ W/m², respectively). The validation results of SENSE2 demonstrate high accurate nowcasted values of GHI which are in line with similar models. The recorded positive bias could be reduced by applying improvements in the NWC SAF cloud retrieval input to the SENSE2 regarding partially cloudy pixels. Next SENSE2 was also improved due to the SENSE2 improvements. We also show that compared to the persistence method, the model works much better (as expected) at locations with increased cloudiness and for frequent cloudiness changes.

The data and methods involved for the estimation/prediction of the GHI in this study also reveal their limitations. As mentioned, the pixel-based approach of the model inputs (satellite and models) could not always reflect the reality above a (point) ground-based station. However, the model inputs are the state of the art of EO data and can be readily available in regional or global scale, at high spatial and temporal resolution, hence the GHI product is representative of an area (~5km x 5km in this model), which is useful for PV parks covering a wider area. In general, evaluating the performance of such EO based GHI models with ground-based measurements must account for these comparison spatial representativity issues. The optical flow algorithm for calculating CMVs is also based on assumptions like 2D clouds and brightness constancy. However, it is a method based on cloud inputs from satellite data in real time and the applicability of those methods is demonstrated here compared with the persistence approach.

Since satellite cloud information is the only real time input, a new straightforward configuration for estimating GHI was applied (SENSE2). The advantage of calculating clear sky GHI from the previous day, is what increases the accuracy of this product, since it is based on a detailed LUT of ~16M combinations of 7 different inputs, considering apart from AOD, additional aerosol optical properties and atmosphere/surface state inputs. Thus, the uncertainties in the estimated clear sky GHI practically result only from uncertainties in the model inputs. The new scheme ~~of for~~ calculating all skies GHI by multiplying the clear sky GHI with CMFmsg (derived in real time by multiparametric function of MSG COT and SZA) was improved by applying a suitable CMFmsg correction. The correction was successful and improved the model performance, especially for areas with high cloudiness. Additionally, the new configuration of the SENSE2 is more flexible, and it is easy to adapt and provide more products like DNI, UV index, PAR, etc. which is one of the prospects for the new model ~~or to~~ run in a retrospective way, using reanalysis data or in situ observational data for certain locations.

According to the results, high resolution (every 15 min, at ~5km x 5km) and quite accurate GHI real time estimates/forecasts are produced from the upgraded SENSE2/NextSENSE2 operational systems that can contribute to solar energy systems management and planning.

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Appendix A

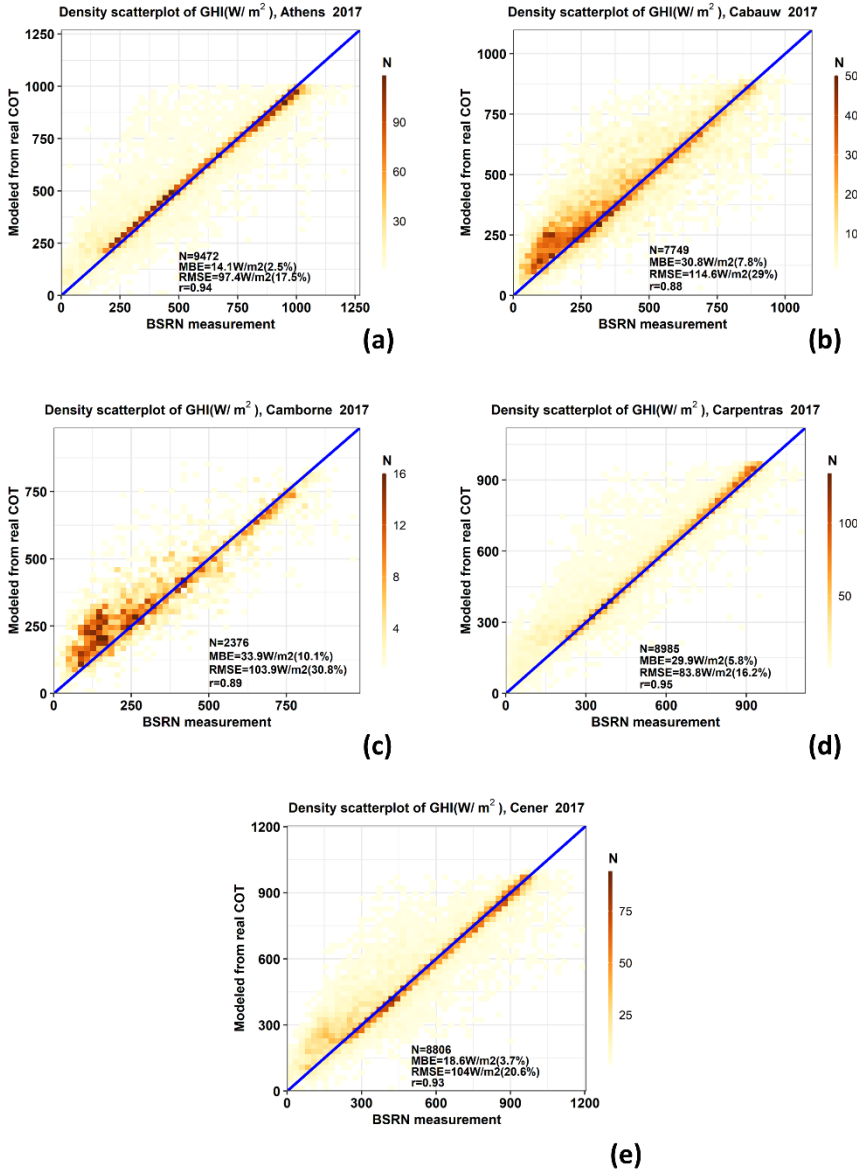
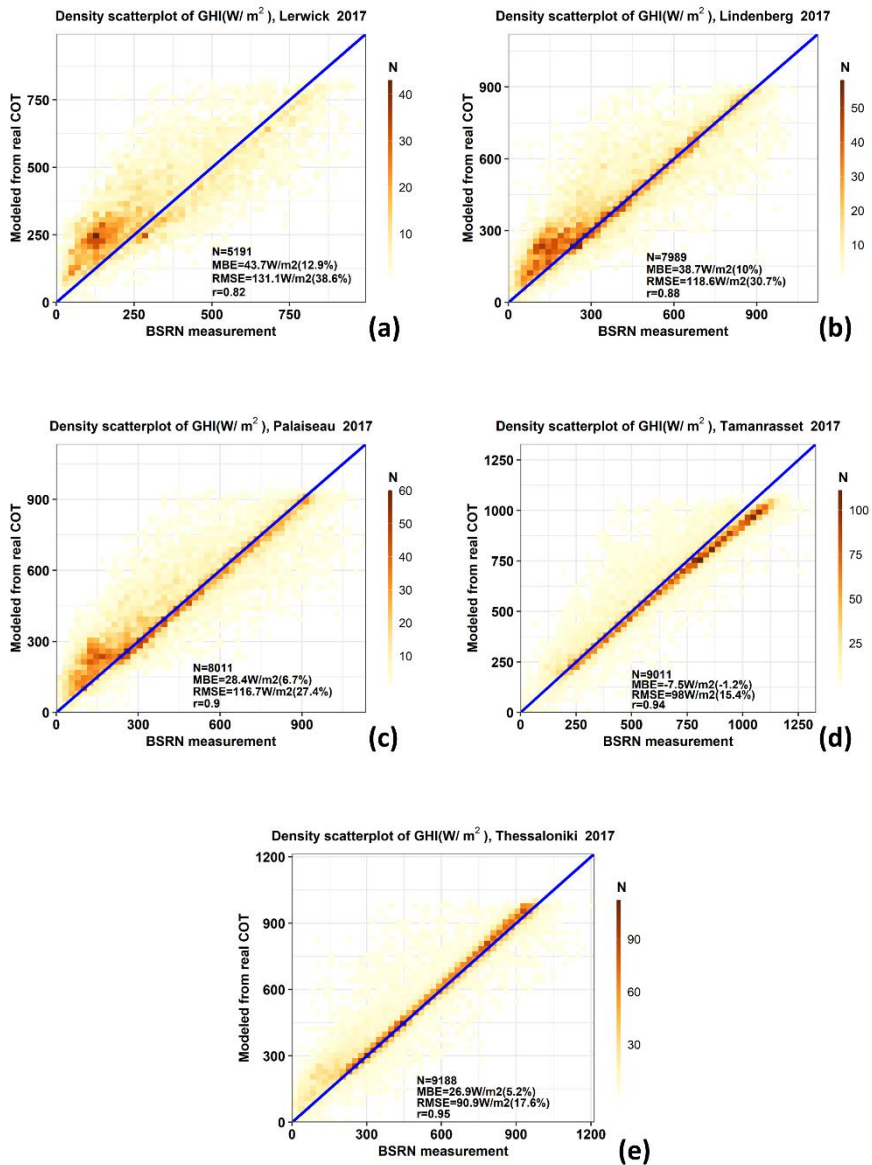


Figure A 1 Comparison of the global horizontal irradiance (GHI) modeled versus measured for (a) Athens, (b) Cabauw, (c) Camborne, (d) Carpentras and (e) Cener, for 2017.



815

Figure A 2 Comparison of the global horizontal irradiance (GHI) modeled versus measured for (a) Lerwick, (b) Lindenberg, (c) Palaiseau, (d) Tamanrasset and (e) Thessaloniki, for 2017.

Appendix BA

820 To see if the CMF differences (MSG modelled against measured) changing with SZA, the MBE of CMF was calculated for bins of SZA every 10 degrees. The observed CMF was considered the one derived from GHI measurements (Eq. 7) and the modelled one derived by the Eq. 2. The results are presented in Fig. A1, for all cases and under different cloudiness conditions,

along with the relative values of CMF MBE expressed in percentages. We can see again the fact that the main overestimation of CMF values by MSG COT comes from the cloudy conditions (CMF < 0.9). Specifically, for the partially cloudy conditions (0.4 < CMF < 0.9 and > 0.4) the MBE reach values up to ~ 0.20 and for overcast skies (CMF ≤ 0.4) there are SZA bins (0 and 70 degrees) that the MBE reach values up to 0.4. However, for those two categories the MBE hardly changes with SZA.

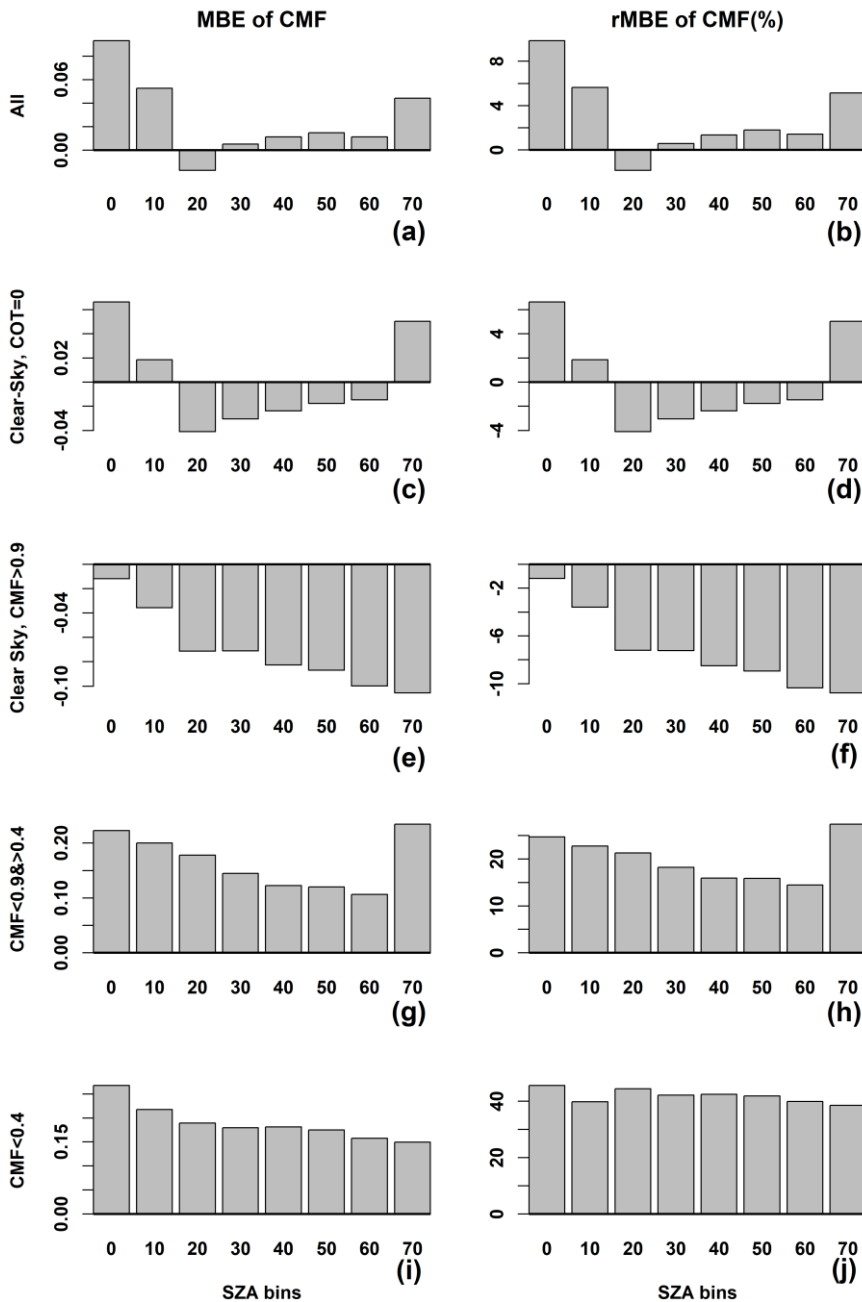


Figure A-B 31 Cloud modification factor (CMF) mean bias error (MBE – left column) and relative MBE (% - right column) as a function of solar zenith angle (SZA) under all cases and under different cloudiness conditions.

Author contributions.

Idea and initialization, KP and SK; Model parameterization, IF, KP, IPR; resources, AFB, BEP, IPR, CK; data provision and curation, AFB and BEP; cloud function approach, NP and AK; overview and revision, CK, MH, SK; 1st draft writing, visualization, analysis and interpretation, KP; writing, review and editing, all authors. All authors gave final approval for
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