Cloud analysis from METEOSAT data using image segmentation for climate model verification

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Abstract

The satellites of the METEOSAT series have continuously measured the state of the atmosphere as well as the land and sea surfaces over the past 30 years. With the second generation (MSG) in operation and the third generation (MTG) in preparation another 30 years of consistent measurements can be expected. This unique data set is ideal for climate analysis. A pixel based cloud detection algorithm using spectral information from all seven window channels was developed for MSG-SEVIRI. The algorithm is based on the APOLLO cloud detection scheme for AVHRR. The detected clouds were analysed using Object Based Image Analysis (OBIA). With the grouping of neighbouring pixels under consideration of spectral and spatial homogeneity meaningful objects are created. Besides spectral information an object has geometrical, neighbourhood and hierarchical information. The comparison between satellite derived cloud information with model output data is difficult on a pixel basis. The use of objects can be more helpful to detect strengths and weaknesses of the model.

Overview

Little is known of the impact of a global temperature rise on the appearance of clouds that are the most prominent part of the water cycle and can easily be observed from ground and space. Due to their reflectivity of solar radiation and the absorption of terrestrial radiation clouds play an important role in the climate process. The long term cloud analysis is therefore vital to evaluate their impact on the climate change. The observation of clouds from space is the only feasible way of building a continuous and global dataset.

With the commissioning of MSG a high temporal and for climate questions adequate spatial resolution of atmospheric data is available. An automated cloud detection algorithm was developed at the Institute for Meteorology and Climate Research (IMK) (Huckle et al. 2007). The algorithm only uses MSG data and is based on the principals developed for the AVHRR sensor in the APOLLO scheme (Saunders and Kriebel, 1988).

Comparing clouds derived from satellite data with clouds from a climate model on a pixel basis has the disadvantage that only small spatial or temporal differences between the observed and the modelled clouds lead to non agreement between the two data sets (Huckle et al., 2007). Moving away from pixels to segments and objects the spatial shift of modelled clouds can be compensated. Additionally with the
creation of objects these hold more information than a single pixel. Besides the spectral information it has statistical values (e.g. mean, std.), geometrical (e.g. size, length/width), neighbourhood information and relations to smaller and bigger objects (child and parent). With these information an automated cloud analysis and classification is possible.

Object Based Image Analysis


In the past decades automated image analysis with computers was mainly based on pixels. Pixels can hold various information, e.g. measured values from sensors, land use/cover etc. With a single pixel point information is available, but the connection to the surrounding area is limited.

For the past 15 years the advances in automated image analysis have been significant, bringing the software from the labs to commercially available and usable products. Going from pixels to objects is the combination of similar pixels in a meaningful way.

Neighbouring pixels with e.g. similar spectral values are grouped together to form an image segment. Depending on the feature one wants to extract these segments can be small (e.g. a single tree) or bigger (e.g. an entire forest). When creating these segments the spatial and spectral homogeneity is optimised.

Segments still have the same spectral information as pixel, but now with statistical values (mean, std, min, max, median), geometrical attributes (size (area), length/with, curvature, compactness) and – very important - a relation to neighbouring segments. The segmentation of an image on different levels brings a “vertical” connection between smaller and bigger objects. The process of “region merging” connects smaller objects to bigger ones, thereby borders are deleted but no new ones are created.

The analysis of the segment’s properties lets the segment become an object. It can bring further discrimination of objects with a similar spectral characteristic (e.g. cirrus clouds belonging to a thunderstorm or cirrus not connected with a thunderstorm). The “region merging” of the segments implies that every smaller object belongs exactly to one bigger object. In this way a small object containing a tree is merged into a bigger object containing a forest (made up of single trees, clearings, tracks etc.). Once the properties of the objects are known, classes can be formed. Classes contain objects with similar properties. The similarity is defined with fuzzy logic algorithms that are fed with expert knowledge.

For a convective situation this is shown in Figure 1 and Figure 2. On a small segmentation level single clouds are extracted and within bigger ones several segments are created (Figure 1). With a bigger segmentation level small clouds are grouped onto one object including cloud free areas and larger clouds are entirely in one object (Figure 2).
With the creation of meaningful objects an automated image analysis is possible extracting many more features and giving better discriminated results than using only pixel based information.

![Image](image1.png)

**Figure 1:** Segmentation on small level. Single cumuli are extracted, as well different parts of a thunderstorm and segmentation of the cloud free land.

![Image](image2.png)

**Figure 2:** Segmentation on a bigger level. Cumuli are combined to a field of cumuli, the entire thunderstorm is one segment and the cloud free land is not segmented.

The next step from creating objects is to combine them with further information (intelligence). This is currently done by creating rule sets for different applications. For the future this knowledge can be used already in the creation of the objects. Currently the automated detection of condensation trails is very difficult as the Software does not extract thin and long trails, but rather smaller and more compact segments. When importing the knowledge of form and spectral characteristics into the object creation this could be very helpful when looking for specific features.
**Detecting convective Clouds**

Convective clouds were chosen for the first application using objects in analysing and classifying clouds. They have the advantage of being very distinct especially high reaching thunderstorms. For the segmentation process the following MSG channels were used: VIS006, VIS008, NIR016, IR039, IR087, IR108 and IR120. Additionally the pixel based cloud mask was used to identify if an object is cloudy or not.

**Cumulonimbus (Cb)**

The most prominent convective systems are cumulonimbus or thunderstorm systems. They mostly form over hot surfaces or mountainous terrain. There characteristic feature of these high reaching clouds when viewed from space is the high reflectance (only during day) and the very cold cloud top (often below -50°C).

The temperature does not change between day and night, but the reflectance is dependant of the sun elevation. In order to avoid thresholds for every time of the day a maximum of possible reflectance was calculated for every segment. If the measured reflectance was near this value the segment is classed as a Cb.

*Figure 3: Detection of convective systems (red). The criteria cold and bright apply to more than just single cumulonimbus clouds. Clouds in a cold front have the same spectral characteristics.*

These two physical parameters however apply to all high and optically thick clouds (Figure 3). Therefore more criteria are needed to discriminate cumulonimbus clouds. The creation of segments results in geometric features. These can be used for identifying Cb clouds, i.e. image objects. A Cb in general is compact and round or if the anvil has developed, fans out into one direction, with an elliptical form. Using these form parameters many objects in the cold front over Central and Eastern Europe are expelled. To reduce the available objects further down to those representing a single Cb, the difference to the surrounding area is used. In a cold
front all the clouds have a similar temperature. A Cb however develops over a warm ground, therefore the difference between the top of a Cb and the surrounding land is very high. With this criterion most of the objects in the cold front are eliminated and only convective system over the Alpine region and northern Italy remain (Figure 4).

![Figure 4: Detection of convective systems (red). Including geometrical features and the relation to neighbouring objects reduces the objects significantly to the desired type.](image)

The selection criteria above detect the centre of a thunderstorm. Depending on the segmentation level one thunderstorm can be in several segments that form objects like the centre of the Cb, the surrounding of the Cb and the outer limit of the thunderstorm with very thin cirrus clouds. Moving away from the centre of a Cb the temperatures will rise slowly, as these parts of the cloud are slightly lower and when moving out even further the anvil will become thinner and more radiation from the surface will propagate through the cloud thus raising the measured Brightness Temperature (BT). To detect the entire thunderstorm more classes are introduced, containing the above mentioned criteria and additionally the neighbourhood to the centre of a Cb. This means that without a Cb the classes of surrounding clouds will not be activated.

**Thin Cirrus (Ci)**

The detection of thin cirrus is done by taking the difference between the IR108 and the IR120 channel. If the difference is bigger than 2°C thin cirrus is present. Depending on the neighbourhood to the Cb classes defined above this cirrus can belong to a thunderstorm (i.e. bordering to Cb classes) or is not connected with such a system. Although the physical parameters are the same the connection (neighbourhood) to a convective system can assign the thin cirrus to a different class.

**High and Low Cumulus (Cu)**
Convective clouds can have different vertical extents, depending on their stage and the atmospheric conditions. The detection of these cumuli clouds follows similar rules as the identification of the Cb clouds. The cloud top temperature is dependant on the height of the cloud top. The most distinctive criterion to non convective clouds in that temperature range of high or low cumulus clouds is the difference to the neighbouring (cloud free) areas. The size of the objects is also relative small, in comparison to for example low stratus cloud cover.

The Alpine area is completely analysed for convective clouds and thin cirrus, the results are displayed in Figure 5.

![Figure 5: Detection of convective systems. Complete analysis of convective clouds in the Alpine region. Cb-centre (red/pink), Cb-surrounding (orange), Ci-near Cb (light green), Ci not near Cb (light violet), high Cu (purple), low Cu (yellow)](image)

**Validation of regional climate model**

The results from the MSG cloud mask and cloud analysis were compared with the Climate version of the Lokal Modell (CLM) from the Deutscher Wetterdienst (DWD). A pixel based comparison is described in Huckle et al (2007). With the use of object based image analysis a new approach to a validation of model clouds can be done.

The detection and analysis of convective clouds in satellite data is comparably easy and reliable. On the other hand numerical weather and climate models have always been struggling with convective situations. Therefore choosing convective clouds to show the ability of OBIA in validating clouds is favourable.

Comparing MSG clouds and CLM clouds on a pixel basis a small spatial shift can lead to a non agreement between the two datasets, especially in convective
situations (Figure 6). The modelling of clouds at the exact position in space and time is very difficult and especially in a climate context not really necessary. The cloud amount in an area is often more important the modelling every single cumuli. These small differences between the datasets can not be sufficiently depicted on a pixel level.

Moving from pixels to objects the comparison of satellite and model data reveals much new information. With the help of objects on different scales the amount of clouds in the two data sets can be compared more easily. In Figure 7 one segment in Southwest Germany contains convective clouds. The pixel wise agreement is pretty bad, but the total amount of clouds in the MSG and the CLM data is nearly identical. This shows that the modelled clouds match the satellite derived clouds much better than by plainly looking at the pixel values (see Table 1).

Table 1: Amount of clouds in the different data sets (MSG or CLM) in the selected Segment (Figure 7)

<table>
<thead>
<tr>
<th></th>
<th>Number of sub-pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small cumulus clouds</td>
<td>180</td>
</tr>
<tr>
<td>Clouds MSG only</td>
<td>248</td>
</tr>
<tr>
<td>Clouds CLM only</td>
<td>202</td>
</tr>
<tr>
<td>Clouds MSG and CLM</td>
<td>106</td>
</tr>
</tbody>
</table>
Figure 7: Comparison on object basis. In the Object in Southwest Germany the agreement is not very high. But the amount of clouds in the MSG data and the CLM is very similar.

**Conclusions**

The segmentation of images into meaningful objects creates a vast amount of additional information which can be used for analysis. When classifying clouds the discrimination between clouds with a similar spectral characteristic, e.g. single convective clouds and clouds in a cold front, is much easier than on pixel basis. The same cloud type (e.g. thin cirrus) can be classified due to its neighbourhood and form sup-level objects (e.g. cumulonimbus and thin cirrus form a thunderstorm).

The validation of model data is more meaningful when done on object level, as small spatial shifts do not change the result as dramatically.

Further use of the cloud detection is for example possible in the now casting. Automatically identifying developing thunderstorms and tracking of these can be of great benefit.

Moving from pixels to objects provides valuable information for cloud analysis and model validation.

**References**