Satellite based snow identification and its impact on monitoring photovoltaic systems

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Abstract
Satellite based earth observation allows the detection of snow cover and the discrimination of cloud from snow cover using multispectral measurements. Using this data enables photovoltaic (PV) plant management to distinguish failures due to snow coverage on a PV system from other error sources. It is also possible to improve yield estimates in solar siting. This paper gives an overview on satellite-based snow cover information which is available in different spatial scales. Results of a validation study from January to April 2006 with ground measurements from German and Swiss meteorological stations are presented. Quality measures introduced are the „false alarm rate“, the „error due to underestimation“, the „availability“ of the data sets, and the „classification accuracy“. Depending on how defensively satellite measurements are evaluated, the error shifts from too much recognized snow (error due to underestimation of surface solar irradiance) to too little recognized snow causing a false alarm in PV monitoring. For pure power plant operations monitoring the data record of LSA SAF is the most suitable as it has a symmetrical and small error pattern (false alarm rate 26 % / error due to underestimation 23 %), but the data availability is low (65 %). The IMS data set has a low false alarm rate (4 %) and good data availability (100 %), but a large error due to underestimation (59 %). Also, the DLR data set has a rather small symmetrical error pattern (false alarm rate 37 % / error due to underestimation 26 %) and a good availability (99 %). If a cumulative snow cover algorithm is applied to achieve information on every day, the preciseness of all datasets declines and both the DLR and the LSA SAF datasets become comparable in their results.

1. INTRODUCTION
A photovoltaic (PV) monitoring system observes electrical power data as well as environmental parameters such as global radiation and surrounding air temperature. Taking the whole PV power plant into consideration, an efficiency factor chain can be built lasting from global irradiation on the panels, the system’s characteristic losses and finally to the inversion to the power delivered into the grid. Using this model and characteristic data for the specific PV system, it is possible to calculate the theoretical power output for a given irradiation.

It is possible to detect plant failures by comparing an estimated theoretical and an observed actual power output. A defect in the power plant can be detected because the two datasets become unequal over time. The basis for proper estimates is a reliable input dataset either from on-site or satellite measurement - incorrect input data might cause a false alarm. One of the observed problems is snow. Snow covered PV panels deliver only a small enery yield, even though there is high global radiation available. Using an additional information “snow coverage”, the false alarm rate could be reduced. Satellite based monitoring systems rely on irradiance data derived from a meteorological satellite. They are replacing on-site measurements with a reference cell or a pyranometer to determine the estimated energy yield of a PV system (Drews et. al., 2007). Earth observation also allows the detection of snow cover and the discrimination of cloud from snow cover in different spatial scales. This information can be accessed by the monitoring system instead of indicating snow cover on the basis of locally measured temperature and radiation parameters only. There are several satellite based snow cover services available ranging from regional to world-wide scales.
Chapter 2 describes error sources in solar energy plant monitoring in snowy conditions and introduces appropriate quality measures. Chapter 3 gives an overview on existing satellite-based services offering snow cover information. Chapter 4 shows the results of a validation study. First, all datasets are used as supplied by the provider and evaluated for every day. Secondly, a cumulative algorithm is applied to interpolate those datasets with information gaps on days with cloud cover.

2. METHODS

2.1 Error sources in snow conditions

When comparing snow cover information derived from satellites with the actual snow cover several more or less relevant faults can be observed. Most relevant are snowy cases without correct snow cover detection. A high solar yield would be estimated from satellite irradiance measurements, but there is only very small yield actually observed. The plant management system interprets this as a plant’s fault and generates an alarm engaging the maintenance team to check on the site even though there is only a snow cover on the modules. In a yield estimate such error cases lead to a longer amortization period of the power plant and therefore to losses for operator and investor. An investment decision could be made in favor of the wrong location and due to snow cover a lower profit will be made than at the optimal location.

<table>
<thead>
<tr>
<th>ground conditions</th>
<th>satellite measurement</th>
<th>snow on Panel</th>
<th>no snow in picture element</th>
<th>missing / cloud</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td>case A</td>
<td>case B</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>correct information</td>
<td>underestimation of snow cover</td>
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<td></td>
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<td>satellite displays low yield plant has low yield</td>
<td>satellite displays high yield plant has low yield</td>
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<td></td>
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<td>case D</td>
<td>too much snow displayed cloud is interpreted as snow</td>
<td>correct information</td>
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<td>Effect on irradiance calculation</td>
<td>satellite displays low yield plant has high yield possible error in the plant will not be detected</td>
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<td>satellite displays low yield due to cloudiness plant has low yield due to clouds</td>
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Table 1 Error sources for photovoltaic plant monitoring in snow conditions

There are three possible conditions measured by the satellite, namely cloud, cloudfree with and without snow cover, but only the two conditions snow and snow-free on the ground. There are two correct classifications A and E and two incorrect cases D and B (Table 1).

Case A: If an existing snow cover is identified correctly as snow in the satellite pixel, the plant management system will calculate a low yield matching the actual power output of the plant. A site audit will estimate the yield correctly.

Case E: In this case there is no snow on the module and also no snow in the pixel. There is no influence on the plant management or site auditing. The full yield can be estimated.

Case B: This case describes the most problematic fault due to erroneous snow detection in plant monitoring. The satellite dataset does not index an existing snow cover. This would also happen without auxiliary snow detection, but now the problem is even more serious since snow, as this cause of an error is supposed to be eliminated. The plant management obtains high global radiation without snow cover as input parameter and calculates consequently a high power output that can not be reached in the observed power output. This leads to a false alarm as well as to a yield overestimation.
Case D: If there is no snow cover on the ground, but the satellite dataset indicates a snow cover a monitoring system observes a higher yield than estimated. In site audits this causes an error due to underestimation of solar energy yield. For yield estimations any variation either positive or negative is problematic. In monitoring schemes, no alarm will be created, as this is not an indicator for a fault in the plant. Therefore, this case is not as important for plant monitoring as case B. Nevertheless, the sensibility decreases because a potential system error would be indicated as a loss due to snow and not detected early enough.

Looking closer at the topic, visibility of the ground by the satellite needs to be introduced additionally. If the satellite detects a cloud, there is no information available on the situation on the ground. Some data providers set such pixels to “Missing / Cloud”, but not all datasets contain this information. This leads to two more cases C and F.

Case C: If there is snow on the ground and the satellite indexes a cloud cover there are two possibilities, either snow was confused with a cloud or a cloud over snow was indexed correctly. This is uncritical in the management system as well as in the yield estimates because the observed power output of the plant will be either low due to snow or cloud cover and the estimated output is also low.

Case F: The case with no snow on the ground and the satellite indexing a cloud is also unproblematic. This means that a cloud cover was indexed correctly and both observed output and estimated outputs are low. Please note, that the frequent case of an erroneously indexed cloud over snow free surfaces is not treated in this snow-specific validation study.

2.2 Quality measures
For a comparison of satellite datasets, several quality measures are defined. These rely on different basic populations (\(N\)) used:

\[
N_{\text{total}} = \text{total number of values}
\]

\[
N_{\text{cloudless}} = \text{cloud free values indexed as either snow or snow free}
\]

\[
N_{\text{snow}} = \text{values with snow cover indexed by the satellite}
\]

\[
N_{\text{snowfree}} = \text{values without snow cover indexed by the satellite}
\]

The following subsets (\(M\)) are being used:

\[
M_{\text{csnow}} = \text{subset indexed correctly as snow cover}
\]

\[
M_{\text{csnowfree}} = \text{subset indexed correctly as snow free}
\]

\[
M_{\text{corr}} = M_{\text{csnow}} + M_{\text{csnowfree}}
\]

\[
M_{\text{fsnowfree}} = \text{subset indexed falsely as snow free}
\]

\[
M_{\text{fsnow}} = \text{subset indexed falsely as snow cover}
\]

\[
M_{\text{cloud}} = \text{subset indexed as cloudy}
\]

The introduced quality measures are:

\[
A_{\text{class}} = \text{classification accuracy}
\]

\[
E_{\text{alarm}} = \text{false alarm rate}
\]

\[
E_{\text{est}} = \text{error due to underestimation}
\]

\[
A = \text{availability}
\]

The quotient of the corresponding statements of ground and satellite (\(M_{\text{corr}}\)) over all cloud free values (\(N_{\text{cloudless}}\)) equals the classification accuracy (\(A_{\text{class}}\)). Because of some datasets having the condition “cloudy”, only those values with information on snow cover are used for the basic population. Days with no information on snow cover and indexed as cloudy, are not taken in consideration. This is to assure that a correctly identified cloud will not be treated as error in the dataset.

\[
A_{\text{class}} = \frac{M_{\text{corr}}}{N_{\text{cloudless}}} \times 100\%
\]

A false alarm rate \(E_{\text{alarm}}\) is introduced as the quotient of pixels indexed as snow free in spite of a snow cover over the basis \(N_{\text{snow}}\) (case E). This basic population is used to eliminate the dependency of \(E_{\text{alarm}}\) on the total amount of snow covered days in the period under observation. Equal to \(A_{\text{class}}\) only the days without clouds are taken into consideration:

\[
E_{\text{alarm}} = \frac{M_{\text{fsnowfree}}}{N_{\text{snow}}} \times 100\%
\]

In the opposite case an error due to underestimation \(E_{\text{est}}\) of solar irradiance and therefore energy yield (case D) describes values with an indexed snow cover in spite of snow free ground. The basic
population are the values with snow free ground and no cloud cover indexed \(N_{\text{snowfree}}\). This ensures that \(E_{\text{est}}\) has no dependency on total days without snow in datasets with different availabilities.

\[
E_{\text{est}} = \frac{M_{\text{snow}}}{N_{\text{snowfree}}} \times 100\%
\]

To compare different algorithms the availability \(A\) as percentage of days with information on snow cover is introduced. \(A\) has to be taken into consideration together with the other quality characteristics to assess all datasets justly. Otherwise, datasets supplying information also on cloudy days would degrade in comparison with those datasets without such information.

\[
A = 1 - \frac{M_{\text{cloudy}}}{N_{\text{total}}} \times 100\%
\]

3. DATA

3.1 Satellite Data Sources

The STAR algorithm operated by NOAA/NESDIS for the GOES (Geostationary Operational Environmental Satellite) satellites (Romanov et al., 2003) was also ported to the Meteosat Second Generation (MSG) satellite. The only difference is, that SEVIRI (Spinning Enhanced Visible and InfraRed Imager) channel 3 (1.6 µm) is taken instead of GOES channel 2 (3.9 µm). The Carl von Ossietzky University of Oldenburg supplies global irradiance data using the Heliosat method (Hammer et al., 2003) applied to SEVIRI measurements aboard MSG. Since 2006, the SAMSAT algorithm was introduced into Heliosat taking care of snow cover situations. A snow index (NDSI), calculated from the difference of 0.6 and 1.6 µm channels divided trough the sum of both channels, is applied to decide between snow and snow free surfaces in clear sky conditions (Heinicke, 2006). The dataset provided by Carlo Gavazzi Space (CGS) is designed for hydropower plant management (Tampellini et al., 2005). It is based on MODIS reflectance data with 250 m (MOD09GQK) and 500 m (MOD09GHK) ground resolution. The coverage of the dataset is limited to the Alpine region. The MOD09GQK dataset is used to indicate snow cover, whereas the MOD09GHK data is used to determine clouds. Additionally, the snow cover map is corrected for errors introduced by coniferous forests. The DLR algorithm is based on APOLLO, a cloud discrimination algorithm that has been running for 15 years now (Kriebel et al., 2003; Saunders and Kriebel, 1988), but now it is ported to MSG SEVIRI data. The algorithm uses a dynamic threshold created for every scene. Reflectances from the 0.6 and 1.6 µm channels as well as 12.0 µm brightness temperatures are used to calculate a snow index for every pixel. If the snow index exceeds a threshold, the pixel is indicated as snow covered. To create this dynamic threshold, the average \(\text{nsl}_\text{mean}\) and the standard deviation of the snow index histogram \(\text{snisdev}\) are calculated for every MSG scene. The threshold equals \(\text{nsl}_\text{mean} + 0.5 \times \text{snisdev}\). Afterwards, temporal and spatial filters are applied following Ruyter et al. (2007). NOAA/NESDIS started snow monitoring in 1966, by now the product is available worldwide in a 4 km by 4 km grid. The analysts combine all NOAA satellites including geostationary satellites and microwave sensors in a semi-manual scheme and provide a classification for every day. (Ramsey, 1998; Helfrich et al., 2007; NOAA, 2004) Visible imagery is primary taken from POES, MODIS and geostationary satellites as GOES, GMS and MSG. In addition, ground weather observations and microwave products from the POES AMSU and the DMSP Program are incorporated. The LSA SAF snow cover dataset is based on a cloud mask created by the Nowcasting SAF on a daily bases using MSG data and a threshold based algorithm for reflectance and brightness temperatures (LSA SAF, 2006). The LSA SAF algorithm derives snow information from the cloud mask and performs spatial smoothing and a temporal integration of the previous 24 hour satellite scenes to produce a daily composite snow cover map. The MODIS/Terra Snow Cover Daily L3 Global 500m Grid (MOD10A1) detects snow using a Normalized Difference Snow Index (NDSI, Hall et al., 2002; Klein et al., 1998; Hall et al., 2006).

3.2 Meteorological ground station data for validation

14 meteorological stations in Southern Germany and 15 stations in Swiss regions attractive for PV systems but with a typical annual snow cover are used in this study. The measurement of snow depth in Germany is taken at 18:00 UTC, while Swiss stations report at 17:40 UTC. In both countries the measurement is done manually with an accuracy of ± 1 cm (Ernst, 2008; Glatt, 2008). A study period from January through April 2006 was selected as a very snowy winter case in Central Europe. Two datasets, from CGS and University Oldenburg, were generated especially for this survey and last only to March 2nd, 2006 (CGS) and March 31th, 2006 (Univ. Oldenburg).
4 RESULTS

4.1 Daily values

First, daily values as provided by the different data producers are compared to ground measurements as they are and when they are available. Overall, 3300 values are examined. Differences in data availability in cloudy situations or due to viewing geometry are neglected. This is justified as it is the typical user perspective of using data when it is existing.

The LSA SAF dataset achieves the highest overall $A_{class}$ with 76 % (Fig. 1), while the datasets of DLR and Carlo Gavazzi Space reach 70 %. LSA SAF and DLR use temporal and spatial information of the frequent Meteosat scenes, while the CGS dataset has advantages because of the high resolution of MODIS and specific adaptations to the Alpine region for hydropower management. This leads to the good classification in Switzerland. Global products as IMS (72 %), NOAA-STAR (78 %) and MODIS (79 %) as well as the product from the University of Oldenburg show with over 70 % good results in Germany, whereas the classification in more difficult regions like Switzerland drop to 49 % (IMS) or 53% (Univ. Oldenburg). The IMS product uses additional microwave sensors to get information even at cloudy days. These sensors in general have a low resolution. Switzerland is represented by 70 pixels in SMM/I resolution only, which leads to quantification errors and the product looses overall quality. On the other hand it offers information in cloudy cases at all in contrary to other datasets.

$E_{alarm}$ gives a different impression. The best value is achieved by IMS with 4 %. This means that in the period under observation at all the stations 4 % of the days were indicated as snow free in the satellite information while there was a snow cover measured at the ground. Fig. 2 illustrates $E_{alarm}$ as rising bars from the zero line and $E_{est}$ as bars descending from that line. Both errors combined are a measure for the total error, but it has to be taken into consideration that a different basic population is applied. $E_{alarm}$ refers to days with a snow covered ground whereas $E_{est}$ is based on the days without snow. Fig. 2 demonstrates different strategies of the respective algorithms. The error shifts from an overestimation to an underestimation of indicated snow, depending upon how defensively snow detection is handled. The IMS dataset combines a small $E_{alarm}$ with a high $E_{est}$ (63%), whereas the LSA SAF dataset has the most symmetrical error pattern (26 % to 23 %). Both, DLR and CGS have a better balanced error pattern (37 % to 26 % and 24 % to 39 %, respectively). The patterns of NOAA-STAR (14 % to 44 %) and University of Oldenburg (15 % to 61 %) datasets are shifted towards $E_{est}$. For all these analyses $A$ (Fig. 3) has to be considered as additional criterion. While IMS and NOAA-STAR state a value every day, the MODIS dataset only delivers a value on 29 % of the days. NOAA-STAR, LSA SAF and the University of Oldenburg datasets have a much higher probability to match a cloud free window due to the 15 minute sample rate of MSG. Differences in $A$ are caused by the fact, that information of preceding days as an additional input parameter is used partly. University of Oldenburg uses the same input values as LSA SAF but gets a higher $A$, because it classifies snow as soon as one slot is indicated as snow covered while LSA SAF requests consecutive slots to be detected as snow. The DLR product reaches almost $A = 100 \%$, because it is a cumulative product.

4.2 Daily cumulative values

For plant management it is beneficial to have a classification every day. Basically, a cumulative algorithm keeps the snow cover information of one day at a pixel until a new classification is received. As a result snow cover information can be given even at cloudy days relying on preceding days. Obviously, such an interpolation causes a decrease of $A_{class}$ for those datasets delivered by the provider with gaps due to cloud cover (CGS +12 %, LSA SAF +6 %, University of Oldenburg +2 %, and MODIS +9 %) as shown in fig. 4. A higher $A$ is also linked to a degradation of the error measures (Fig. 5). $E_{alarm}$ increases (CGS +6 %, LSA SAF +9 %, University of Oldenburg +2 %, and MODIS +16 %) as well as $E_{est}$ (CGS +15 %, LSA SAF +4 %, University of Oldenburg +4 %, and MODIS +2 %). It should be noted that this approach leads to a leveling of the leading position of the LSA SAF dataset compared with the DLR dataset in the validation.
Fig. 1 Classification accuracy for Germany and Switzerland for all data sets

Fig. 2 Error measures for Germany, Switzerland and all stations together

Fig. 3 Data availability $A$ for Germany, Switzerland and both regions together
5 CONCLUSION
There are two main objectives for the use of satellite based snow observation in the management of photovoltaic systems. For the PV plant monitoring system, avoiding a false alarm is of high importance, therefore every day with a snow cover needs to be identified correctly. The error due to underestimation, representing indicated snow even though there is none, is less critical. A classification accuracy was defined as the agreement of satellite and ground measurements both in snow and snow free cases. All datasets achieve over 70% classification accuracy in Germany with a maximum of 79% for the LSA SAF dataset. In Switzerland the datasets of IMS, NOAA-STAR, MODIS and University of Oldenburg archive less than 60%. The IMS product has the lowest false alarm rate with 1% in Germany and 8% in Switzerland. In the opposite case, the error due to underestimation shows the values with an indexed snow cover in spite of a snow free ground. For pure power plant monitoring the dataset of LSA SAF is the most suitable one. This dataset has a symmetrical and small error pattern (false alarm rate 26% / error due to underestimation 23%), but the data availability is low (65%). The IMS dataset has a low false alarm (4%) rate and good data availability (100%), but a large error due to underestimation (59%). Also the DLR dataset has a rather small symmetrical error pattern (false alarm rate 37% / error due to underestimation 26%) and a good availability (99%). The availability measure shows how often a dataset contains missing values due to cloud cover. DLR,
NOAA-STAR and IMS supply a value for every day, whereas the MODIS product contains only information on 29% (CGS 42%, LSA SAF 65%, University of Oldenburg 81%) of days. If a cumulative algorithm is applied to achieve information for every day the preciseness of the datasets declines. In this case the DLR dataset and the LSA SAF dataset are comparable in their results.

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