1 Introduction

It is an accepted fact that changes to the climate could have disastrous consequences for mankind. The earliest possible identification, the prognosis and the estimation of consequences are of enormous importance in order to appropriately react to changes in climate. Even though the anthropogenic influence on regional and global climate has not been doubted for a long time, there is a lack of clear evidence because of too many domains of uncertainty concerning the collected observation and forecast data. *Stott et al.* [2004] showed that with a probability greater than 90% the European heatwave of 2003 was at least partly anthropogenic. Only the adduce of such evidences (e.g. by lessening domains of uncertainty) can exert pressure on governments and lead to the implementation of climate protocols such as the Kyoto protocol.
Clouds are the dominant factor of the radiation budget of the earth atmosphere. On the one hand, they cool the earth by reflection of incoming solar radiation and on the other hand they cause a greenhouse effect by absorbing the thermal radiation emitted by the earth. Referring to *Rossow and Zhang* [1995], in the global annual average clouds cause a net cooling of $5K$ compared to a hypothetical cloud free earth. As mentioned in *Hartmann et al.* [1992] the radiation budget of clouds depends considerably on their type (distinguished by their macro and micro physical properties). High thin clouds tend to have a warming effect, while low clouds have a cooling effect. *Hansen et al.* [1981]

estimated that a reduction of the global cloud coverage of low clouds by only 4% would affect the radiation budget at surface level in the same way as a doubling of atmospheric CO_2 would do. Therefore, minor errors in the cloud mask can already disable it for detecting climate changes. Next to the exact monitoring of cloud coverage, a reliable cloud mask is also required for faultless deriving nearly every following cloud, atmospheric, and surface parameter. In this context, too, minor cloud mask errors can already lead to major misrepresentations of climatologies of the higher products mentioned before.

In August 2002, the geostationary satellite METEOSAT-8 was launched as the first satellite of the MSG (**M**ETEOSAT **s**econd **g**eneration) series. With its successors MSG-2, MSG-3, MSG-4, MTG, etc. (launches planned for 2005, 2009, 2011, and 2015), the long time series since 1977 of meteorological products derived from METEOSAT satellite data will be proceeded and supplemented. The SEVIRI instrument aboard MSG offers excellent conditions for remote sensing surface parameters (e.g. surface classification or sea and land surface temperatures), cloud parameters (e.g. cloud top temperature or cloud phase) and atmospheric parameters (e.g. atmospheric motion vectors or integrated water vapor) on a high temporal resolution. As the majority of SEVIRI channels are located in the thermal infrared spectral region, most meteorological products can be extracted not only at daytime but also at nighttime. Consequently, there are extensive requirements on a universally applicable cloud detection algorithm for SEVIRI data such as: 1) Assignment of high classification confidence levels to the largest possible amount of pixels, considering a certain amount of mixed pixels because of the not negligible pixel size. 2) Usability for conservative cloud free identification as well as conservative cloud covered identification both with adjustable certainty thresholds. 3) Usability for cloud coverage statistics. 4) Usability at daytime and nighttime. 5) Well-known classification quality in order to be able to estimate systematic errors in derived products induced by erroneous cloud masking. Referring to climatological aspects, this is especially important for product statistics and cloud coverage statistics.

Since the beginning of atmospheric remote sensing from satellites, many different cloud detection techniques have been developed. The method development strongly depends on the satellite sensor specifications like spatial, spectral, and temporal resolution. Depending on the sensor properties, clouds can especially be discriminated from cloud free regions due to their spectral features, spatial structures, or characteristics in time series. Computational aspects also have to be considered in algorithm design. In *Rossow* [1989] some cloud detection techniques are reviewed which have been developed before 1989. In this publication the reviewed techniques are divided by (simple) radiance threshold methods, spatial variance methods, temporal variance methods, and methods using an independend dataset to estimate clear sky radiances.

Some cloud detection schemes for environmental satellites in operational use will briefly be introduced in the following:

The ISCCP (**i**nternational **s**atellite **c**loud **c**limatology **p**roject) cloud detection algorithm was developed for the geostationary satellites METEOSAT, GMS, and GOES. As described by *Rossow and Garder* [1993a], it utilizes some static and some dynamic threshold tests for one window channel in the visible and one window channel in the thermal infrared spectral region. Spatial and temporal information is analyzed by variance tests. The dynamic thresholds are calculated by a clear sky temperature and clear sky reflectance estimation method. Their accuracy considerably affects the cloud mask's quality.

The APOLLO (**A**VHRR **p**rocessing scheme **o**ver c**l**ouds, **l**and, and **o**cean) cloud detection algorithm described in *Saunders and Kriebel* [1988], *Kriebel et al.* [2003] has been developed for the AVHRR instrument on the polar orbiting NOAA satellites. It utilizes all five AVHRR channels to discriminate cloudy, partly cloudy, and cloud free pixels. It is based on spatial and spectral static and dynamic threshold tests. The dynamic thresholds are derived from histogram-based scene analyses.

The NASA cloud mask product (MOD06) for the MODIS instrument aboard the polar orbiting satellites TERRA and AQUA is based on the cloud detection algorithm described in the publications of *Ackerman et al.* [1998, 2002]. This algorithm uses 19 of the 36 spectral channels of the MODIS instrument. Hence, its main strategy is the analysis of spectral information. Spatial uniform tests are applied only for those pixels where the spectral tests have given ambiguous results. Some of the spectral tests are similar to the tests of the APOLLO and the ISCCP cloud detection algorithm but others are based on channels which are not available for these cloud detection schemes (e.g. detection of high clouds with observations at $1.38\mu m$ or at $13.94\mu m$). Each test is based on at least two scene dependent static thresholds. The test results represent cloud free confidence levels. All test results are logically combined to the final cloud mask output.

The operational EUMETSAT cloud detection for the SEVIRI instrument aboard MSG is described in *EUMETSAT* [2004a]. It is one result of the EUMETSAT scene analysis (SCE) and is part of the EUMETSAT cloud analysis (CLA) product. The underlying algorithm is based on several static and dynamic threshold tests on the basis of *Saunders and Kriebel* [1988] and *Lutz* [2003]. In addition it utilizes estimated clear sky radiances and clear sky brightness temperatures. Contrary to the temporal-based method introduced in chapter 3, the EUMETSAT clear sky brightness temperatures estimation algorithm is primarily based on a spatial method finding closest clear sky pixels. If this fails, clear sky values are estimated by radiative transfer calculations from forecasted input data.

The cloud detection algorithm developed in the context of the publication at hand takes advantage of SEVIRI's high temporal resolution and its constant viewing geometry by estimating up-to-date diurnal cycles of the brightness temperature at $10.8\mu m$ as well as of the spectral information from the SEVIRI channels at $13.4\mu m$, $12.0\mu m$, $10.8\mu m$, $8.7\mu m$, $3.9\mu m$, $1.6\mu m$, $0.8\mu m$, and $0.6\mu m$. A neural network approach was set up in order to calculate cloud coverage probabilities from different input vector compositions. The calculation of probabilities makes the cloud detection algorithm usable for various applications. Some examples for other cloud detection schemes based on neural network techniques are given in chapter 4. In order to quantify the performance of the developed algorithm, a validation by means of synoptical observations was carried out. The performance of the developed cloud detection scheme was compared to the performance of the operational EUMETSAT cloud detection.

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