Land Surface Albedo Derived on a Daily Basis From Meteosat Second Generation Observations

Bernhard Geiger, Dominique Carrer, Laurent Franchistéguy, Jean-Louis Roujean, and Catherine Meurey

Abstract—Land surface albedo determines the repartition of downwelling solar radiation into components that are either reflected back to the atmosphere or absorbed by the surface. As more sophisticated soil–vegetation–atmosphere transfer schemes are being implemented in numerical meteorological models, it will become increasingly important to accurately characterize the spatial and temporal albedo variations. Within the scope of the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility for Land Surface Analysis, we have developed a daily albedo product, which is derived in near real time from observations provided by the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument onboard the Meteosat Second Generation series. The basic algorithm concept comprises an atmospheric correction scheme, the inversion of a linear semi-empirical model of the bidirectional reflectance distribution function, the angular integration of the bidirectional reflectance distribution function to obtain spectral albedo, and the application of suitable conversion relations to derive broadband albedo estimates. The reflectance model inversion is performed each day based on the available set of clear-sky observations. In addition, constraints on the model parameters are taken into account in the inversion process. By specifying these constraints according to the previous model output in a recursive manner, a complete spatial coverage of the resulting albedo maps is achieved while, at the same time, preserving a high temporal resolution. This paper primarily concentrates on the description of the methodology. In addition, examples for the obtained albedo maps and time series, as well as the first validation results, are presented.

Index Terms—Geostationary satellites, land surface modeling, near real time, operational processing, surface albedo.

I. INTRODUCTION

THE EUROPEAN Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) maintains a number of decentralized processing centers dedicated to different scientific themes. The Satellite Application Facility on Land Surface Analysis (Land-SAF) is hosted by the Portuguese Meteorological Institute based in Lisbon [1]. Its objective is to provide value-added products for the meteorological and environmental science communities, with applications in the fields of land surface modeling, numerical weather prediction, hydrology, and climatology. The project started with research and development in 1999 and entered its Initial Operational Phase in 2005. Since then, data from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument onboard the Meteosat Second Generation (MSG) series satellites are routinely processed in near real time by the Land-SAF operational system. Currently, the delivered products consist of land surface albedo and temperature, short-wave and long-wave downwelling radiation fluxes, snow cover, leaf area index, and vegetation cover fraction.

Land surface albedo quantifies the fraction of energy reflected by the surface of the Earth. As a corollary, it therefore also determines the fraction of energy absorbed by the surface and transformed into heat or latent energy. Hence, land surface albedo is a key variable for characterizing the energy balance in the coupled surface–atmosphere system and constitutes an indispensable input quantity for soil–vegetation–atmosphere transfer models. Owing to strong feedback effects, the knowledge of the surface energy balance is essential for determining atmospheric conditions in the boundary layer (e.g., [2]). As numerical weather prediction models become more sophisticated, it will become increasingly important to accurately describe spatial and temporal albedo variations. On longer timescales, studies carried out with global circulation models have shown the sensitivity of climate with respect to surface albedo (e.g., [3] and [4]).

Rapid surface albedo changes are caused by rain and snowfall. The effects of the latter are also the most significant in terms of their magnitude. One of the main objectives of the delivered product is, therefore, to improve the quantification of the albedo evolution on short timescales, which is expected to improve short-range weather forecasts based on numerical models (e.g., [5]). The snow physical characteristics, areal coverage, and duration of snow cover have a direct impact on the environmental system. Snow albedo varies as a function of environmental conditions, land cover, and snow metamorphism. Therefore, the seasonal monitoring of snow is important for numerical weather prediction, climate studies, and hydrology.

The most relevant albedo quantity for applications concerning the energy budget is related to the total short-wave broadband interval comprising the visible and near-infrared wavelength ranges where the solar downwelling radiation is dominant. In more refined models, albedo values in the visible and near-infrared broadband ranges may also separately be exploited. Furthermore, estimates for the normalized reflectance...
factor values and the spectral albedo in the satellite instrument channels are also pertinent for some applications. In addition to serving as an intermediate product for deriving the broadband albedo quantities, the spectral estimates contain a wealth of information about the physical state of the surface. This information can be used for a variety of purposes such as vegetation monitoring and land cover classification, which, in turn, also constitute important elements for setting up adequate surface modeling schemes.

The land surface schemes that are currently employed in meteorological models generally rely on climatologic databases in order to specify the surface properties. These were derived by combining land cover classification maps with *in situ* measurements and/or satellite data (e.g., [6]–[8]). Since albedo is closely linked to the physical quantities observable by remote sensing, its “direct” determination by means of satellite instruments is relatively straightforward and has also been addressed by many projects. The potential of using surface reflectance models for the determination of albedo from space observations was analyzed, for example, in [9]. In the last decade, albedo products were derived from a number of instruments including the Advanced Very High Resolution Radiometer (AVHRR, e.g., [10] and [11]), POLarization and Directionality of the Earth’s Reflectances (POLDER, e.g., [12]), Moderate Resolution Imaging Spectroradiometer (MODIS, e.g., [13]–[15]), Meteosat Visible and Infrared Imager (MVIRI)/Meteosat (e.g., [16]), and VEGETATION (e.g., [17]). The applied methods increasingly take into account and exploit the dependence of the surface reflectance on variations in the sun-sensor geometry, which occur as a function of satellite orbit, sensor design, geometrical position of the target, and time of the year. In the aforementioned studies, the retrieval problem is simplified by separating the treatment of atmospheric and surface effects, and in many of them, linear semi-empirical models of the bidirectional reflectance distribution function (BRDF) were used. These models are based on a decomposition of the surface reflectance factor into a number of geometric kernel functions, which are associated to the dominant light scattering processes (e.g., [18]–[22]; for an overview, see, e.g., [23]). On the other hand, different parameterized models and a simultaneous modeling of atmosphere and surface properties were considered for retrieving albedo products from the Multi-angle Imaging Spectroradiometer [24] and MVIRI/Meteosat [25], [26]. For practical reasons related to the near-real-time constraints of the Land-SAF project, the technically simpler approach based on linear kernel models was chosen in this paper for deriving an albedo product from observations of the SEVIRI instrument onboard the MSG satellites. The potential of MSG for land surface applications was also investigated in [27].

The objective of this paper is to provide a comprehensive documentation of the method operationally applied in the Land-SAF project. After recalling the physical definition of albedo (Section II), the main part of this paper (Section III) is therefore dedicated to the scientific and technical description of the methodology, with emphasis on its innovative aspects. Section IV then presents examples for the results achieved and shortly discusses initial validation studies. Finally, conclusions and perspectives for further development are given in Section V.

## II. ALBEDO DEFINITION

The spectral albedo at wavelength $\lambda$ of a plane surface is defined as the ratio between the hemispherical integrals of the upwelling (reflected) spectral radiance $L^\lambda(\lambda, \theta_{out}, \phi_{out})$ and the downwelling spectral radiance $L^\lambda(\lambda, \theta_{in}, \phi_{in})$ weighted by the cosine of the angle between the respective reference direction and the surface normal

$$a(\lambda) := \frac{\iint L^\lambda(\lambda, \theta_{out}, \phi_{out}) \cos \theta_{out} d\Omega_{out}}{2\pi}$$

where $d\Omega_{out} = \sin \theta_{out} d\theta_{out} d\phi_{out}$, and $d\Omega_{in} = \sin \theta_{in} d\theta_{in} d\phi_{in}$. The symbols $\theta_{out/in}$ and $\phi_{out/in}$ denote the zenith and azimuth angles, respectively, of outgoing or incoming light paths. The expression in the denominator defines spectral irradiance $E^\lambda(\lambda)$. By introducing the bidirectional reflectance factor $R$, the upwelling radiance distribution can be expressed in terms of the downwelling radiation as

$$L^\lambda(\lambda, \theta_{out}, \phi_{out}) = \frac{1}{2\pi} \iint R(\lambda, \theta_{out}, \phi_{out}, \theta_{in}, \phi_{in}) \times L^\lambda(\lambda, \theta_{in}, \phi_{in}) \cos \theta_{in} d\Omega_{in}$$

and (1) becomes (3), shown at the bottom of the page. From the result, it can be seen that, in general, the spectral albedo of non-Lambertian surfaces depends on the angular distribution of the incident radiation, which, in turn, depends on the concentration and properties of scattering agents (e.g., aerosols) in the atmosphere and, in particular, on the presence of clouds. Therefore, the spectral albedo is not a true surface property but rather a characteristic of the coupled surface-atmosphere system.

In the idealized case of purely direct illumination at incidence angles $(\theta_{dh}, \phi_{dh})$, the downwelling radiation is given by $L^\lambda(\lambda, \theta_{in}, \phi_{in}) = (\sin \theta_{dh})^{-1} \delta(\theta_{in} - \theta_{dh}, \phi_{in} - \phi_{dh}) E_0(\lambda)$, which results in $E^\lambda(\lambda) = E_0(\lambda) \cos \theta_{dh}$ and

$$L^\lambda(\lambda, \theta_{out}, \phi_{out}; \theta_{dh}, \phi_{dh}) = \frac{1}{2\pi} R(\lambda, \theta_{out}, \phi_{out}, \theta_{dh}, \phi_{dh}) E_0(\lambda) \cos \theta_{dh}.$$
By inserting these expressions into (1) or (3), one obtains the spectral directional–hemispherical (or “black-sky”) albedo 
\[ a_{\text{dh}}(\lambda; \theta_{\text{dh}}, \phi_{\text{dh}}) \]
\[ = \frac{1}{2\pi} \int_{2\pi} R(\lambda, \theta_{\text{out}}, \phi_{\text{out}}, \theta_{\text{dh}}, \phi_{\text{dh}}) \cos \theta_{\text{out}} d\Omega_{\text{out}}. \]  
(5)

On the other hand, for completely diffuse illumination, the downwelling radiance \( L^i(\lambda, \theta_{\text{in}}, \phi_{\text{in}}) = L_0(\lambda) \) is constant, and the irradiance becomes \( E^i(\lambda) = \pi L_0(\lambda) \). By inserting these terms into (3) and after making use of (5), the spectral bi-hemispherical (or “white-sky”) albedo \( a_{\text{bh}}(\lambda) \) can be written as
\[ a_{\text{bh}}(\lambda) = \frac{1}{2\pi} \int_{2\pi} a_{\text{dh}}(\lambda; \theta_{\text{in}}, \phi_{\text{in}}) \cos \theta_{\text{in}} d\Omega_{\text{in}}. \]  
(6)

These two quantities, i.e., the functional dependencies \( a_{\text{dh}}(\lambda; \theta_{\text{dh}}, \phi_{\text{dh}}) \) and \( a_{\text{bh}}(\lambda) \), are true surface properties and correspond to the limiting cases of point source \([a_{\text{dh}}(\lambda; \theta_{\text{dh}}, \phi_{\text{dh}})]\) and completely diffuse illumination \([a_{\text{bh}}(\lambda)]\). For partially diffuse illumination, the actually occurring spectral albedo value may be approximated as a linear combination of the limiting cases [28]
\[ a(\lambda; \theta_s, \phi_s) = [1 - f_{\text{diffuse}}(\lambda; \theta_s, \phi_s)] a_{\text{dh}}(\lambda; \theta_s, \phi_s) + f_{\text{diffuse}}(\lambda; \theta_s, \phi_s) a_{\text{bh}}(\lambda) \]  
(7)

where \( f_{\text{diffuse}} \) is the fraction of diffuse radiation, and \((\theta_s, \phi_s)\) is the solar direction.

In the terminology of Nicodemus et al. [29], the quantities \( a_{\text{dh}}(\lambda; \theta_{\text{dh}}, \phi_{\text{dh}}) \) and \( a_{\text{bh}}(\lambda) \) are referred to as the directional–hemispherical reflectance factor and the bi-hemispherical reflectance factor, respectively. Pinty et al. [30] denoted the latter by the acronym BHRiso.

For many applications, the quantity of interest is not the spectral but rather the broadband albedo, which is defined as the ratio of upwelling to downwelling radiation fluxes \( F \) in a given wavelength interval \([\lambda_1, \lambda_2]\)
\[ a_{[\lambda_1, \lambda_2]} := \frac{\int_{\lambda_1}^{\lambda_2} L^i(\lambda, \theta_{\text{out}}, \phi_{\text{out}}) \cos \theta_{\text{out}} d\Omega_{\text{out}} d\lambda}{\int_{\lambda_1}^{\lambda_2} L^i(\lambda, \theta_{\text{in}}, \phi_{\text{in}}) \cos \theta_{\text{in}} d\Omega_{\text{in}} d\lambda}. \]  
(8)

In analogy to (3), it can be expressed in terms of the bidirectional reflectance factor as (9), shown at the bottom of the page. The directional–hemispherical broadband albedo
\[ a_{\text{dh}}^{[\lambda_1, \lambda_2]}(\theta_{\text{dh}}, \phi_{\text{dh}}) = \frac{\int_{\lambda_1}^{\lambda_2} a_{\text{dh}}(\lambda; \theta_{\text{dh}}, \phi_{\text{dh}}) E^i(\lambda)d\lambda}{\int_{\lambda_1}^{\lambda_2} E^i(\lambda)d\lambda}. \]  
(10)

and the bi-hemispherical broadband albedo
\[ a_{\text{bh}}^{[\lambda_1, \lambda_2]} = \frac{\int_{\lambda_1}^{\lambda_2} a_{\text{bh}}(\lambda) E^i(\lambda)d\lambda}{\int_{\lambda_1}^{\lambda_2} E^i(\lambda)d\lambda}. \]  
(11)

can be written as integrals of the respective spectral quantities weighted by the spectral irradiance. In contrast to the spectral albedo quantities defined in (5) and (6), the corresponding broadband albedo values are not pure surface properties since the wavelength dependence of the spectral irradiance \( E(\lambda) \) appearing as a weight factor in (10) and (11) may vary as a function of the atmospheric composition. In analogy to (7), the broadband albedo for partially diffuse illumination conditions may be expressed as a weighted average of \( a_{\text{dh}}^{[\lambda_1, \lambda_2]}(\theta_s, \phi_s) \) and \( a_{\text{bh}}^{[\lambda_1, \lambda_2]} \).

III. ALGORITHM

Satellite observations provide top-of-atmosphere (TOA) radiation measurements for certain configurations of the illumination and observation geometry. The computation of surface albedo according to the equations given in the previous section requires the knowledge of the complete BRDF of the surface. To obtain an estimate of the surface properties from the limited set of TOA measurements, it is, in principle, necessary to solve the radiative transfer problem in the coupled surface–atmosphere system. Due to the technical near-real-time constraints, a simplified approach is adopted in the Land-SAF algorithm. Fig. 1 depicts a flowchart of the processing scheme. In the first step, an atmospheric correction is performed in order to derive top-of-canopy (TOC) reflectance factor values corresponding to the occurring angular observation configurations (Section III-A). In the second step, a semi-empirical kernel-based reflectance model is adjusted to the measurements (Section III-B). Angular integration of the reflectance distribution then delivers spectral albedo estimates, which are finally transformed to broadband albedo by applying suitable conversion relations (Section III-C).
A. Atmospheric Correction

The Land-SAF operational system provides the satellite data, as well as all the auxiliary information needed to perform the atmospheric correction at the temporal resolution of the image acquisition and the spatial resolution of the instrument. The TOA radiance measurements in the spectral channels of the SEVIRI instrument are first converted to TOA reflectance factor values. Pixels are considered for atmospheric correction if they are not marked as cloud covered or contaminated in the cloud mask, which is generated in the system with software components developed by the Satellite Application Facility on Support to Nowcasting and Very Short Range Forecasting [31]. TOC reflectance factor estimates are obtained by applying SMAC, a simplified method for the atmospheric correction [32]. In the following methodological discussion, we assume that all atmospheric effects are correctly accounted for, and we consider the obtained results as true bidirectional reflectance factor values. In practice, inaccurate knowledge of the atmospheric composition, as well as simplifications in the correction approach, can introduce random, as well as systematic, uncertainties.

B. Modeling the Surface Reflectance Distribution

1) Theory of Linear Model Inversion: We consider a linear model of the TOC reflectance factor $R_{\beta}$ in the spectral channel $\beta$ of the measuring instrument

$$R_{\beta}(\theta_{in}, \theta_{out}, \phi) = k_{\beta} \mathbf{f}(\theta_{in}, \theta_{out}, \phi).$$  \hspace{1cm} (13)

Here, $k_{\beta} = (k_{0,\beta}, k_{1,\beta}, k_{2,\beta}, \ldots)^T$ and $\mathbf{f} = (f_0, f_1, f_2, \ldots)^T$ represent the vectors formed by model parameters $k_{i,\beta}$ and angular kernel functions $f_i$, respectively. $\phi$ denotes the relative azimuth angle between the directions of incoming and outgoing light paths.

Observations provide a set of $n$ surface reflectance estimates $R_{j,\beta}(j = 1, \ldots, n)$ in different spectral channels $\beta$ given at irregularly spaced time points $t_j$ and varying discrete values of the view zenith $\theta_{vj}$, solar zenith $\theta_{sj}$, and azimuth angles $\phi_j$. The reflectance factor model is separately applied for each spectral channel. In the following, the index $\beta$ referring to the channel is omitted to simplify the notation.

We therefore obtain a system of $n$ linear equations

$$R_j(\theta_{vj}, \theta_{sj}, \phi_j) = \sum_{i=0}^{m-1} k_i f_i(\theta_{vj}, \theta_{sj}, \phi_j), \hspace{1cm} (j = 1, \ldots, n)$$ \hspace{1cm} (14)

constraining the $m$ model parameters $k_i (i = 0, \ldots, m-1)$. Introducing the vectors $k = (k_0, k_1, \ldots, k_{m-1})^T$ and $\mathbf{r} = (R_1, R_2, \ldots, R_n)^T$, we have

$$\mathbf{r} = \mathbf{A} \mathbf{k},$$  \hspace{1cm} (15)

where the matrix $\mathbf{A}$ is given by

$$\mathbf{A} = \begin{bmatrix} f_0(\theta_{v1}, \theta_{s1}, \phi_1) & \cdots & f_{m-1}(\theta_{v1}, \theta_{s1}, \phi_1) \\ \vdots & \ddots & \vdots \\ f_0(\theta_{vn}, \theta_{sn}, \phi_n) & \cdots & f_{m-1}(\theta_{vn}, \theta_{sn}, \phi_n) \end{bmatrix}.$$  \hspace{1cm} (16)
quantified by its first and second moments corresponds to rewriting (16) and (17) in the form

\[
(A^T A + C_{ap}^{-1}) k = A^T b + C_{ap}^{-1} k_{ap}
\]

with \( k_{ap} = (k_{0,ap}, \ldots, k_{m-1,ap})^T \) and the covariance matrix \( C_{ap} \). For uncorrelated a priori information on the parameters, matrix \( C_{ap} = \text{diag}(\sigma_{ap}^2[k_0], \ldots, \sigma_{ap}^2[k_m]) \) is diagonal. Absence of a priori information on a given parameter—like it is the case for \( k_0 \) in the sample case leading to (19)—corresponds to \( \sigma_{ap}[k_1] \to \infty \) and \( \sigma_{ap}^2[k_1] \to 0 \).

In the following, the discussion is restricted to a model with three parameters of the form:

\[
R(\theta_{out}, \theta_{in}, \phi) = k_0 + k_1 f_1(\theta_{out}, \theta_{in}, \phi) + k_2 f_2(\theta_{out}, \theta_{in}, \phi).
\]

While \( k_0 \) quantifies an isotropic contribution to the reflectance factor \((f_0 = 1)\), the functions \( f_1 \) and \( f_2 \) are often chosen to represent the angular distribution related to “geometric” and “volumetric” surface scattering processes, respectively. The functioning of the algorithm is independent of the particular model choice. The technical implementation includes the model by Roujean et al. [18] in the following RLD92; the Li-Ross model used in the MODIS albedo algorithm; and the hot-spot variant of the Li-Ross model, as discussed in [39]. For the time being, the RLD92 model is used in the operational application.

2) Weighting of Measurements: Knowledge of the angular configurations for each measurement point \( t_j \) allows us to calculate matrix \( F_{ji} = f_i(\theta_{v_j}, \theta_{s_j}, \phi_j) \). In order to determine scaled reflectance vector \( b \) and matrix \( A \), it is necessary to specify weight factor \( w_j \). An expression of the form

\[
w_j = w_0(\theta_{v_j}, \theta_{s_j}) w_i(t_j)
\]

is chosen, which simultaneously characterizes the angular, as well as the temporal, dependence of the weight attributed to each measurement point.

Owing to the 15-min repeat cycle of the SEVIRI instrument, a large number of observations are potentially available, which not only represents an advantage regarding the information content but also increases the technical complexity of the algorithm implementation. The model inversion according to (20) and (21) is therefore carried out for each day, with the observations accumulated during the considered day only. The temporal factor for directly weighting individual observations is kept constant \([w_i(t_j) = 1]\) during this short period. This factor was nevertheless introduced in (23) in order to support an argument developed in Section III-B4, where we describe the composition of information over longer periods, which is handled in a different way.

The angular component

\[
w_0(\theta_{v_j}, \theta_{s_j}) = \frac{1}{\sigma[R_j(\theta_{v_j}, \theta_{s_j})]} \]

of the weight function is conveniently defined as the inverse of the estimated uncertainty of the TOC reflectance factor, whose
directional dependence is assumed to be a linear function of the relative air mass $\eta(\theta_{\text{v,j}}, \theta_{\text{s,j}})$

$$\sigma[R_j(\theta_{\text{v,j}}, \theta_{\text{s,j}})] = \sigma[R_j(\theta_{\text{v}} = 0^\circ, \theta_{\text{s}} = 0^\circ)] \eta(\theta_{\text{v,j}}, \theta_{\text{s,j}}).$$  \hspace{1cm} (25)

Estimates for the values of the reference uncertainties $\sigma[R_j(\theta_{\text{v}} = 0^\circ, \theta_{\text{s}} = 0^\circ)]$ at normalized geometry are expressed as a linear function of the reflectance factor value

$$\sigma[R_j(\theta_{\text{v}} = 0^\circ, \theta_{\text{s}} = 0^\circ)] = c_1 + c_2 R_j$$  \hspace{1cm} (26)

with coefficients for the three spectral bands, as specified in Table I. A lower limit of 0.005 and an upper limit of 0.05 are imposed in order to avoid extreme values for reflectance outliers. These uncertainty estimates were obtained from a statistical analysis of atmospherically corrected SEVIRI scenes, in which the residual variability of TOC reflectance factor estimates acquired with nearly identical geometries over a sufficiently small period of time is attributed to the random (noncorrelated) measurement noise. A detailed description of the method applied for obtaining these uncertainty estimates for data from the VEGETATION instrument in the context of a different project is given in [40].

For the inversion process, all clear-sky reflectance observations are taken into account for which the solar zenith angle and the view zenith angle do not exceed a threshold of 85°. In order to further decrease the weight for reflectance measurements taken at extreme angles close to this limit, the zenith angles are rescaled in the calculation of the relative air mass as follows:

$$\eta(\theta_{\text{v,j}}, \theta_{\text{s,j}}) = \frac{1}{2} \left( \frac{1}{\cos \theta_{\text{v,j}}} + \frac{1}{\cos \theta_{\text{s,j}}} \right)$$

with

$$\tilde{\theta}_{\text{v,j}} = \theta_{\text{v,j}} \frac{90^\circ}{85^\circ}$$

and

$$\tilde{\theta}_{\text{s,j}} = \theta_{\text{s,j}} \frac{90^\circ}{85^\circ}. \hspace{1cm} (27)$$

The motivation for this rescaled prescription is potential systematic problems in the atmospheric correction for very large solar and view angles, for which the employed scheme was not specifically designed, as well as a divergence of the $f_1$ kernel function for very large angles in the RLD92 model.

In order to reduce the sensitivity to outliers due to undetected clouds, observations are eliminated from the analysis if the considered pixel is marked as cloudy in the slot acquired directly before or afterward. The large number of available SEVIRI observations makes it possible to apply an aggressive strategy in this respect. In addition, observations for which the respective flag of the cloud mask product indicates bad quality are penalized in the weighting scheme by multiplying the reflectance uncertainty estimate by a factor of 10. The same approach is adopted for the observations of pixels that might be contaminated by cloud shadow according to their location next to cloudy pixels and considering the solar azimuth direction. The cloud mask product also delivers information on snow cover. If more than half of the valid observations available during one day for a given pixel are classified as snow covered, then the pixel is flagged as snow covered for further processing steps and in the final product. Otherwise, the pixel is considered as snow free.

3) Illustration of the Model Inversion: In order to illustrate the functioning of the model inversion approach, Fig. 2 depicts an example for the series of atmospherically corrected reflectance factor values obtained in the operational system from the SEVIRI image slots acquired during one day at intervals of 15 min as a function of the solar zenith angle. The bars attached to each data point (from the center to each end) correspond to the uncertainty estimates used in the weighting scheme. Image slots for which the considered pixel was flagged as cloudy are marked with a rhombus symbol at the abscissa. In the shown example, this occurs for a number of slots close to local solar noon at a zenith angle of roughly 26°. The solid lines in the graphs represent the result obtained by recalculating the reflectance factor with (15) from the retrieved best-fit model parameters in the same geometric configuration as the observations. The graphs show that the angular dependence becomes increasingly important for large incidence angles. Fig. 3 depicts the dependence of the (recalculated) reflectance factor as a function of the direction of the outgoing light ray for different incidence angles in the principle plane (i.e., with a relative azimuth angle $\phi$ of 0° and 180°) and thereby illustrates the capacity of the model fit for interpolation and extrapolation to unobserved angular configurations.

4) Recursive Temporal Composition: In order to reduce the sensitivity of the resulting estimates to reflectance outliers and extended periods of missing data because of persistent cloudiness, it is necessary to combine the information over a time period that is longer than one day. To generate an albedo product with high temporal resolution on a daily basis, a recursive temporal composition scheme has been developed and implemented. At each execution of the algorithm, the previous parameter estimate $k_{in}$ and the corresponding uncertainty measure $C_{in}$ are read from the relevant internal product files. Since these quantities now serve as input information, the index or exponent “in” was added to the symbols in order to distinguish them from the new estimates to be derived. The previous estimates are then used as follows as a priori information for the linear model inversion specified in (20) and (21):

$$k_{ap} = k_{in}$$

$$C_{ap} = C_{in}^p(1 + \Delta(t_0 - t_{in})/\Delta t) \hspace{1cm} (28)$$

Applying the multiplicative factor with the relative increment $\Delta$ to the covariance matrix reduces the confidence in the a priori estimate as a function of the lapse of time $t_0 - t_{in}$ starting from the previous execution of the algorithm. The result of the inversion, which is constrained in this way with a priori information obtained from previous observations, is mathematically equivalent to directly performing the inversion.

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**TABLE I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>0.6µm</th>
<th>0.8µm</th>
<th>1.6µm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1$</td>
<td>0.001</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>$c_2$</td>
<td>0.07</td>
<td>0.02</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Fig. 2. Example for the results of the model inversion in the three used SEVIRI channels (49.02° N, 2.53° E; July 1, 2006). (Dot) TOC reflectance factor data point. (Solid line) Model fit. The negative (positive) values of the solar zenith angles correspond to observations acquired before (after) local solar noon.

Fig. 3. Dependence of the 0.8-μm channel TOC reflectance factor on the direction of the outgoing light ray for different incidence directions according to the model fit of the sample case from Fig. 2.

with the complete set of observations by attributing less weight to those observations acquired before day \( t_0 \). A multiplicative factor in the weights translates into the inverse of the square root of this factor in the elements of the covariance matrix resulting from the model inversion. The recursive multiplication process can therefore be identified with the presence of an effective temporal weight function [cf. (23)] of the form

\[
w_t(t) = (1 + \Delta)^{-(t_0-t)/(2\Delta t)} \quad \text{for } t \leq t_0
\]

\[
w_t(t) = 0 \quad \text{for } t > t_0
\]

which is shown in Fig. 4. We define the characteristic temporal scale \( \tau \) of the process as the full width at half mean of this weight function. The temporal scale was chosen as five days in the present configuration of the algorithm running in the operational system, and the relative increment \( \Delta = 2^{2/(\tau/\Delta t)} - 1 \) in (28) was accordingly specified. This value represents a compromise between temporal resolution and sensitivity to the remaining small-scale variations in the reflectance factor values that are due to residual atmospheric effects.

If no new observations are available during the whole day due to persistent cloudiness, the estimate for the model parameters \( k \) remains unchanged, and only the multiplicative factor is applied for the covariance matrix as in (28). In this case, the snow flag is propagated from the previous result. The “age” of the last observation exploited in the recursive inversion scheme is an important piece of information for potential applications and is therefore also delivered with the product. Numerical problems encountered during the technical implementation of the method are discussed in Appendix A.

In line with the real-time strategy of Land-SAF, the implemented method makes it possible to deliver the best estimate of the state of the land surface at the time of product generation and distribution by giving the largest weight to the most recent observations. At the same time, owing to the successive accumulation of information, a complete spatial coverage is
and (6) gives the expressions Inserting the reflectance model (13) in the albedo definitions (5) achieved this, the albedo determination is straightforward.

Hav-to obtain an interpolation and extrapolation of the reflectance interest of the model fit described in the previous section was

\[ \theta \]

with rising \[ \gamma \]

\[ \sigma \]

of the model parameters (cf. [44]) and the appropriate kernel

\[ C \]

corresponding to the result of the model fit for the sample case discussed in Section III-B3. In the graphs, an increase in \[ a_{\text{dh}} \] with rising \[ \theta_{\text{in}} \] can be noticed, which is characteristic for most types of land surfaces.

In the Land-SAF albedo product files, the directional–hemispherical albedo \[ a_{\text{dh}}(\theta_{\text{ref}}) \] for a specific reference angle \[ \theta_{\text{ref}} \], as well as the bi-hemispherical albedo \[ a_{\text{bh}} \], is delivered.

The solar position at local noon was chosen as the directional reference for the former, which means that the zenith angle \[ \theta_{\text{ref}} \] is determined as a function of each pixel’s geographic coordinates and the day of the year. For the time being, the information on the complete functional dependence \[ a_{\text{dh}}(\theta_{\text{in}}) \] is not available in the (external) product files. Appropriate empirical formulas (e.g., [45] and [46]) may be applied for modeling the evolution of directional–hemispherical albedo \[ a_{\text{dh}}(\theta_{\text{in}}) \] according to the daily solar cycle. In addition, (7) can be applied to calculate a weighted average of the directional and bi-hemispherical estimates as a function of the fraction of diffuse radiation in order to approximate a real-sky situation. A more elaborate discussion of this subject is given in [30].

2) Broadband Albedo Obtained by Spectral Integration:

The kernel approach provides a description of the angular dependence of the reflectance factor. It is separately applied to each instrument channel and provides no information on the spectral behavior outside of the available narrow bands. Broadband albedo is defined as the integral of spectral albedo over a certain wavelength interval weighted by the spectral irradiance \([10] \text{ and } [11]\). Since the integral can be approximated as a weighted sum of the integrand at discrete values of the integration variable, broadband albedo may be expressed as a linear combination of the spectral (or rather narrow-band) albedo values in the available instrument channels.

In the algorithm, the broadband albedo estimates for a given target interval \[ \gamma \] are derived from the spectral quantities by applying a linear transformation of the form

\[ a_{\text{bd}} = c_{0} + \sum_{\beta} c_{\beta} a_{\beta}. \]

Three different broadband albedo intervals are considered:

1) the total short-wave range from 0.3 to 4 \( \mu \)m; 2) the visible wavelength range from 0.4 to 0.7 \( \mu \)m; and 3) the near-infrared range from 0.7 to 4 \( \mu \)m. Table II summarizes the applied conversion coefficients \( c_{0} \) and \( c_{\beta} \), which were derived by van Leeuwen and Roujean [47]. For this purpose, they generated an extensive data set of synthetic spectral canopy reflectances for different surface types by using the Advanced Spaceborne Thermal Emission and Reflection Radiometer spectral library [48] and the SAIL radiative transfer model [49]. After calculating the narrow-band albedo values in the SEVIRI
uncorrelated, i.e., their uncertainty covariance matrix the TOC reflectance factor values are Gaussian and mutually
assumption that the probability distributions of the errors of
sion problem in a least-squares sense implicitly includes the
stipation needs to be checked with appropriate validation
framework of the applied BRDF model, and their quantitative
validity of these estimates is, strictly speaking, restricted to the
pixel as a function of the respective observation conditions. The
quantities represent the most general quality indicator opera-
tional delivered by the algorithm. They are calculated for each
parameters. Hence, the albedo uncertainty estimates preserve
formal Gaussianity and also reflect uncertainties due to the
noncorrelated part of the reflectance error structure, whereas
correlated (systematic) errors are not taken into account.
The instrument calibration uncertainty may be considered
a posteriori in a simplified way by “root-sum-squared addition”
to the delivered albedo uncertainty estimates.

A potential problem for the uncertainty treatment is caused
by non-Gaussian outliers in the reflectance observations, owing
to undetected clouds. Imperfections in the cloud screening
method can lead to a significant contribution of outliers in the
probability density distributions of the TOC reflectance errors.
This can affect the quality of the inversion results, as well
as the validity of the uncertainty estimates. Nevertheless, the
strategies employed for penalizing or eliminating potentially
unreliable observations mentioned in Section III-B2 reduce the
occurrence of this problem.

With the implementation of the recursive temporal composi-
tion method, the uncertainty estimates also express the temporal
aspect of the relevance of the observations. In periods without
useful observations, the uncertainty estimates increase. This
reflects the loss of knowledge about the estimated variable
due to “aging” of the observational information on which the
estimate is based. The timescale for this process corresponds
to the effective temporal resolution specified for the product
(cf. Section III-B4). In the persistent absence of observations,
the uncertainty values therefore need to be interpreted in a
Bayesian sense and must not be misunderstood as "error bars”
necessarily characterizing the discrepancy between the esti-
mated and the “true” value.

IV. RESULT

A. Product Generation and Distribution

Technically, the processing chain comprises two distinct
modules: one for atmospheric correction and one for model
inversion and directional and spectral integration. For operational application, these modules are implemented in the near real-time system of the Land-SAF project, which is located at the Portuguese Meteorological Institute in Lisbon. The atmospheric correction module is separately applied on each SEVIRI image available at intervals of 15 min directly after acquisition. On the other hand, the inversion and albedo calculation module, which operates on a set of TOC reflectance images collected during one day, is typically launched a little after midnight (UTC) and exploits the MSG input data accumulated during the past day.

The Land-SAF products are separately processed over four geographical regions (Europe, North Africa, South Africa, and South America). The product files are generated in HDF5-format, with the projection and spatial resolution corresponding to the characteristics of the MSG/SEVIRI instrument data. The pixel size is 3 km at the subsatellite point, approximately 5 km in Central Europe, and then rapidly increases toward the edge of the observed region. The products are distributed in near real time, i.e., within 3 h after the last image acquisition, by Eumetsat’s broadcast system EUMETCast via satellite. They can also be ordered on the project website http://landsaf.meteo.pt and retrieved by file transfer protocol. A more detailed technical description is given in the Product User Manual available on the website.

B. Examples for the Derived Albedo Maps

Fig. 6 shows images of the albedo product generated with the recursive temporal composition method for March 1, 2006. Spectral estimates are provided for the three considered channels (0.6, 0.8, and 1.6 μm) of the SEVIRI instrument, and broadband estimates are available for the total short-wave [0.3 μm, 4 μm], visible [0.4 μm, 0.7 μm], and near-infrared [0.7 μm, 4 μm] wavelength intervals. At the date corresponding to the selected sample case, a large part of Central and Eastern Europe was covered by snow. These areas appear in a light green-bluish color in the composite of the three spectral albedo values, because the reflectance factor of snow is low in the 1.6-μm channel assigned to the red color scale in the representation. In the broadband images, however, snow albedo typically saturates the color scale, and with the selected palette, the corresponding areas show up in red.

For each albedo variant, the respective uncertainty estimates are included in the delivered product files. In addition, the “age” of the last available clear-sky observation exploited by the algorithm is provided as well. The example shown in the figure illustrates that the uncertainty estimates are typically high in regions with less favorable geometric configurations for model inversion, e.g., at high northern latitudes, and/or when no useful observations are available for an extended period of time due to persistent cloudiness (e.g., in the Amazon region).

C. Examples for the Temporal Evolution

Fig. 7 depicts the temporal evolution of albedo within a period of one year for three sample pixels corresponding to the locations of Barrax (Spain, 39.04° N 2.08° W), Évora (Portugal, 38.54° N 8.00° W), and Marktoberdorf (Germany, 47.78° N 10.62° E). Since August 15, 2005, the shown results have been obtained in the operational Land-SAF system. The data points included before that day were reprocessed offline.

The spectral albedo time series—particularly for the site of Évora—show a clear seasonal trend mainly owing to the evolution of the vegetation state. The effect is attenuated for the broadband quantities since the variations in different spectral ranges partially tend to cancel out. In addition to these slow albedo changes, there are also variations on the timescale of days, owing to humidity changes after rain fall, which considerably reduces surface albedo in the case of bright soils. In the graphs, this can be seen particularly well for the site of Barrax during the months of September to November, where, several times, the albedo level drops before recovering the previous value after a few days. However, the most important albedo changes in terms of absolute level are caused by snowfall and snowmelt. Among the sample cases shown in the figure, the site of Marktoberdorf was snow covered from December to the beginning of April, and a snow event can also be perceived for Barrax at the end of January.

The graphs include the uncertainty estimates delivered with the albedo product in the form of vertical bars. When a large number of observations are available and the angular configuration is acceptable, the formal uncertainty is very small, and the vertical bars are hidden by the data symbol. In contrast to that, the rapidly increasing uncertainty estimates that can be seen, for example, at the end of December reflect the lack of information during extended periods without useful observations due to persistent cloudiness (cf. Section III-B4).

The shown product time series may still contain high-frequency noise caused by uncorrected atmospheric effects (e.g., due to variations of the aerosol concentration on small timescales) or by potential problems in the elimination of observations affected by clouds or cloud shadows. The methods for minimizing these effects by penalizing potentially contaminated observations in the weighting scheme, as mentioned in Section III-B2, have only been introduced in the system after the end of the period depicted in the figure. Nevertheless, it may be useful to further explore appropriate filtering techniques for removing possibly remaining outliers (cf. [37] and [50]).

D. Validation Studies

Direct validation of the albedo product with ground measurements is difficult due to the large size of the SEVIRI image pixel and potential geolocation uncertainties. As an initial validation study, we have therefore carried out a comparison with the corresponding product derived from observations of the MODIS instrument, which is generally considered as being of good quality (e.g., [51]) and suitable as a reference quantity.

The MODIS product with a higher spatial resolution of 1 km was reprojected to the MSG/SEVIRI grid within the Land-SAF European continental window. For each original MODIS pixel, the “closest” SEVIRI pixel was determined, and afterward, the albedo estimates for all MODIS pixels assigned to a given SEVIRI pixel were averaged. The MODIS product is generated with a temporal composition window of 16 days.
Fig. 6. Albedo product generated for March 1, 2006. (Top left) Color composite derived from the three spectral directional–hemispherical albedo estimates. (Top right) Visible broadband (VI) directional–hemispherical albedo. (Middle left) Total short-wave broadband (BB) directional–hemispherical albedo. (Middle right) Near-infrared broadband (NI) directional–hemispherical albedo. (Bottom left) Uncertainty estimate for the total short-wave broadband albedo. (Bottom right) “Age” of the last available observation used for each image pixel.
Fig. 7. Albedo product time series between June 1, 2005, and May 31, 2006 for image pixels corresponding to three example sites. For spectral albedo, the red, orange, and magenta dots correspond to the 0.6-, 0.8-, and 1.6-μm SEVIRI channels, respectively. For broadband albedo, the colors gray, blue, and green correspond to the total short-wave range, the visible, and the near infrared, respectively. The vertical bars indicate the respective uncertainty estimates. A red cross on the time axis indicates that no product file was generated by the operational system for the respective day. The blue star indicates that the pixel was flagged as snow covered.
In order to reproduce the temporal characteristics as closely as possible with the MSG data, the internal TOC reflectance files provided by the operational system were reprocessed to generate independent albedo estimates for each day, which were then averaged over the relevant MODIS period. For expressing the validation results in a quantitative way, the bias, which is defined as the average of the difference between the two estimates, and the standard deviation of that difference are considered. The temporal evolution of the validation statistics from June 2005 to September 2006 is visualized in Fig. 8. The calculation of the statistics was restricted to those pixels for which the Land-SAF uncertainty estimate is below 0.10, and the MODIS quality flag indicates a high confidence.

During most of the period, except winter, the biases between the Land-SAF and MODIS products are negligible for the near-infrared and total short-wave ranges and in the order of +0.015 for the visible broadband range. The standard deviation in absolute units ranges between 0.015 for the visible range and up to 0.03 for the near-infrared and total short-wave ranges. However, owing to the lower level of the albedo values, the discrepancies in relative units are the largest for the visible broadband estimates. A part of the variations seen in the validation results may be caused by the fact that, in the MODIS algorithm, the atmospheric correction is performed with individual aerosol estimates for each data point, whereas a static model is currently employed in the Land-SAF operational system. In winter, the results tend to deteriorate, which is probably related to the unfavorable observation conditions (clouds and low solar elevation), the much smaller number of data points entering the validation statistics due to the often very large uncertainty estimates (cf. Fig. 7), and the different treatment of snow cover in the Land-SAF and MODIS algorithms.

The validation studies will also be pursued at the level of spectral albedo and normalized reflectance factor values. Results will be investigated in detail as a function of geographic location, surface type, snow cover, precipitation, and atmospheric conditions. In addition, in situ measurements will be considered for validation purposes.

V. CONCLUSION AND PERSPECTIVE

An innovative algorithm has been developed for the determination of land surface albedo in an operational context based on observations acquired by the SEVIRI instrument onboard the MSG satellites. Products are reliably generated and delivered to the users in near real time on a daily basis. Preliminary validation studies show a good general consistency with products derived from other satellite instruments. The method delivers spatially complete maps and allows the quantification of albedo variations on timescales of a few days, which constitutes a unique advantage and originality of our approach based on MSG data compared to other available products. A quantitative uncertainty estimate is delivered with the product, which is particularly useful for data assimilation purposes and therefore suits the needs of the primary user communities in the fields of land surface modeling and numerical weather prediction. Furthermore, the intermediate internal product containing normalized spectral reflectance factors is used in the operational system for generating the Land-SAF vegetation products, which therefore benefit from the work described here and inherit the temporal and spatial characteristics.
Concerning the content of the albedo product files, some modifications are possible. Currently, the directional–hemispherical albedo is given for a reference angle corresponding to the local solar noon. We plan to provide a parameterization that enables the user to calculate the complete diurnal albedo cycle. Since the product is provided on a daily basis, it would be possible to deliver the appropriate albedo estimate for any given day according to the information on the actually occurring illumination conditions provided by the cloud mask. We intend to test the application of the product in land surface and numerical weather prediction models in order to get a more direct user feedback and adapt further development according to the respective needs.

The treatment of aerosols is a weak point in the current algorithm setup. The first step for improvement could be to employ a better aerosol climatology as input information for the atmospheric correction scheme. While this could help to correct possibly existing overall biases for certain regions, it would, of course, not account for the occurrence of rapid variations. A preferable approach is to ingest near-real-time aerosol information into the operational system once such a product becomes operationally available. Due to the modularity and flexibility of the albedo algorithm and the operational system, this would not cause major technical problems. The impact of artifacts due to atmospheric effects could also be mitigated by increasing the constant $\tau$ of the effective temporal weight function. However, the high temporal resolution of the delivered albedo product is a unique feature, and in order to preserve the capacity to react to rapid surface albedo changes, this parameter is kept relatively small. In the long term, surface and atmosphere effects should simultaneously be treated by adapting a combined model to the directly measured quantities at the top of the atmosphere. Due to the nonlinearity of the problem, such an approach is more demanding in terms of computation time. However, the propagation of the previous estimates, like in the method presented here, would also offer the possibility of initializing and hence speeding up nonlinear inversion problems.

An interesting consequence of the recursive temporal composition scheme is the complete spatial coverage of the resulting albedo maps gradually achieved after the initialization of the method. In extended periods of missing data, an estimate based on two of the model parameters. In this way, the propagation of the previous estimates, like in the method presented here, would also offer the possibility of initializing and hence speeding up nonlinear inversion problems. It is therefore planned to deliver a product variant with temporal characteristics corresponding to those of a simple composition window with fixed size in order to represent the surface properties over a more extended period (cf. Appendix B). Potential applications include the derivation of climatologies for the retrieved surface variables. Products generated according to this approach can suffer from gaps when no useful observations are available during the chosen period. However, the missing information could be filled with the help of a land cover classification map by using probabilistic concepts, which are analogous to those developed in this paper (cf. [17]).

The recursive temporal composition method is conceptually similar to a Kalman filter and represents a step toward the assimilation of remote sensing data in land surface models. Currently, the approach is exclusively based on satellite observations and does not make use of any external knowledge about the evolution of the surface properties. It could further be developed by adding a time-dependent model component, which takes over the prescription of the temporal evolution in the absence of observational constraints, i.e., during periods when the uncertainty estimate of the currently available product is particularly high. This could be achieved with a true physical model or based on empirical results by exploiting the typical behavior observed in previous years for each image pixel or for each land cover class (cf. [43]).

The Land-SAF project recently entered its Continuous Development and Operational Phase, which will last until 2012. A major effort will consist of the implementation of the processing chains for exploiting the data acquired by the AVHRR instrument onboard the satellites of the MetOp series forming the European Polar System. Owing to the complementary observation geometry resulting from the polar orbit, the additional information will be particularly beneficial for the albedo product, provided that technical problems such as geo-location and channel intercalibration can be controlled with sufficient precision. The fusion of information stemming from instruments of different types for the purpose of albedo determination was discussed on the basis of simulations in [52] and [47], but it has not yet been operationally realized due to the technical complexity. The methodological concept and the technical implementation of the present Land-SAF algorithm have already been designed in view of the forthcoming extension to MetOp data. It is planned to merge the data at the level of the TOC reflectance factor by inverting the BRDF model with observations from both the SEVIRI and AVHRR instruments. In particular, for high latitudes during winter, this will significantly improve the constraints for model inversion and hence the quality of the result.

The Satellite Application Facility for Land Surface Analysis will provide services during the lifetime of the MSG and European Polar System programs until at least 2018 and probably beyond. The consistent generation and distribution of its suite of land surface products will constitute a valuable tool for environmental and meteorological applications.

APPENDIX

A. Some Numerical Subtleties

Numerical instabilities can occur in the inversion process when the information content of the available observations is very scarce. In order to prevent potential problems, a regularization term is added when calculating the result according to (20) and (21). In practice, the parentheses in these two equations therefore additionally include the term $C_{\text{reg}}^{-1}$ and the right-hand side of (20) additionally includes the term $C_{\text{reg}}^{-1}k_{\text{reg}}$. The numerical values were chosen such that the regularization term corresponds to the constraints of $k_1 = 0.03 \pm 0.05$ and $k_2 = 0.3 \pm 0.5$ on two of the model parameters. In this way, the inversion can be carried out with a single available observation,
even when the previous result is not used as a priori information. Of course, in such a case, the confidence is low, and this is naturally quantified by the resulting covariance matrix. The specific numbers chosen for the constraints correspond to typical values for the parameters of the RLD92 model, and the standard deviations are sufficiently large to avoid a noticeable prejudice in the inversion result.

Other numerical problems are related to the storage of the elements of the covariance matrix with reduced precision as integer variables between successive executions of the algorithm. For the diagonal elements of the covariance matrix $C_{k}^{in}$, a lower limit of $10^{-6}$ is applied in order to avoid zero values. This corresponds to a maximum precision of 0.001 for the model parameters. A more serious rounding problem is given here. In some (rare) cases, the reloaded covariance matrix $C_{k}^{rp}$ can lose its essential property of being positive definite, which can perturb the successive calculations. To avoid this problem, the off-diagonal elements of the reloaded covariance matrices are currently set to zero in the algorithm implemented in the operational system. It has been checked that this approximation does not substantially affect the derived uncertainty estimates. The problem could rigorously be solved by storing a Cholesky decomposition of the covariance matrix, which would assure positive definiteness of the reloaded matrix by construction.

### B. Classical Temporal Composition Window

In addition to the daily-generated product based on the recursive approach, it is planned to deliver a second variant to support the operational system. It has been checked that this approximation does not substantially affect the derived uncertainty estimates. The problem could rigorously be solved by storing a Cholesky decomposition of the covariance matrix, which would assure positive definiteness of the reloaded matrix by construction.

\[
\left( \sum_j C_{k,j}^{-1} \right) \mathbf{k} = \sum_j C_{k,j}^{-1} k_j \tag{34}
\]

\[
C_{k} = \left( \sum_j C_{k,j}^{-1} \right)^{-1} \tag{35}
\]

in analogy to (20) and (21). Neglecting numerical effects, the result is mathematically equivalent to directly performing the inversion with all reflectance observations collected during the composition period. This would however be very demanding in terms of computing resources since it requires to simultaneously provide the algorithm with a huge number of input files corresponding to all available SEVIRI slots during the composition period.

At the time of writing, the corresponding algorithm code has not yet been implemented in the Land-SAF system; therefore, this product variant is not operationally available. It is foreseen to generate it every ten days, with a (sliding) composition window of 20 or 30 days.

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