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Cloud and surface classification using SCIAMACHY polarization measurement devices

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Abstract

A simple scheme has been developed to discriminate surface, sun glint and cloud properties in satellite based spectrometer data utilizing visible and near infrared information. It has been designed for the use with data measured by SCIAMACHY's (**SC**anning **I**maging **A**bsorption SpectroMeter for **A**tmospheric **CH**artographY) Polarization Measurement Devices but the applicability is not strictly limited to this instrument. The scheme is governed by a set of constraints and thresholds developed by using satellite imagery and meteorological data. Classification targets are ice, water and generic clouds, sun glint and surface parameters, such as water, snow/ice, desert and vegetation. The validation is done using MERIS (**ME**dium **R**esolution **I**maging **S**pectrometer) and meteorological data from METAR (**MÉT**éorologique **A**viation **R**égulière – a network for the provision of meteorological data for aviation). Qualitative and quantitative validation using MERIS satellite imagery shows good agreement. The comparison with METAR data exhibits very good agreement.

1 Introduction

Cloud, sun glint and surface classifications utilizing space-borne measured data have a long history. The motivation for cloud and surface classifications are manifold, for example the creation of global thematic maps for civil and military use, generate time-series for climate studies or derive correction factors and climatologies for geophysical parameter retrieval. This study is focusing on the latter issue, i.e. the use of global classified values in order to provide adequate input values especially for retrievals of atmospheric parameters.

The retrieval of atmospheric parameters can significantly be hampered by wrong input assumptions. For this reason precise cloud and surface classifications have to be derived. Some examples for affected retrievals are:

– Cloud top height retrievals of partially cloud covered ground scenes from the O2-

A-band need a precise input ground albedo (Kokhanovsky et al., 2005), especially in regions, where changes from a water to snow/ice surface lead to an significant increase of the surface albedo.

– Aerosol retrievals are known to be error-prone over sun glint occurrences. Therefore sun glint areas need to be flagged out of the aerosol retrievals (de Graaf and Stammes, 2005).

– Trace-gas (Buchwitz et al., 2005) and aerosol (von Hoyningen-Huene, 2006) retrievals known to be very sensitive to the existence of even small fractions of clouds in the field of view need a reliable cloud-flagging algorithm.

Here and in the following we consider sun-glint, the specular reflection of light into the detector also as a surface effect.

Necessary classifications for a broad set of parameters can be retrieved using satellite imagery at moderate spectral and comparatively high spatial resolution. Examples for such instruments are MERIS (**ME**dium **R**esolution **I**maging **S**pectrometer) aboard ESA's ENVISAT (**ENVI**ronmental **SAT**ellite) and MODIS (**MOD**erate Resolution **I**maging **S**pectroradiometer) which is a key instrument aboard NASA's Terra (EOS AM) and Aqua (EOS PM) satellites.

Retrievals of atmospheric trace gases often take advantage of the spectral fine structure of the absorption process in question. Among lot of very successful atmosphere satellite missions within the last decade the **SC**anning **I**maging **A**bsorption Spectro**M**eter for **A**tmospheric **CH**artograph**Y** (SCIAMACHY, as MERIS installed aboard ENVISAT) is one of the outstanding instruments whose primary objective is the global measurement of trace gases in the troposphere and stratosphere. However, the spatial resolution is low compared to an imager such as MERIS or MODIS.

This study aims to analyze the feasibility to classify clouds and surfaces utilizing solely measurements from the atmospheric sensor, such as SCIAMACHY. In principle a multi-sensor approach using for example MERIS classifications with SCIAMACHY retrievals is possible. However, failures or missing imagery data are propagating into the analysis of the atmospheric sensor. Yet another problem is the enormous amount of imagery data to be gridded to match the low spatial resolution of the atmospheric sensor which is a very time consuming computational step. The approach presented here is therefore intentionally set up as an "autonomous" one: only SCIAMACHY data are involved to classify the geophysical parameters in question. We therefore have developed a set of algorithms and constraints to have an independent, fast and simple approach. Yet another advantage is that the spectral as well as spatial sensitivity of the classification is compatible to the sensitivity of the retrieval of the atmospheric parameters.

In this study satellite imagery is used primarily to validate SCIAMACHY classifications and secondarily for the adjustment of the algorithms. As clouds or sun glint [1] are highly variable spatio-temporal objects a close temporal coincidence between SCIAMACHY-based classifications and those of the imagers must be ensured. Since MERIS is located on the same platform and has basically the same measurement geometry as SCIAMACHY (in nadir mode) synchrony between both data sets is ensured. On the other hand, SCIAMACHY and MERIS sensitivities for surfaces and clouds are likely to be different due to significant deviation in spatial and spectral resolutions.

The paper is organized as follows, first we will briefly explain some technical background information about the sensors SCIAMACHY and MERIS used within this study. In the next section we will explain the algorithms used and finally show comparisons with independent data.

2 Instruments

2.1 SCIAMACHY

The **SC**anning **I**maging **A**bsorption spectro **M**eter for **A**tmospheric **CH**artograph**Y**, SCIAMACHY, is a passive hyperspectral UV/VIS/NIR grating spectrometer (Bovensmann

[1] and to less extend some surfaces as snow and ice

et al., 1999). It was launched on-board the ENVISAT satellite in March 2002 into a polar sun-synchronous orbit, crossing the Equator on its descending node (i.e. southwards) at 10:00 a.m. local time. The instrument covers the solar radiation transmitted, backscattered and reflected from the atmosphere at relatively high spectral resolution (0.2 nm to 1.5 nm). It records data in eight separate main channels (non-continuously), over the spectral range 240 nm to 2380 nm, and in selected regions between 2.0 μm and 2.4 μm. The nominal spatial resolution in nadir viewing geometry, however, is comparatively poor being 60 km×30 km. The swath width of SCIAMACHY is 960 km.

From its orbit, SCIAMACHY can observe the Earth from three distinct viewing geometries nadir, limb and lunar/solar occultation. In this study only nadir measurements are used.

Beside the main channels, also called science channels, there are seven additionally broadband detectors which measure the polarization of the incoming light. These **P**olarization **M**easurement **D**evices (PMD) (see Table 1) cover the spectral range of the science channels (2 to 6 and 8) and are provided to apply corrections to the polarization sensitivity of the science channels. The PMDs are mainly sensitive to parallel polarized light (parallel to the instrument slit), while the science channels measure sensitive to both polarization components. Information on the polarization of the incoming light is therefore obtained by combining the two measurements.

The PMDs are read out at 40 Hz, but are down-sampled to 32 Hz for processing. This still gives a spatial resolution of ∼7 km×30 km which is better compared to the science channels, where the fastest read-out occurs at 8 Hz, but more commonly at 1 Hz. Therefore, the advantage of working with PMD data is that information is given at higher spatial resolution and it is used as sub-pixel information for the much larger SCIAMACHY measurements based on science spectra.

2.2 MERIS

MEdium **R**esolution **I**maging **S**pectrometer (MERIS) aboard of ENVISAT provides 15 spectral bands, which are programmable in position, width and gain. In practice, these technical characteristics are kept constant most of the time.

Measurements are performed in the 390 nm to 1040 nm spectral range (see Table 2) with an average channel width of about 10 nm . MERIS is a "push-broom" spectrometer and has a 68.5° field of view around nadir. The swath width of 1150 km is slightly larger than SCIAMACHY's. The instrument acquires data in Reduced Resolution mode (RR) and Full Resolution mode (FR). The spatial resolution is about 1.1 km in RR mode and 300 m in FR mode. We focus in this study on data in RR mode due to a broad availability of the data.

3 Algorithms

We developed a suite of algorithms and constraints which we called SPICS (**S**CIAMACHY–**P**MD based **I**dentification and classification of **C**louds and **S**urfaces). All of them use ratios of two PMD radiance values each (see Krijger et al., 2005), the PMD reflectance value for a wavelength λ and values derived therefrom. PMD reflectance $R(\lambda)$ for a wavelength λ is defined as:

$$R(\lambda) = \frac{I(\lambda)}{I_0(\lambda) \cdot \mu_0} \tag{1}$$

where I is the PMD radiance value, I_0 is the PMD solar irradiance and μ_0 is the cosine of the solar zenith angle.

SPICS is organized with respect to three classification groups: clouds, sun glint and surfaces. It is capable to differentiate between five surface types: vegetation, snow/ice, desert, water and land/soil as well as three cloud types: ice, water and generic clouds.

All results obtained with the methods described below were tuned with respect to independent data sources such as co-located MERIS and meteorological data sources such as METAR.

3.1 Cloud phase

Cloud phase retrieval with SCIAMACHY has been performed before using the science detectors (Accareta et al., 2004; Kokhanovsky et al., 2005). Introducing PMDs instead of them results in a better spatial resolution.

Ice clouds, for example, appear brighter and normally whiter than water clouds when looking from space. Liquid water clouds usually let light penetrate deeper and absorption is leading to an increased level of grayness. To quantify cloud grayness we have selected the radiance values of PMD_2, PMD_3 and PMD_4.

First we define the grayness b of a scene as the (scaled) average of the three selected PMD reflectances (R_2, R_3, R_4):

$$b = av(R_2, R_3, R_4) * S \tag{2}$$

For convenience the factor S scales the values of b from 0 up to 100. Seldom occurrences of brightness values larger 100 have been clipped. A similar concept for cloud/snow/ice–discrimination has been applied successfully by (Krijger et al., 2005).

In order to determine the range between the individual reflectance values the quantity r is also used. r is defined as the range of the three PMD reflectances normalized to the average value:

$$r = \frac{\max(R_2, R_3, R_4) - \min(R_2, R_3, R_4)}{av(R_2, R_3, R_4)} \tag{3}$$

The determination of r is essential for having a measure of goodness of the gray value. For example, a large value of r indicates more color but not a high degree of grayness. A well-tuned set of thresholds for b, r and R_5 helps to classify ice, water and generic clouds as well as different surface types (see Tables 3/4).

3.2 Surface classification

Each surface classification approach is briefly explained in the following. Tables 3 and 4 summarize all applied thresholds. Multiple classifications are allowed.

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However, from each classification group only one parameter may contribute to the overall result.

For vegetation and sun glint the gray-value concept is not used. In the latter case it turned out that vegetation classification is clearly superior using a modified NDVI (Normalized Differenced Vegetation Index) approach. For vegetation we therefore define the NDVI n analogous:

$$n = \frac{R_4 - R_3}{R_4 + R_3} \tag{4}$$

Applying a cutoff value of <1.18 removes non-vegetation ground pixels reliably. However, light reflected from vegetation is able to induce a considerable polarization component depending on the health state of the plant. Therefore, this modified NDVI is a first estimation.

Sun glint is specular reflection of sun light by adequately tilted facets of water into the detector. Careful analysis of this effect could for example help to improve aerosol retrievals, otherwise it can strongly be affected by this effect (see de Graaf and Stammes, 2005).

Sun glint is able to exhibit a considerable degree of polarization. This can be observed when investigating SCIAMACHY's PMD signals. To uncover sun glint's polarization features we define the ratio $\rho_{74}=I_7/I_4$. I_7 and I_4 (ATBD, 1999) are the radiance values for PMD seven and four and are primarily sensitive to Stokes vector elements U and Q (Coulson, 1988), respectively. Following standard text books the ratio U/Q can be related to $\chi=0.5\arctan U/Q$, which is the tilt angle of the polarization ellipsoid. Thus the ratio ρ_{74} is related to χ. It should be noted that for unpolarized light U and Q are zero, therefore χ is undefined.

Examining the ratio ρ_{74} globally over three months of data a clear contrast of sun glint regions to others can be found. If the angle χ over water is larger (or equals) zero and smaller 32.6° ($0<\rho_{74}<2.168$) sun glint can be classified reliably. Without limitation to water this approach would also detect sun glint over various desert regions due to increased amounts of polarization of the reflected light – and therefore a well-defined value χ. The water-land discrimination procedure is using the radiance ratio from PMD_5 and PMD_4 which exhibit a clear water-land contrast. The threshold intervals to eliminate land pixels can be found in Table 4. Please note, that the water-land discrimination is not strongly affected by changing the threshold limits. This enables also occasional detections over land which can be identified as lakes, wetlands or flood plains.

The last test is to ensure proper geometrical conditions: An absolute value of an azimuth difference of 40 ° between line-of-sight and sun position may not be exceeded (same condition seen in Qin et al., 2006). As mineral dust aerosols contribute to the depolarization of the detected light and the ratio U/Q lies within a limit where significant polarization is expected, no substantial impact of (desert) aerosols is observed. In Fig. 1 sun glint detections are shown for the central Mediterranean.

Note, that the quality of the ratio U/Q from SCIAMACHY PMD measurements was under discussion (Krijger and Tilstra, 2003; Schuttgens et al., 2004). The background of the discussion is that the PMDs provide essential input for the Polarization Correction Algorithm (PCA) of SCIAMACHY. For the PCA the requirements regarding the accuracy of the PMD measurements are comparatively high. However, the approach presented here is not affected – as the ratio ρ_{74} or the angle χ is not needed as an absolute value.

Liquid water classification can be an important issue for several other retrievals where the derivation of a geophysical parameter is either hampered, like for instance in case of the retrieval of CO, CH_4 (Buchwitz et al., 2005) or only possible like in case of chlorophyll concentration (Vountas et al., 2007). The thresholds used for the classifications where derived on the base of comparison with a large amount of MERIS-pixels. We found that b (as defined in Eq. 2) must be smaller 40, indicating a low level of brightness (obviously, as water appears blue). Since water reflects (for both polarizations) very poorly in the near infrared R_5 will be low. A reliable threshold for water pixels is $R_5<0.020$.

The Snow/ice classification is based on the radiance ratio for PMD five to four, ρ_{54}, as already proposed by Krijger et al. (2005). However, we adjusted the thresholds to the daily updated AMSR-E sea ice maps (see Heygster and Borgmann, 2008) but derived slightly different thresholds and an additional constraint. We propose that the radiance ratio should be within the following interval: $0 \geq \rho_{54} P > 0.2$ where the reflectance R_5 should be $0.06 \geq R_5 < 0.018$

Desert classification is also based on the radiance ratio for PMD five to four, ρ_{54}. Comparisons with data from the global land cover 2000 project (GLC, 2000) showed that ρ_{54} should be larger or equal 1.7 indicating that both channels exhibit a sufficient contrast over desert. In order to distinguish clouds over desert the reflectance for PMD five must be: $0.110 \geq R_5 < 0.245$. Desert classification, however, has been limited to a corridor between $\pm 60^\circ$ in order to avoid having mismatches with snow/ice classifications on antarctica.

Land/soil classification is based on r which must be smaller or equal 25, the ground scene will have to be more grayish than in case of water classifications. An additional constraint using R_5 ensures reliable classification of land pixels: $0.05 \geq R_5 < 0.092$.

4 Validation

The analysis of classifications of vegetation, water and land (soil or desert) is comparatively trivial when comparing with true or pseudo-true color imagery. Sun glint is a rapidly changing parameter over the orbit but can also be identified very easily through visual analysis. This holds for the cloud detection using SPICS. As MERIS measures the same scene at the same time as SCIAMACHY it is straightforward to use it for the comparisons. As a first qualitative test we have prepared pseudo- RGB (red/green/blue) images using eight channels of MERIS. MERIS level 1 data in reduced resolution (1.1 km×1.1 km) were used for the RGB representation and mapped. SPICS classifications were overlayed the MERIS pseudo-RGB for several scenes and showed good agreement. Exemplarily Fig. 1 shows two orbits of two consecutive days (21 and 22 August 2007) over central Mediterranean Sea. The classifications are in

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good agreement with the underlying MERIS image. Broken clouds near Italy as well as large cloud formations in the west are well represented. Water and land classifications for the eastern orbit over cloud-free Greece and the Aegean Sea are reproducing the actual MERIS scene reliably. The transition from vegetation to soil and desert over Tunisia is also well classified. Furthermore the clear surface/sun-glint contrast classified by SPICS at the east coast of Tunisia is obviously reproducing the actual conditions during the measurement represented by MERIS' RGB imagery. Gaps with missing classifications are due to inadequate threshold intervals. They are more frequent in regions of partial or complete cloud coverage, as can be seen in some regions of the western orbit.

A first attempt was made to further validate the discrimination of general cloud and ice cloud classification in the next section.

4.1 Cloud phase classification

As explained above SPICS allows the discrimination of cloud types. The types can roughly be classified as ice clouds, water clouds and generic clouds. The latter includes those which were classified as clouds but the phase discrimination could not be performed.

In order to make a first step towards a validation we compared SPICS' cloud type classification with results of MERIS level 2 data. MERIS cloud type products (Meris Products specifications, 2007) are available at reduced spatial resolution of about 1.1 km×1.1 km. To use this data within SCIAMACHY's field of view their results must be gridded down. MERIS provides basically nine cloud types which we have re-classified to family A, B and C clouds.

– Family A: high clouds with large amount of ice crystal (Cirrus, Cirrostratus and deep convection).

– Family B: middle clouds. Mainly water clouds frequently containing super cooled droplets, as well as small amounts of ice crystals (Altocummulus, Altostratus, Nimbostratus).

- Family C: low water clouds (Cummulus, Stratocummulus, Stratus)

The comparison was performed over one set of SCIAMACHY measurements in South-East Europe. Figure 2a) shows the results for SPICS, Fig. 2b) MERIS cloud family classifications which have been gridded to SCIAMACHY PMD ground pixel sizes and Fig. 2c) a full resolution true color image of MERIS for improved visualization which was provided by European Space Agency (ESA) via web front-end (unfortunately no full resolution level 2 data were available). In some cases the gridding of MERIS classifications to create Fig. 2b) led to multiple cloud family detections within one SCIAMACHY PMD ground pixel. In such cases we selected the predominant family by taking the classification providing at least 75% of the whole amount of pixels gridded.

For clarity both Figs. (2a and b) show only cloud (phase) classifications, simultaneous surface classifications are not shown. Good qualitative agreement between SPICS ice and water cloud classifications with MERIS family A and B cloud classifications can be found. Both figures also reveal strengths and weaknesses: SPICS is capable to detect even geometrically thin clouds (especially near river Dniester at about 26° lon/48° lat) where MERIS did not detect clouds. However, MERIS is able to detect comparatively small clouds due to its high spatial resolution (for example, at Danube Delta, over Black Sea and near Crimea). When comparing with the (pseudo-) true color image of MERIS (Fig. 2c) in full resolution the frazzled and whitish-thin appearance of lot of clouds within this scene give reason to suspect that cirrus clouds are involved. However, neither MERIS nor SPICS classifications could proof this for the ground pixels in question.

To elaborate the classifications quantitatively the validation will be extended to the comparison involving thermal infrared measurements in a future study. Here, data of AATSR (Advanced Along-Track Scanning Radiometer) aboard ENVISAT will be utilized in order to be able to discriminate cloud phase information more reliable (Kokhanovsky, 2006).

4.2 Quantitative validation using MERIS

To validate SPICS classifications on a global scale, MERIS level 2 data were used again for obvious reasons. MERIS classifications for water, land and clouds are available from level 2 data at reduced spatial resolution of 1.1 km×1.1 km. The simultaneous MERIS classifications for 22 August 2007 were matched to SCIAMACHY ground pixel size and location. Here, MERIS classifications were gridded to SCIAMACHY PMD size and location. Typically more than 100 MERIS classifications were gridded to one SCIAMACHY PMD ground pixel. Among the individual MERIS classifications the number of occurrences were stored. More than 22 million MERIS pixels were gridded to over 120 000 SCIAMACHY PMD ground pixel. Multiple classifications for one ground pixels are possible for both data sets, however, for different reasons: while SPICS classifies different surface or cloud properties through the exploitation of a set of thresholds related to different spectral or polarization sensitivities of SCIAMACHY, MERIS is capable to deliver classifications at SCIAMACHY's sub-pixel level.

Related to the total amount of SCIAMACHY PMD ground pixels 22.5% of all water classifications using SPICS could be matched to MERIS (absolute number of matches and mismatches can be found in Table 5). 30.6% of all land classifications and 47.4% of all cloud classifications from SPICS could be matched to MERIS. 0.16% of all values could not be matched in any of the three classes.

However, the amount of mismatches is not negligible: If we require that at least 130 (87% of possible MERIS values) gridded into one SCIAMACHY PMD ground pixel follow one classification, for example water, the amount of mismatches is 5.9%. For land this is 2.5%. Requiring at least 100 (ca. 67% of possible MERIS values within one SCIAMACHY PMD ground pixel), the amount of mismatched pixels increases to 11% and 5%, respectively. If we require only the maximum of one classification, the amount of mismatched pixels increases to 15% and 7.5%. This indicates that the mismatches are due to the significant difference in the spatial resolution.

Moreover, this behavior reveals a potential weakness of the comparison: while classifications using SPICS are based on broadly spatially averaged spectral information, MERIS classifications were based on spectral information averaged over a much smaller area. Water mismatches are relatively frequent due to the inability of SPICS to detect small coverage of water within one SCIAMACHY PMD ground pixel, i.e. in the vicinity of bright cloud fields, small patches of water and land are outshone.

Regardless of the mismatch in spatial resolution the comparison reveals (Table 5) that still 22% of all classifications match for water, 31% for land and 47% for clouds – without requiring a certain amount of land or water pixels within the SCIAMACHY pixels. However, these results can at best be considered as satisfactory. Obviously, the averaging of MERIS radiance/reflectance values to be done prior classification. This approach is avoided here due immense computational effort necessary. Instead the validity of the individual approaches used within SPICS is checked using "ground truth" data from METAR–**MÉT**éorologique **A**viation **R**égulière (Metar online, 2008).

4.3 Comparisons with METAR data

METAR delivers relevant meteorological data for aviation. However, the data are useful also for the validation of SPICS – especially for regions of mixed snow/ice and clouds. Hourly data of 72 METAR (airport based) measurement stations were collected over three months which resulted into a complete data set with over 280 000 records. Co-located station data sets were compared with SPICS classifications.

Figure 3 shows a large area of Greenland with two METAR stations: Kulusuk Lufthavn (METAR station code: BGKK) and Constable Pynt (METAR station code: BGCO). Classifications have been computed for SCIAMACHY orbit 29 423. Two consecutive MERIS scans have been overlayed the data set to provide additional pseudo-true color information.

Station BGKK reports complete overcast during SCIAMACHY and MERIS measurements with a horizontal visibility larger than 1 km and a surface temperature of 0° Celsius. The reported cloud bottom height was 1.2 km. From preceding and succeeding orbits, as well as meteorological METAR data we found that the headland where the station is located was snow-clad. This has also been the case for station BGCO. BGCO, however, reports clear sky during over-flight of ENVISAT with a visibility larger than 10 km and a surface temperature of -8° Celsius (14:50h UTC).

The observations reported are in agreement with SPICS' classification: snow classifications are determined for BGCO station and vicinity whereas cloud classifications agree with the reports from BGKK. Underlying MERIS pseudo-true color images support that the snow and cloud classifications generally worked well but the visual discrimination based on MERIS imagery remains difficult in the vicinity of the two stations. However, the underlying MERIS pseudo-true color images are useful for the western part of the measurement cycle near BGKK station. Here the imagery shows a large field of clouds over ice which exhibits a clear (textural) contrast to the surrounding ice field. However, there are also numerous failed classifications in these regions where the classification thresholds are not adequate and have still to be fine-tuned further.

To evaluate the quality of SPICS results more generally we have extended the comparison to all stations. Co-locations were defined within a circle with 3 km radius around the center coordinates of the station which had to include the PMD's center coordinates and with a maximum temporal difference of 15 min. As common for aviation data METAR's cloud fraction is given in two oktas and refer either to a measured or human-observed quantity within the visual horizon.

58 co-locations met the requirements. Analyzing the data set carefully revealed that 55 SPICS classifications were in agreement with METAR. The following results were obtained:

– In 50 cases SPICS classified the SCIAMACHY pixel as cloudy and METAR reports for the corresponding co-location at least 25% cloud fraction.

– In five cases SPICS is able to classify the surface and METAR reports sufficiently low cloud fraction which is less or equal 25%. The experience made from MERIS comparisons (see chapter 4.2) showed that SPICS has the ability to detect the surface when a small fraction of the ground pixel is cloud covered. In four of five

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cases SPICS classified the surface being snow/ice covered and the meteorological databases confirmed it.

- In three cases SPICS classifies the surface and METAR reports medium to high values for the cloud fraction (larger 25% and smaller 88%). This scenario can be disputed, as SPICS/SCIAMACHY has only limited ability to classify surfaces in the presence of larger and optically thick cloud fields within the field of view.

- In no cases SPICS classified the pixel as cloudy and METAR reported complete cloud free conditions.

Reducing the temporal interval to one minute led to no mismatches and 10 agreements.

5 Conclusions

A scheme has been developed to identify and classify clouds and surfaces which we have called SPICS: SCIAMACHY-PMD based Identification and classification of Clouds and Surfaces. It is based on SCIAMACHY's polarization measurement device data utilizing a set of thresholds and constraints. The approach was motivated to create an independent, fast, simple and spectral as well as spatial compatible way classifying important geo-physical parameters. The quantities classified are: ice, water and generic clouds, sun glint and surface parameters, such as water, snow/ice, desert and vegetation.

The applicability is not limited to SCIAMACHY. Other instruments designed with similar concepts, as for example GOME-2 (Global Ozone Monitoring Experiment) could benefit from the classification scheme after adapting corresponding thresholds.

The validation of SPICS results was performed against MERIS qualitatively and quantitatively. Qualitatively the comparison was successful but the quantitative analysis showed that the capability of SPICS classifying multiple characteristics (out of three

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groups: clouds, sun glint and surfaces) was not always sufficient to reproduce the rich variability of the measured imager scene. Due to the comparatively low spatial resolution of SCIAMACHY's PMD measurements (7 km×30 km), SPICS has only limited capability to resolve sub-pixel information. If, however, the amount of homogeneity within one SCIAMACHY PMD ground pixel is sufficient (as a rule of thumb: > 80%), SPICS and MERIS classifications are in reasonable agreement. The mismatches of classification results observed could, however, not only be led back to the deficiencies of SCIAMACHY's spatial resolution. For example, MERIS full resolution (FR) imagery showed optically (and geometrically) thin clouds which were classified by SPICS as such but the MERIS classification did not detect clouds at all.

The validation was additionally performed against METAR (a network for the provision of meteorological aviation) data. Here, the agreement at co-located data points was very promising. Forcing even tighter limits decreases the number of co-locations, as expected, but increases the number of classification matches, while the amount of mismatches drops to zero. It is planned to extend the local METAR data set in order to perform the validation on a broader spatial and temporal base and use these results to potentially fine-tune SPICS' thresholds. Another future work step planned is the validation of cloud phase classifications which has to be consolidated using AATSR data.

The validation to show SPICS' capability to separate clouds and snow/ice covered surfaces has been done using MERIS imagery and METAR data. First promising results for Greenland could be shown. However, the study is planned to be extended: more METAR data have to be collected to provide a large data base to ensure a sufficient amount of temporal and spatial coincidences with SPICS. Furthermore, it is planned to test the utilization of cloud fractions derived by SPICS data as sub-pixel information for SCIAMACHY science pixels.

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Table 1. SCIAMACHY PMD channels.

Channel		Range (nm)
1		310–365
2		455–515
3		610–690
4		800–900
5	NIR	1500–1635
6		2280–2400
7	45°	800–900

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Table 2. MERIS channels.

Channel		Width (nm)
1	412.5	10
2	442.5	10
3	490.0	10
4	510.0	10
5	560.0	10
6	620.0	10
7	665.0	10
8	681.3	7.5
9	705.0	10
10	753.8	7.5
11	760.6	3.8
12	775.0	15
13	865.0	20
14	885.0	10
15	900.0	10

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Table 3. Constraints for cloud type assignment.

Parameter	Description	Range				
Clouds						
Ice cloud	Bright white	70	$\leq$	b	$<$	100
		0.0	$\leq$	r	$<$	5.0
		0.050	$\leq$	R_5	$<$	0.100
	White	50	$\leq$	b	$<$	80
		0	$\leq$	r	$<$	10.0
		0.050	$\leq$	R_5	$<$	0.10
	Milk white	30	$\leq$	b	$<$	60
		0.0	$\leq$	r	$<$	20.0
		0.050	$\leq$	R_5	$<$	0.090
	Gray	20	$\leq$	b	$<$	45
		0.0	$\leq$	r	$<$	40.0
		0.050	$\leq$	R_5	$<$	0.090
Water cloud	Bright white	70	$\leq$	b	$<$	100
		0.0	$\leq$	r	$<$	5.0
		0.100	$\leq$	R_5		
	White	50	$\leq$	b	$<$	80
		0	$\leq$	r	$<$	10.0
		0.100	$\leq$	R_5		
	Milk white	30	$\leq$	b	$<$	60
		0.0	$\leq$	r	$<$	20.0
		0.090	$\leq$	R_5		
	Gray	20	$\leq$	b	$<$	45
		0.0	$\leq$	r	$<$	40.0
		0.090	$\leq$	R_5		

Legend:
b brightness, R_i reflectance $\mathrm{PMD_i}$
r rel. range, ρ_{54} radiance ratio I_5/I_4

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Table 4. Constraints for surface type assignment.

Parameter **Surfaces**	Description	Range				
Sun glint				t	<	40
				ρ_{74}	<	2.168
				R_4	<	0.0600
				R_5	<	0.0725
Water				b	<	40
				n	<	1.00
		0.000	≤	R_5	<	0.020
Snow and ice	All except	0.00	≤	ρ_{54}	<	0.20
	Antarctica	0.0015	≤	R_5	<	0.0360
	Only			latc	<	−60
	Antarctica	0.00	≤	ρ_{54}	<	0.40
Vegetation		1.18	≤	n		
Desert		−60	≤	$latc$	<	60
		1.670	≤	ρ_{54}		
		0.000	≤	n	<	1.110
		0.110	≤	R_5	<	0.260
Land		20	≤	b		
		25	≤	r		
		1.200	≤	ρ_{54}		
		0.084	≤	R_5	<	0.185

Legend:
b brightness, R_i reflectance PMD$_i$
r rel. range, ρ_{54} radiance ratio I_5/I_4
n NDVI, ρ_{74} radiance ratio I_7/I_4
t max. ϕ difference, latc/lonc center lat/lon
ϕ relative azimuth

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Table 5. SPICS and MERIS matches and mismatches.

Classification	Matched	mismatched
water	27 801	20 898
land	37 787	9301
cloud	58 488	18 659

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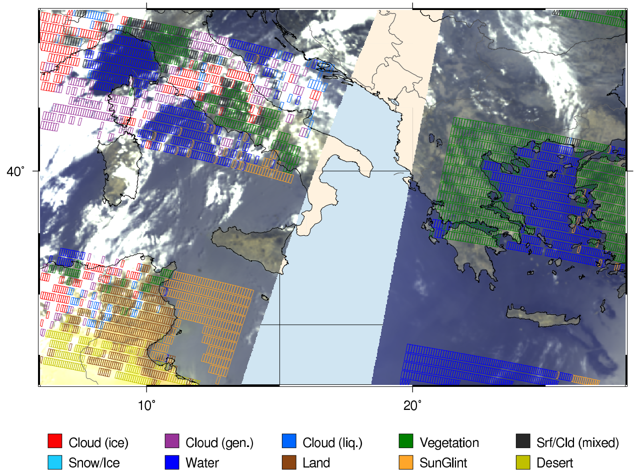

Fig. 1. Classification for the central Mediterranean Sea.

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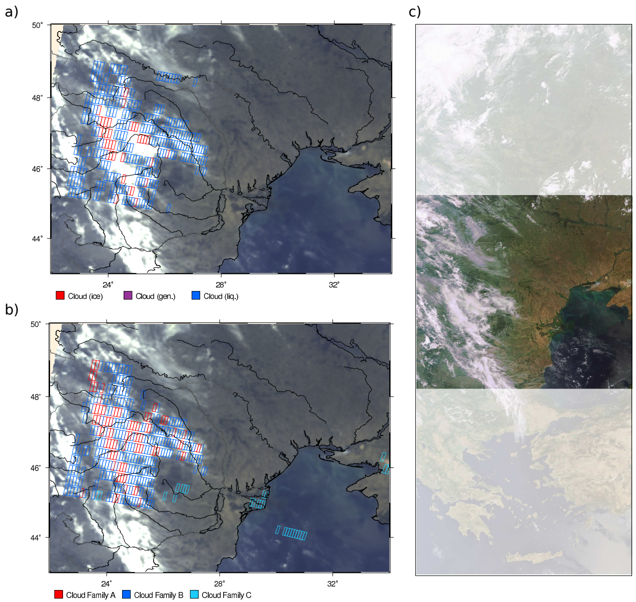

Fig. 2. Cloud classification for Southeast Europe and Black Sea. **(a)** Cloud classifications from SPICS with underlying MERIS true color image with low spatial resolution; **(b)** MERIS results after classifications into three altitude families and gridding (see text); **(c)** MERIS full resolution true color image of the (highlighted) regions of interest.

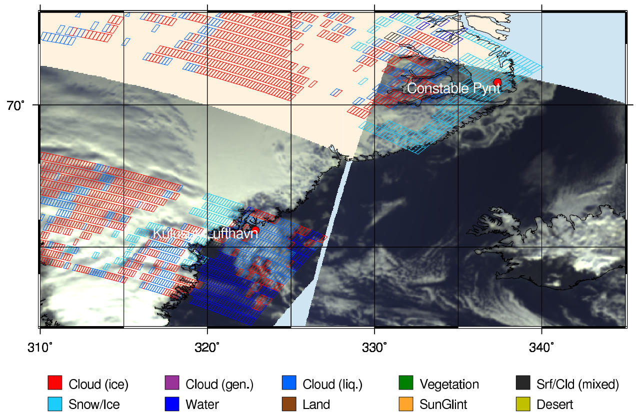

Fig. 3. Classification for Greenland for 16 Oct. 2007 (start time of the SCIAMACHY Orbit 29 423 was 14:10h UTC).