Rainfall-Rate Assignment Using MSG SEVIRI Data—A Promising Approach to Spaceborne Rainfall-Rate Retrieval for Midlatitudes

MEIKE KÜHNLEIN,* BORIS THIES, THOMAS NAUß,* AND JÖRG BENDIX

Laboratory for Climatology and Remote Sensing, Faculty of Geography, Philipps-University Marburg, Marburg, Germany

(Manuscript received 14 May 2009, in final form 29 January 2010)

ABSTRACT

The potential of rainfall-rate assignment using Meteosat Second Generation (MSG) Spinning Enhanced Visible and Infrared Instrument (SEVIRI) data is investigated. For this purpose, a new conceptual model for precipitation processes in connection with midlatitude cyclones is developed, based on the assumption that high rainfall rates are linked to a high optical thickness and a large effective particle radius, whereas low rainfall rates are linked to a low optical thickness and a small effective particle radius. Reflection values in the 0.56–0.71-μm (VIS0.6) and 1.5–1.78-μm (NIR1.6) channels, which provide information about the optical thickness and the effective radius, are considered in lieu of the optical and microphysical cloud properties. An analysis of the relationship between VIS0.6 and NIR1.6 reflection and the ground-based rainfall rate revealed a high correlation between the sensor signal and the rainfall rate. Based on these findings, a method for rainfall-rate assignment as a function of VIS0.6 and NIR1.6 reflection is proposed. The validation of the proposed technique showed encouraging results, especially for temporal resolutions of 6 and 12 h. This is a significant improvement compared to existing IR retrievals, which obtain comparable results for monthly resolution. The existing relationship between the VIS0.6 and NIR1.6 reflection values and the ground-based rainfall rate is corroborated with the new conceptual model. The good validation results indicate the high potential for rainfall retrieval in the midlatitudes with the high spatial and temporal resolution provided by MSG SEVIRI.

1. Introduction

Precipitation affects all aspects of human life. However, despite its great importance, the correct spatio-temporal detection and quantification of this key factor of the global water cycle is still associated with large uncertainties. This is mainly due to the high spatial and temporal variability of precipitation distribution. In this context, optical sensors aboard geostationary weather satellites provide information about rainfall distribution in a high spatial and temporal resolution.

The variety of existing satellite-based rainfall retrieval techniques can be categorized by their complexity. Because the identified demand for area-wide precipitation detection in a high spatiotemporal resolution necessary for a quasi-continuous rainfall monitoring in near–real time can only be fulfilled by geostationary satellite systems, the following overview is restricted to optical sensors available on geostationary satellite systems. A comprehensive overview of existing satellite-based rainfall retrieval methods can be found in Stephens and Kummerow (2007), Anagnostou (2004), Levizzani et al. (2001), Levizzani (2003), Scofield and Kuligowski (2003), Kidd (2001), and Kidder and Vonder Haar (1995). An overview of existing retrieval techniques based on passive microwave sensors can be found in Joyce et al. (2004), Weng et al. (2003), Levizzani et al. (2002), Kummerow et al. (2001), Petty (1995), and Wilheit et al. (1994). Regarding explanations of the Tropical Rainfall Measuring Mission (TRMM) precipitation radar (PR), the reader is referred to Iguchi et al. (2000) and Ferreira et al. (2001). The following overview is arranged by the complexity of the algorithms according to Barrett and Martin (1981).

Cloud index methods use thresholds for IR cloud-top temperature to detect rain areas, to which a rainfall rate is assigned. The most popular cloud index method is the Geostationary Operational Environmental Satellite (GOES) precipitation index (GPI; Arkin and Meisner...
1987), which uses a cloud-top temperature of 235 K as a threshold to delineate precipitating clouds. A constant rainfall rate is assigned to these raining pixels. Kerrache and Schmetz (1988) transferred the GPI to Meteosat. Menz and Zock (1997), Ba and Nicholson (1998), and Todd et al. (1999) used the GPI successfully over eastern Africa. The autoestimator technique (Vicente et al. 1998) uses the GOES 10.7-μm band to compute real-time precipitation amounts based on a power-law regression algorithm. Coppola et al. (2006) presented a neural network approach, which combines numerical weather model information with the IR satellite imagery to derive daily rainfall values.

Feature-based methods rely on the assumption that the relationship between the satellite cloud-top brightness temperature and surface rainfall rate is non unique for most pixel-based rainfall estimation algorithms. Wu et al. (1985) proposed a visible (VIS)/IR pattern recognition technique to assign rainfall rates. Hsu et al. (2002) developed a feature-based classification scheme using IR cloud-top temperature. The relationship between cloud-top temperature and rainfall rate is retrieved for the respective classified cloud types.

Bellerby (2004) described a methodology that translates mathematical representations of cloud shapes and textures into precipitation estimates through the use of an artificial neural network. The Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) Cloud Classification System algorithm by Hong et al. (2004) first separates 10.7-μm cloud images into distinctive cloud patches and then extracts different cloud features. Therefore, the cloud patches are clustered into subgroups, which the rainfall rate is assigned to as a function of cloud-top IR temperature.

Bispectral methods are based on the assumption that precipitating clouds have a high VIS reflectivity and a cold IR cloud-top temperature, which is ideally valid for deep convective clouds. A prominent example is the “RAINSAT” algorithm developed by Lovejoy and Austin (1979) and Bellon et al. (1980). Cheng et al. (1993) and Cheng and Brown (1995) transferred the algorithm to Meteosat. Tsonis and Isaac (1985) and Tsonis (1987) used a cluster analysis to identify potentially raining clouds from a two-dimensional VIS/IR histogram. Additionally, O’Sullivan et al. (1990) incorporated the textural structure in a 10 × 10 pixel environment around the respective pixel.

Lensky and Rosenfeld (1997) and Rosenfeld and Lensky (1998) used the 3.7-μm reflectance and the 11-μm brightness temperature to detect rain areas and estimate rainfall rates. Lensky and Rosenfeld (2003a,b) used information about cloud microstructures revealed by the 3.7- and 11-μm brightness temperature difference to detect precipitating clouds.

Yan and Yang (2007) proposed a dual spectral rain algorithm for the Moderate Resolution Imaging Spectroradiometer (MODIS). The 0.65-μm channel, together with the water vapor absorption channel at 1.38 μm, is applied to form multiregression curves for daytime rainfall estimation.

Kurino (1997) used the 11- and 12-μm temperature differences together with the 11- and 6.7-μm temperature differences to derive rainfall probability and mean rainfall rate in comparison with ground-based radar data. Wei et al. (2006) demonstrated a multispectral spatial convolution approach using two infrared channels together with a water vapor channel. The GOES multispectral rainfall algorithm (Ba and Gruber 2001) combines information from five channels for the detection of precipitating cloud areas. The rainfall rate is assigned by the product of rainfall probability and mean rainfall rate, calculated as a function of the 11-μm temperatures.

Life cycle methods consider the temporal variability of convective systems and the involved precipitation processes. Griffith et al. (1978) used the cloud-top temperature difference between two consecutive scenes as a measure for the activity of convective clouds. Negri et al. (1984) classified different life cycles of convective clouds based on a single scene and attained comparable results to Griffith et al. (1978). Amorati et al. (2000) showed that life cycle methods perform well for events with extensive convective systems, but are unsuitable for the detection of stratiform and shallow convective precipitation systems in the midlatitudes.

Cloud model techniques try to explicitly consider the physical processes that clouds undergo. The assigned rainfall rates are based on numerically simulated cloud-top temperatures and the corresponding rainfall rate (Gruber 1973; Wylie 1979). Based on studies of Adler and Mack (1984), Adler and Negri (1988) developed the Convective Stratiform Technique (CST) for subtropical convective systems. The CST has become a widely used and intensively validated technique. While it can be applied successfully in the subtropics and tropics (Bendix 1997, 2000), it shows deficiencies in nontropical regions (Pompei et al. 1995; Levizzani et al. 1990; Negri and Adler 1993). For this reason, Reudenbach (2003) developed the Enhanced Convective Stratiform Technique (ECST) for convective systems in the midlatitudes. By additionally considering the water vapor channel they achieved a more reliable differentiation between convective cores and nonraining cirrus clouds.

Despite the variety of existing satellite-based rainfall retrieval techniques, most retrieval schemes developed
for Geostationary Earth Orbit (GEO) systems rely on a relationship between IR cloud-top temperature, rainfall probability, and rainfall rate (e.g., Adler and Negri 1988). Such IR retrievals are appropriate for convective clouds that can easily be identified by their cold cloud-top temperature in the IR channel (e.g., Levizzani et al. 2001; Levizzani 2003), but show considerable drawbacks concerning the detection and quantification of rain from stratiform clouds in connection with extratropical cyclones (e.g., Ebert et al. 2007; Früh et al. 2007). Such precipitating clouds are characterized by relatively warm and spatially homogeneous cloud-top temperatures that differ insignificantly from raining to nonraining regions. Therefore, retrieval techniques based solely on IR cloud-top temperature lead to an underestimation of the detected rain area and to uncertainties concerning the assigned rainfall rate (e.g., Ebert et al. 2007).

To overcome these drawbacks, several authors suggest using optical and microphysical cloud parameters derived from multispectral data of new generation satellite systems to improve rainfall retrievals (e.g., Lensky and Rosenfeld 2003a,b; Ba and Gruber 2001; Nauss and Kokhanovsky 2006, 2007; Thies et al. 2008a,b). They could show that cloud areas with a high optical thickness and a large effective particle radius possess a high amount of cloud water and are characterized by a higher rainfall probability than cloud areas with a low optical thickness and a small effective particle radius.

Recently, Thies et al. (2008c) showed the possibility of separating areas of differing precipitation processes and rainfall intensities within rain areas by using cloud properties retrieved with the Meteosat Second Generation (MSG) Spinning Enhanced Visible and Infrared Instrument (SEVIRI). The day and night techniques for precipitation process separation and rainfall-rate differentiation rely on information about cloud-top height, cloud water path, and the cloud phase in the higher parts. Rainfall-rate differentiation takes place by using pixel-based confidences for each subarea, calculated as a function of the respective value combinations of the above mentioned variables. To calculate the confidences, the value combinations are compared with ground-based radar data. The proposed technique was validated against ground-based confidences for each subarea, calculated as a function of the respective value combinations of the above mentioned variables. To calculate the confidences, the value combinations are compared with ground-based radar data. The proposed technique was validated against ground-based confidences for each subarea, calculated as a function of the respective value combinations of the above mentioned variables. To calculate the confidences, the value combinations are compared with ground-based radar data.

Based on the enhanced information content on cloud properties provided in high spatial and temporal resolution by MSG SEVIRI and on the encouraging results concerning rain area delineation and rainfall-rate differentiation, the objective of the present study is to investigate the potential of MSG SEVIRI for improved rainfall-rate assignment based on reflection values in the 0.56–0.71-µm (VIS0.6) and 1.5–1.78-µm (NIR1.6) channels, which provide information on optical thickness and effective particle radius.

As mentioned in the above described retrieval techniques, this investigation is based on the conceptual model that raining cloud areas with a high optical thickness (high VIS0.6 reflectivity) and a large effective particle radius (low NIR1.6 reflectivity) are characterized by higher rainfall rates compared to cloud areas with a low optical thickness (low VIS0.6 reflectivity) and a small effective particle radius (high NIR1.6 reflectivity) (cf. Thies et al. 2008c).

Until now, only a few studies have investigated the potential of using cloud microphysical and optical properties to estimate rainfall rates (e.g., Thies et al. 2008c; Roebeling and Holleman 2009). In this context, this study presents a new approach to assign rainfall rates based on visible and near-infrared reflectances.

Over the past decades, various algorithms have been developed to retrieve optical thickness and effective radius (Nakajima and King 1990; Nakajima and Nakajima 1995; Kawamoto et al. 2001; Han et al. 1994; Liou and Wittman 1979; Arking and Childs 1985; Strabala et al. 1994; Platnick et al. 2003; Kokhanovsky et al. 2003; Kokhanovsky and Nauss 2005). Most of the retrieval techniques have been developed for optical sensors aboard polar-orbiting satellites (e.g., King et al. 1997; Platnick et al. 2003). At present, only a few techniques are available for geostationary satellite systems (e.g., Han et al. 1994; Feijt et al. 2004; Roebeling et al. 2006). The results presented by Roebeling et al. (2008) confirmed that optical thickness and effective radius can be retrieved with high accuracy from SEVIRI. Unfortunately, the retrieval algorithms are either not yet available to the public or have to be adapted to existing processing chains. However, most of the mentioned algorithms are computationally time expensive and processing normally exceeds the image repetition rate of SEVIRI (15 min). Because of the inherent information on microphysical and optical properties in the solar SEVIRI bands, the presented method, with its fast computation time, is most appropriate for operational applications. For this reason, the authors decided to use reflection values in the 0.56–0.71-µm (VIS0.6) and 1.5–1.78-µm (NIR1.6) channels instead of retrieved cloud properties for applying a statistical approach of rainfall-rate assignment for the
presented investigation study, to enable the investigation of the potential to assign rainfall rate as a function of optical and microphysical cloud properties. As discussed above, VIS$_{0.6}$ reflectances are closely related to cloud optical thickness, whereas NIR$_{1.6}$ reflectances are related to cloud particle size. However, these relationships are nonlinear. Therefore, an empirical relationship is developed between VIS$_{0.6}$, NIR$_{1.6}$ reflectances, and rainfall rate. If an appropriate retrieval technique is made available, the proposed algorithm can be readily applied to the retrieved cloud properties.

Since existing retrieval techniques account for the solar zenith angle, the satellite zenith angle, and the relative azimuth angle, the effect of differing viewing and illumination geometries is eliminated in the retrieved cloud properties. These effects of differing viewing and illumination geometries are not considered in the presented approach. Concerning potential uncertainties introduced by neglecting the impact of varying viewing geometries, higher satellite zenith angles would result in a longer path distance for the radiation in the atmosphere. Thus the extinction of the radiation should be stronger for a higher satellite zenith angle. Therefore, if a lookup table (LUT) with a rainfall rate as a function of the VIS and NIR reflectance calculated for a lower satellite zenith angle is applied to a region with a significantly higher satellite zenith angle, the assigned rainfall rate will most likely be underestimated.

To enable the analysis of the potential of rainfall-rate assignment based on VIS$_{0.6}$ and NIR$_{1.6}$ reflectances, the effect of varying viewing geometries should be minimized to the greatest extent possible. To this end, a small study area was chosen (see section 2). It is expected that the mentioned effects on the empirical function and the retrieval results can be neglected within the study area.

The structure of the article is as follows: in section 2, the data and methods used for comparing the satellite data with the ground-based rainfall measurements are introduced. In section 3, the relationship between both datasets is analyzed. Based on that, a lookup table approach for SEVIRI rainfall-rate assignment is introduced in section 4. Afterward, the validation of the retrieval scheme is presented. Sections 5 and 6 give a summary and some conclusions.

2. Data and methods

a. Study area

The north German plain was chosen as the study area, because this region is dominated by frontally induced precipitation processes in connection with extratropical cyclones. At the same time, precipitation processes are only marginally modified by the low orography. For these reasons, this region represents an adequate study area for analyzing the relationship between satellite-based cloud properties and ground-based rainfall rates without potential modifications by external parameters (e.g., orography).

b. Study period

The dataset used for this study is divided into two parts. The first part, encompassing the period between 24 July and 31 August 2006, is used to calibrate the relationship between visible and near-infrared cloud reflectances and the rainfall rate. The second part, encompassing the periods between 16 and 31 May 2006 and between 19 and 26 October 2005, are used for the validation of the rainfall-rate retrievals.

1) Weather in the calibration period: 24 July–31 August 2006

The time period between 24 July and 31 August 2006 was dominated by the passage of several cyclones. In the first week, the cold front of cyclone Wally, accompanied by several thunderstorms with higher rainfall intensities, slowly passed the investigation area.

Afterward, the large-scale weather situation over the Atlantic Ocean changed. As a result, the cold front of North Atlantic Cyclone Xavier crossed Germany with high rainfall rates. On 10 August 2006 the occluded frontal system of Cyclone Bärbel passed over Germany, resulting in unsteady weather conditions with thunderstorms and high precipitation rates. In the following week, Cyclone Carmen, accompanied by widespread rain areas, dominated the northern part of Germany. Afterward, the southwestern currents of Cyclone Dörthe transported warm air masses over Germany. A height trough over western Europe caused the warm air masses to rise, leading to strong shower activities. In the last week, the investigation area was dominated by Cyclone Florence (Berliner Wetterkarte 2006).

2) Weather in the first validation period: 19–26 October 2005

Between 19 and 26 October 2005, the study area was dominated by Atlantic cyclones. The highest rainfall rates occurred with the Cyclone Heido, which passed Germany between 24 and 25 October (Berliner Wetterkarte 2005).


The period between 16 and 31 May was characterized by Atlantic frontal systems passing central Europe
moving east. The study area was dominated by cold fronts, together with postfrontal rain showers and thunderstorms (Berliner Wetterkarte 2006).

c. Methods

1) MSG SEVIRI

SEVIRI scans the full disk every 15 min and provides a nominal spatial resolution of 3 km × 3 km at sub-satellite point. The MSG SEVIRI data required for this study were received at the Marburg Satellite Station (Reudenbach et al. 2004; Bendix et al. 2003). The raw data were preprocessed by the FMet tool (Cermak et al. 2008).

According to the conceptual model introduced in section 1, raining cloud areas with a high optical thickness (high VIS0.6 reflectivity) and a large effective particle radius (low NIR1.6 reflectivity) are characterized by higher rainfall rates compared to cloud areas with a lower optical thickness (low VIS0.6 reflectivity) and a smaller effective particle radius (high NIR1.6 reflectivity). The optical thickness and the effective particle radius can be retrieved by using a combination of a nonabsorbing channel in the visible spectrum and a slightly absorbing channel in the near-infrared spectrum (e.g., Nakajima and Nakajima 1995; Kawamoto et al. 2001). However, because no operational technique for the explicit retrieval of \( \tau \) and \( a_e \) for water and ice clouds for MSG SEVIRI is currently available to the public, the authors decided to use the original reflectance of the 0.56–0.71-\( \mu \)m (VIS0.6) and 1.5–1.78-\( \mu \)m (NIR1.6) SEVIRI channels, inherently encompassing this information (see section 1).

2) RAIN GAUGES

Altogether, 15 stations of the German Weather Service (DWD) with a temporal resolution of 10 min are available and distributed over the entire investigation area (see Fig. 1; Table 1). The precipitation is automatically measured at each station using the weighting principle. The weight of the collecting vessel is measured every minute and the precipitation amount is calculated from the weight increase. The original data are stored as 10-min sums and are quality controlled afterward by the German Weather Service (Deutscher Wetterdienst 2001).

d. Validation procedure

The different spatial and temporal characteristics of the satellite data (area-wide raster data, snapshot-like information every 15 min) and the rain gauge data (point measurements, continuously over 10 min) implies uncertainties concerning the comparison of both datasets. The spatial and temporal offsets caused by their differing measurement characteristics must be compensated to investigate a potential relationship between both datasets (Ha and North 1999; Ha et al. 2002). The different aspects of potential spatial and temporal offsets are discussed in the following section, together with possible solutions to remedy the inherent uncertainties.
The overall assumption required for a comparison of both datasets is that the rainfall rate measured at the station is representative for the whole satellite pixel within which the station is located. A potential spatial offset between both datasets is mainly due to the fact that the satellite data are area-wide raster data and the rain gauge data are obtained by point measurements. Hydrometeors falling inside or outside the cloud can be drifted horizontally by the wind in and below the cloud. Thus, the satellite measurements of the cloud top do not necessarily coincide with the measurement on the ground within the respective pixel. Thus the rainfall rate on the ground that corresponds to the satellite signal might be measured in an adjacent pixel as a result of wind drift. For example, for heavy rain with a falling velocity of 10 m s\(^{-1}\) and a horizontal wind velocity between 5 and 30 m s\(^{-2}\), a hydrometeor falling out of a cloud in a height of 3 km can be drifted between 1.5 and 90 km before reaching the ground (Roe 2005). Further potential spatial offsets are due to the parallax dislocation. This displacement between the geographical position of the cloud top and the corresponding sea level coordinates increases with increasing satellite zenith angle and increasing cloud-top height (cf. Vicente et al. 2002).

To minimize the potential spatial offset between the satellite signal in a pixel and the respective rainfall rate measured on the ground, the surrounding 3 \times 3 pixels of the station pixels (satellite pixels within which a rain gauge station is located) are incorporated.

Since the purpose of the present study was to explicitly evaluate the potential of an improved rainfall-rate assignment based on optical and microphysical cloud properties, only precipitating gauge data are considered. Optical rainfall retrievals consist of two parts: one part for the identification of precipitating cloud areas and one part for the assignment of the rainfall rates. Techniques for rain area identification relying on information about cloud properties have already been developed (e.g., Thies et al. 2008a,b). Based on the improved rain area delineation, the second step is the assignment of the associated rainfall rate. Only precipitating gauge data are considered in the study, to develop and evaluate a technique for rainfall-rate assignment independent of uncertainties due to a satellite-based rain area delineation scheme.

To assure that only cloudy pixels within the 3 \times 3 pixel environment are incorporated, the cloud mask developed by Cermak and Bendix (2008) is applied. To ensure sufficient solar illumination in the VIS\(_{0.6}\) and NIR\(_{1.6}\) channels, only pixels with a corresponding solar zenith angle lesser than 70° have been considered. Furthermore, the VIS\(_{0.6}\) and NIR\(_{1.6}\) reflectance values were normalized by dividing the values by the cosine of the solar zenith angle to account for varying illumination effects.

The spatial aggregation method to retrieve single VIS\(_{0.6}\) and NIR\(_{1.6}\) values out of the 3 \times 3 pixel environment that can be compared with the station measurement is explained in the following. The method aims to extract the most effective signal in each channel with respect to the rainfall rate. This means that the highest reflection values in the VIS\(_{0.6}\) channel (representing high \(\tau\) and, thus, a thick cloud), together with the lowest reflection values in the NIR\(_{1.6}\) channel (representing high \(a_{\text{ef}}\), large particles), should be extracted.

For \(n \approx 2\) (\(n\) stands for the number of cloudy pixels in the 3 \times 3 pixel environment), reflection values of maximum and minimum are defined as

\[
\text{Maximum} = \max_{i=1,n}(x_i),
\]

(1)

where \(x_i\) represents the reflection values in the VIS\(_{0.6}\) channel, and

\[
\text{Minimum} = \min_{i=1,n}(y_i),
\]

(2)

where \(y_i\) represents the reflection values in the NIR\(_{1.6}\) channel.

The retrieved maximum VIS\(_{0.6}\) and minimum NIR\(_{1.6}\) values might not occur in the same pixel of the 3 \times 3 environment. In that case, the value combination with the highest difference between the spectral signal in the VIS\(_{0.6}\) and the NIR\(_{1.6}\) channels is chosen.

The maximal difference is given by

1) SPATIAL OFFSET

The table below provides a list of precipitation measurement stations in the north German plain.

<table>
<thead>
<tr>
<th>Station no.</th>
<th>Station name</th>
<th>Height (MSL. mm)</th>
<th>Lon</th>
<th>Lat</th>
</tr>
</thead>
<tbody>
<tr>
<td>01178</td>
<td>Bocholt-Liedern</td>
<td>21</td>
<td>51°50’N</td>
<td>06°32’E</td>
</tr>
<tr>
<td>01350</td>
<td>Werl</td>
<td>85</td>
<td>51°35’N</td>
<td>07°53’E</td>
</tr>
<tr>
<td>01151</td>
<td>Greven</td>
<td>48</td>
<td>52°08’N</td>
<td>07°42’E</td>
</tr>
<tr>
<td>01132</td>
<td>Lingen</td>
<td>22</td>
<td>52°31’N</td>
<td>07°18’E</td>
</tr>
<tr>
<td>01519</td>
<td>Diepholz</td>
<td>39</td>
<td>52°35’N</td>
<td>08°21’E</td>
</tr>
<tr>
<td>01538</td>
<td>Hannover-Langenhagen</td>
<td>55</td>
<td>52°28’N</td>
<td>09°41’E</td>
</tr>
<tr>
<td>03916</td>
<td>Braunschweig</td>
<td>81</td>
<td>52°18’N</td>
<td>10°27’E</td>
</tr>
<tr>
<td>03350</td>
<td>Wiesenburg</td>
<td>187</td>
<td>52°07’N</td>
<td>12°28’E</td>
</tr>
<tr>
<td>03342</td>
<td>Potsdam</td>
<td>81</td>
<td>52°23’N</td>
<td>13°04’E</td>
</tr>
<tr>
<td>03349</td>
<td>Baruth</td>
<td>55</td>
<td>52°04’N</td>
<td>13°30’E</td>
</tr>
<tr>
<td>03360</td>
<td>Doberlug-Kirchhain</td>
<td>97</td>
<td>51°39’N</td>
<td>13°35’E</td>
</tr>
<tr>
<td>03346</td>
<td>Linden berg</td>
<td>98</td>
<td>52°13’N</td>
<td>14°07’E</td>
</tr>
<tr>
<td>03334</td>
<td>Manschnow</td>
<td>12</td>
<td>52°33’N</td>
<td>14°33’E</td>
</tr>
<tr>
<td>03358</td>
<td>Cottbus</td>
<td>69</td>
<td>51°47’N</td>
<td>14°19’E</td>
</tr>
<tr>
<td>03308</td>
<td>Berlin-Schönefeld</td>
<td>45</td>
<td>52°23’N</td>
<td>13°32’E</td>
</tr>
</tbody>
</table>

TABLE 1. Precipitation measurement stations in the north German plain.
MaxDiff = \max_{i=1,n} (x_i - y_i). \quad (3)

The described maximum–minimum method (hereinafter the max–min method) is based on the theoretical assumption that by identifying the pixel with the maximum VIS\(_0.6\) reflectance, the pixel with the highest optical thickness is detected. The same is true for the NIR\(_1.6\) reflectance. By identifying the minimum reflectance value, the pixel with the greatest effective particle radius is detected. Hence, by applying the described max–min method, the pixels with the most effective precipitation signal, that is, clouds with the greatest vertical extension (maximum VIS\(_0.6\) reflection) and the largest particles (minimum NIR\(_1.6\) reflection) compared to the surrounding pixels, are extracted.

2) TEMPORAL OFFSET

Regarding the temporal aspect of both datasets, the satellite data represent a snapshot-like measurement taken every 15 min, while the rain gauge data represent a continuously measured quantity, averaged over a 10-min interval. Thus, for a comparison of both datasets, it has to be assumed that the signal in the satellite channels is representative for the preceding 15 min. Based on this assumption, the satellite data are compared to the continuous rain gauge measurements during the respective time period. This assumption implies some uncertainties, since the time that a hydrometeor falling from a cloud needs to reach the ground can vary depending on cloud height, the type and size of the hydrometeor, and the horizontal and vertical wind velocity. Thus, depending on the environmental conditions, temporal offsets of various dimensions can occur between the measured satellite signal and the ground-based rainfall measurement. To minimize these uncertainties caused by the potential temporal offset, both datasets are aggregated in time.

For the temporal aggregation of the satellite data, the mode of the maximum VIS\(_0.6\) and minimum NIR\(_1.6\) reflection value is calculated using the four 15-min scenes available every hour. The calculation relies on the maximum VIS\(_0.6\) and minimum NIR\(_1.6\) reflection values extracted for every 15-min scene during the spatial aggregation method. If multiple mode values occur, the mean mode is calculated.

By applying the mode calculation, it is assured that the temporally most frequent maximum (VIS\(_0.6\)) and minimum (NIR\(_1.6\)) reflection values, and thereby the temporally most significant precipitation signals, are extracted.

For the temporal aggregation of the rain gauge data, the measured rainfall rates are summed up for a 1-h interval. Apart from the quality check performed by the German Weather Service, no additional correction (e.g., consideration of differences in wind speed) is applied.

Based on the spatially and temporally aggregated satellite data and the temporally aggregated station data, a dataset of VIS\(_0.6\) and NIR\(_1.6\) reflection data pairs with a corresponding rainfall rate is extracted. This dataset is used for analyzing the relationship between the satellite signal in both channels and the ground-based precipitation measurements presented in the next section.

3. Analysis of the relationship between satellite signal and rainfall rate

For the analysis of the relationship between the satellite signal and the ground-based rainfall rate, the temporally aggregated rainfall rate was compared with the spatially and temporally aggregated satellite data for the calibration period between 24 July and 31 August 2006 [see section 2b(1)].

Figure 2 shows a scatterplot of the rainfall rate as a function of the VIS\(_0.6\) and NIR\(_1.6\) reflection values based on the calibration period. The ground-based rainfall rate was temporally aggregated and the satellite data were spatially and temporally aggregated [see sections 2d(1) and 2d(2)].
related to precipitation. No precipitation is registered for value combinations lying above a line with a slope of one. For these areas, the cloud reflectivities are too low at VIS0.6, which indicates low optical thickness, and too high at NIR1.6, which indicates small effective particle radius. On the other hand, precipitation occurs for value combinations of high VIS0.6 reflectivity (high τ) and low NIR1.6 reflectivity (large aef). This corroborates with the aforementioned conceptual model that precipitating cloud areas are characterized by a combination of a sufficiently high τ together with a large aef. With decreasing VIS0.6 reflectivity, the NIR1.6 reflectivity also decreases for raining cloud areas. On the other hand, if the VIS0.6 reflectivity increases, the NIR1.6 reflectivity can also increase, still ensuring a sufficient combination of a high τ and a large aef.

If the respective rainfall rates are observed in more detail, it becomes obvious that low rainfall rates (below 1.6 mm h⁻¹) are scattered over the whole range of value combinations of VIS0.6 and NIR1.6 reflectivity. There is no concentration of lower VIS0.6 together with higher NIR1.6 reflectivity, as the conceptual model might have suggested. On the other hand, for rainfall rates greater than 1.6 mm h⁻¹, such a differentiation is visible. Especially higher rainfall rates of more than 4 mm h⁻¹ are connected with sufficient combinations of high VIS0.6 and low NIR1.6 reflectivity. This relationship between VIS0.6 and NIR1.6 reflectivity and the corresponding rainfall rate is indicated by the alignment of the symbols in the lower part of Fig. 2.

For a more detailed analysis of the relationship between the VIS0.6 and NIR1.6 reflectivity and the rainfall rate, Fig. 3 shows the same scatterplot as Fig. 2, but with separated diagrams for lower rainfall rates (below 1.6 mm h⁻¹; Fig. 3a) and higher rainfall rates (above 1.6 mm h⁻¹; Fig. 3b). For the lower rainfall rates (0.3–1.5 mm h⁻¹) there is only a slight tendency toward higher concentrations in the lower right part of the diagram (high VIS0.6 and low NIR1.6 reflectivity), where the value combination of VIS0.6 and NIR1.6 reflectivity indicates a higher τ and a larger aef.

Figure 3b shows the results for rainfall rates above 1.6 mm h⁻¹ as a function of the VIS0.6 and NIR1.6 reflectivity. It becomes obvious that higher rainfall rates (especially higher than 4.0 mm h⁻¹) are connected to a sufficiently high combination of high VIS0.6 and low NIR1.6 reflectivity. Again, this corroborates the introduced conceptual model that raining cloud areas with higher rainfall rates are characterized by a higher τ (high VIS0.6 reflectivity) and a larger aef (low NIR1.6 reflectivity).

The high scattering observable for lower rainfall rates might be due to the aforementioned difficulty that occurs in comparisons between continuous point measurements (rain gauge) and area-wide snapshot measurements (satellite). The described aggregation methods are perhaps not sufficient to fully compensate for these inherent problems. The wide horizontal drift caused by the wind field within and below the cloud might exert a stronger influence on the slower falling precipitation particles of light rainfall rates. Therefore, it is possible that hydrometeors are drifted out of the 3 × 3 pixel environment around a station pixel or other hydrometeors are drifted into the 3 × 3 pixel environment from outside. In the case of overlapping, noncontiguous cloud layers, the satellite detects the signal of the higher cloud layer, which has no relationship to the precipitation falling.
from the lower cloud layer and the measured rainfall rate on the ground (Lensky and Rosenfeld 1997). However, this only holds true for optically thick cloudlayers. Depending on the optical depth of the cloud-top layer, the cloud layer underneath the top layer might be observed as well. According to Platnick (2001), the radiation in the 1.6-$\mu$m channel penetrates up to 15 optical depths into the clouds, and the radiation in the 0.6-$\mu$m channel penetrates up to 100 optical depths into the clouds. Therefore, in cases of optically thin cloud-top layers, the majority of the observed signal originates from the cloud layer underneath. Furthermore, the high scatter observed in Figs. 2 and 3 might also be due to differing illumination and viewing conditions. Depending on the solar zenith angle, clouds with a high optical thickness can have different VIS$_{0.6}$ reflectances, depending on the viewing conditions. For example, for a solar zenith angle of 70°, a VIS$_{0.6}$ reflectance of 0.6 corresponds to an optical thickness of about 8, while for a solar zenith angle of 40°, the same VIS$_{0.6}$ reflectance corresponds to an optical thickness of about 20.

Moreover, there are also errors concerning the rainfall measurement on the ground with rain gauges that have to be mentioned in this context. A strong wind component often leads to an underestimation of the current rainfall rate, especially for lower rainfall rates (Reiss et al. 1992; Frei and Schär 1998).

To summarize, it can be stated that despite the high scattering for the lower rainfall rates, which hampers a clear differentiation of the rainfall rates by means of the reflectivity values, the alignment of the grouped precipitation classes as a function of the reflectivity values indicates a relationship between the rainfall rate and the satellite signal. This relationship becomes more distinct at higher rainfall rates.

4. Deduction of the rainfall-rate retrieval scheme and its validation

a. Description of the proposed rainfall-rate assignment technique

To verify the reliability of the stated relationship between the rainfall rate and the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity values in terms of a potential satellite-based rainfall-rate assignment technique, the average rainfall rate is calculated as a function of the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity values. The calculation is based on the dataset from the calibration period [24 July–31 August 2006; see section 2d(1)].

Equation (4) shows the calculation of the average rainfall rate ($R_{\text{Mean}}$) as a function of the two reflectivity values,

$$R_{\text{Mean}}(\text{VIS}_{\text{LUT}}, \text{NIR}_{\text{LUT}}) = \frac{\sum R_{\text{Obs}}(\text{VIS}_{\text{Sat}}, \text{NIR}_{\text{Sat}})}{N_r(\text{VIS}_{\text{Sat}}, \text{NIR}_{\text{Sat}})},$$

where VIS$_{0.6}$ and NIR$_{1.6}$ are the two reflectivity values, $R_{\text{Obs}}$ is the observed ground rainfall rate, and $N_r$ is the total of raining pixels as indicated by ground observations.

Based on these calculations, an LUT is compiled with the average rainfall rate as a function of the respective VIS$_{0.6}$–NIR$_{1.6}$ reflectivity value combination. By using this lookup table, it is possible to assign the rainfall rate solely based on the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity values. Figure 4 gives an overview of the calculation of the average rainfall rate as a function of both reflectivity values, the compilation of the lookup table, and the rainfall-rate assignment based on this lookup table. The surrounding 3 x 3 pixels of the station pixels (satellite pixels that a rain gauge station is located in) are incorporated to minimize potential spatial offsets between the satellite signal in a pixel and the respective rainfall rate measured on the ground [see section 2d(1)]. The satellite data are spatially aggregated by using the max–min method [see section 2d(1)]. In the next step, the satellite data are temporally aggregated by using the mode method [see section 2d(2)]. The station data are only temporally aggregated [“Temporal aggregation” in Fig. 4; see section 2d(2)].

Based on the aggregation steps, the synchronized data pairs of ground-based rainfall rate and satellite-based VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity values are extracted. These data pairs are used to calculate the mean rainfall rate as a function of VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity with Eq. (4), and eventually compose the lookup table.

The rainfall-rate assignment is realized by using the compiled lookup table. For this purpose, the respective satellite scenes, which are independent from the dataset used for the calculation of the lookup table, are first spatially and temporally aggregated as described in sections 2d(1) and 2d(2). These steps are depicted by the three lower boxes in Fig. 4. Based on the respective VIS$_{0.6}$–NIR$_{1.6}$ value combination, the rainfall rate is assigned to each cloudy pixel [see section 2c(1)] by means of the lookup table.

The lookup table calculated by using the dataset from the calibration period is depicted graphically in Fig. 5. The mean rainfall rate is displayed with color shades as a function of the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity. The calculated lookup table also shows a relationship between the ground-based rainfall rate and the satellite-based VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity. The stated relationship between the ground-based rainfall rate and the VIS$_{0.6}$–NIR$_{1.6}$ reflectivity values is even more distinct in Fig. 5 when
compared with Fig. 3. Higher rainfall rates clearly coincide with high VIS0.6 reflectivity (high $\tau$) and low NIR1.6 reflectivity (large $a_{sl}$). The discrepancy between the highest rainfall rates in Figs. 3 and 5 is due to the averaging of the rainfall rates in the LUT calculation.

**b. Validation of the proposed rainfall-rate assignment technique**

In the final step, the above stated relationship between the rainfall rate and the satellite sensor signal is validated based on the calculated LUT. For that purpose, the rainfall rate is assigned by using the described LUT approach. The assigned rainfall rate is then validated against the rainfall rate measured on the ground. The validation is performed for two validation datasets, which are independent of the dataset used to calculate the LUT.

First, the results for the first validation period are presented. Afterward, the analysis for the second validation period is discussed. Finally, the results for both datasets are combined and summarized.

1) **First validation period between 16 and 31 May 2006**

Figure 6 shows a scatterplot of RR_{Obs} and RR_{Sat} to provide a visual analysis of the relationship between the ground-based rainfall rate (RR_{Obs}) and the assigned rainfall rates as a function of the VIS0.6 and NIR1.6 reflectivity by means of the calculated LUT (RR_{Sat}). The rainfall rates have been aggregated for 1-, 3-, 6-, and 12-h intervals. The 12-h interval represents the continuous time period of 1 day, which was available during May because of the sufficiently high solar altitude. By extracting the precipitating gauge data and performing the spatial and temporal aggregation methods on the dataset (see section 2d), a total of 476 pairs of RR_{Obs} and RR_{Sat} are made available on an hourly basis. Figure 7 shows the corresponding residuals for the four different aggregation intervals. The calculated statistical indices can be seen in Table 2.

The missing relationship between RR_{Obs} and RR_{Sat}, indicated by the low correlation coefficient and by the scatterplot for the 1-h interval, is due to the averaging effect inherent in the calculation of the mean rainfall rate as a function of the two reflectivity values (VIS0.6, NIR1.6) for the LUT. The satellite and the station data are temporally aggregated to 1 h. By calculating the mean rainfall rate, high rainfall intensities corresponding
to high VIS\textsubscript{0.6} and low NIR\textsubscript{1.6} reflectivity are reduced by lower rainfall intensities that occur for the same value combination of high VIS\textsubscript{0.6} and low NIR\textsubscript{1.6} reflectivity. As a result, high rainfall rates are not included in the rainfall-rate assignment on an hourly basis. The same holds true for very low rainfall rates, which correspond to low VIS\textsubscript{0.6} and high NIR\textsubscript{1.6} values. The few slightly higher rainfall rates occurring for the same VIS\textsubscript{0.6} and NIR\textsubscript{1.6} value combination lead to a higher mean rainfall rate in the LUT. Thus, the averaging reduces the very high rainfall intensities and increases the very small rainfall intensities, which leads to an underestimation of the high rainfall rates and an overestimation of the low rainfall rates in the LUT-based scheme. As a result of the averaging process, it is impossible to reproduce the observed rainfall rate by the assigned rainfall rate for a 1-h time interval in sufficient detail.

As can be seen in Fig. 6, the relationship between RR\textsubscript{Obs} and RR\textsubscript{Sat} increases for a temporal resolution of 3 h. This is further indicated by the correlation coefficient. It becomes obvious that the higher rainfall rates especially (>6 mm h\textsuperscript{-1}) are not correctly assigned by the LUT-based method (Figs. 6, 7).

With increasing temporal aggregation, the relationship between RR\textsubscript{Obs} and RR\textsubscript{Sat} increases too. This can be seen in the scatterplots and statistics for the 6- and 12-h intervals. The correlation coefficient rises to 0.61 for the 6-h interval and to 0.75 for the 12-h interval. The bias is positive for all time intervals and ranges between 0.21 for the 1-h interval and 0.7 for the 12-h interval, indicating an overall overestimation of the rainfall rate by the LUT-based technique.

Figure 8 shows the results on a station by station basis for the 12-h interval. For each station in the investigation area, the observed rainfall rate (RR\textsubscript{Obs}) is compared to the satellite-based rainfall rate (RR\textsubscript{Sat}). Considerable differences between RR\textsubscript{Obs} and RR\textsubscript{Sat} have to be stated for certain single stations. For example, for station Greven.
(01151), the difference between RR_{Obs} and RR_{Sat} is 9 mm (12 h)^{-1}, and for station Lingen (01132), the difference is 6 mm (12 h)^{-1}. Aside from the few outliers presented by some individual stations, the rainfall rate assigned by the satellite-based LUT approach matches well with the rainfall rate registered on the ground. The same holds true for the temporal course of the rainfall rate during the studied time period.

At the same time, no differences can be observed between the stations lying in the western part of the study area (station numbers starting with 01) and the stations lying more in the eastern portion (station numbers starting with 03), which suggests that the performance of the LUT approach is similar over both parts of the study area.

2) SECOND VALIDATION PERIOD BETWEEN 19 AND 26 OCTOBER 2005

Figure 9 shows the scatterplots of RR_{Obs} in comparison to RR_{Sat} for different temporal aggregation intervals of 1, 3, and 6 h. The corresponding residual plots are shown in Fig. 10. Because of the lower position of the sun in autumn, only data pairs between 0900 and 1600 UTC could be considered for the comparison. Therefore, only the results for the 1-, 3-, and 6-h aggregation levels are shown in the figures. After extracting the precipitating gauge data and performing the spatial and temporal aggregation methods on the dataset (see section 2d), a total of 149 pairs of RR_{Obs} and RR_{Sat} are available on an hourly basis.

The statistical indices for the October period are shown in Table 3. No correlation can be found on an hourly basis between RR_{Obs} and RR_{Sat}. As explained above, this is due to the averaging effect when calculating the mean rainfall rate as a function of VIS_{0.6} and NIR_{1.6} reflectivity. For the 3-h interval, the relationship between RR_{Obs} and RR_{Sat} increases, as can be seen in Fig. 9 and as indicated by the correlation coefficient in Table 3. As observed in the May period, higher rainfall intensities especially are not assigned correctly by the proposed LUT scheme. The relationship between RR_{Obs} and RR_{Sat} increases further with an increasing temporal aggregation interval of 6 h, which also corresponds with the results for the May period.

Figure 11 shows the precipitation sums of RR_{Obs} and RR_{Sat} for an aggregation interval of 7 h (0900–1600 UTC) for each station. The first obvious feature is that the stations in the eastern part of the investigation area (station number starting with 03) registered less rainfall than the stations in the west (station number starting with 01). This is reproduced correctly by the satellite-based LUT scheme.

| Table 2. Statistical indices for the first validation period. |
|----------------------|------------------|------------------|------------------|------------------|
|                      | 1 h  | 3 h  | 6 h  | 12 h  |
| $R$                  | 0.24 | 0.47 | 0.61 | 0.75  |
| $R^2$                | 0.06 | 0.23 | 0.37 | 0.56  |
| Bias                 | 0.22 | 0.34 | 0.43 | 0.7   |
| RMSE                 | 1.13 | 1.49 | 1.72 | 2.06  |
| $N$                  | 476  | 310  | 243  | 151   |
The temporal course of the rainfall rate during the studied time period is also reproduced in correspondence with the ground-based measurements. Apart from these good results, some outliers must be mentioned. In four cases, the difference between $R_{Obs}$ and $R_{Sat}$ is higher than 4 mm (7 h)$^{-1}$ for the stations in the eastern part of the investigation area. There are also some stations in the west with higher differences between $R_{Obs}$ and $R_{Sat}$.

FIG. 8. The 12-h precipitation sums of the observed ($R_{Obs}$) and the assigned ($R_{Sat}$) rainfall rates on a station basis. The days between 16 and 31 May 2006 are indicated on the $x$ axis.
However, the overestimation and underestimation is balanced. Therefore, the performance of the LUT-based rainfall assignment scheme appears to be independent of the spatial position of the station.

5. Discussion

The validation of the proposed satellite-based rainfall-rate assignment scheme by means of an LUT approach was conducted for two time periods in spring 2006 and autumn 2005. During both time periods, the study area was influenced by several frontal systems and differing precipitation processes. The rainfall rate was assigned as a function of the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity by means of the calculated LUT. The analysis of the scatterplots and residual plots, together with the statistical indices, revealed an overall encouraging performance of the proposed LUT approach, with few differences between the spring and autumn time periods.

The comparison of RR$_{\text{Obs}}$ and RR$_{\text{Sat}}$ for a 1-h time interval showed no correlation between both parameters, which is due to the averaging of the rainfall rates when calculating the mean rainfall rate as a function of VIS$_{0.6}$ and NIR$_{1.6}$ for the LUT.

With decreasing temporal resolution, the relationship between RR$_{\text{Obs}}$ and RR$_{\text{Sat}}$ increases. This is due to the balancing effect of the temporal aggregation of RR$_{\text{Obs}}$ over a longer time period. The results for the 3-, 6-, and 12-h intervals indicate a clear relationship between RR$_{\text{Obs}}$ and RR$_{\text{Sat}}$. This indicates that a relationship exists that can be used for rainfall-rate assignment between the ground-based rainfall rate and the value combination of VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity. The stated relationship corresponds with the introduced conceptual model that raining cloud areas with higher rainfall intensities are characterized by a higher optical thickness (higher VIS$_{0.6}$ reflectivity) and a larger effective particle radius (lower NIR$_{1.6}$ reflectivity).

Because of the existing relationship between data pairs of VIS$_{0.6}$ and NIR$_{1.6}$ reflectivity and the ground-based rainfall rate, which becomes distinct for a temporal aggregation interval greater than 6 h, it is possible to assign the rainfall rate as a function of both reflectivity values. Furthermore, the results indicate no performance dependence on the spatial position of the station in the study area.

The results indicate great potential for improved rainfall-rate assignment based on satellite-based cloud properties such as $\tau$ and $a_{\text{ef}}$, compared to existing IR
techniques. The presented algorithm should be readily adaptable to other climate regions, because the stated relationship between the optical and microphysical cloud properties and the rainfall rate is also valid for other regions. If the cloud consists of larger droplets and has a higher vertical extension, this should result in higher rainfall intensities.

However, illumination and viewing geometries have to be considered as additional parameters within the retrieval technique to apply the method to other climate regions or a spatially extended investigation area. To this end, the rainfall rate should be calculated as a function not only of the VIS0.6 and NIR1.6 reflectivity, but also of the satellite zenith and the azimuth angle. This could be readily implemented with an appropriate data set of rain gauges for the training stage.

Variable surface albedos should not present a problem, as raining clouds can be considered to be optically thick and are therefore opaque. To assure the validity of this criterion, the implemented cloud mask in connection with the rain area delineation scheme should be applied prior to rainfall-rate assignment.

Despite the good validation results, more research has to be completed until the final technique for rainfall-rate assignment will be available. As a first step, the VIS and NIR reflectance should be replaced by optical and microphysical cloud properties. To this end, a newly developed and particularly fast-computing algorithm based on Kokhanovsky and Nauis (2006) will be implemented for MSG SEVIRI to retrieve optical cloud thickness and effective particle radius. In this context, the promising results presented by Roebeling and Holleman (2009) for MSG SEVIRI as well as by Rapp et al. (2009) for the TRMM satellite accentuate the potential of rainfall-rate assignment based on cloud properties. In a future step the study area will be extended to central Europe. Here, gauge-corrected radar data provided by the German Weather Service will be used instead of rain gauges [Radar Online Aneichung (RADOLAN) product; Deutscher Wetterdienst 2005b]. The parallax must be considered for a detailed comparison of the ground-based radar data and the satellite-based cloud products. Therefore, the correction technique of Vicente et al. (2002) will be applied.

### 6. Summary and conclusions

The aim of the current study was the investigation of the relationship between reflection values in the 0.56–0.71-µm (VIS0.6) and 1.5–1.78-µm (NIR1.6) channels, which provide information about optical thickness and effective particle radius, and the rainfall rate measured by ground-based rain gauges. This investigation was realized by using satellite and precipitation data with a high temporal resolution.

The overall purpose was to investigate and estimate the potential for physically based rainfall-rate assignments by means of cloud properties retrieved by MSG SEVIRI. The focus of the study was on precipitation processes in connection with extratropical cyclones in the midlatitudes. This is due to the deficiencies in existing rainfall retrieval techniques based on the IR cloud-top temperature in connection with stratiform precipitating clouds, which is caused by the relatively warm and spatially homogeneous cloud-top temperature of such stratiform raining cloud areas. As a result of these drawbacks in existing rainfall retrieval techniques available for GEO systems, a new conceptual model is introduced, which connects the rainfall rate of a cloud to its thickness and the size of its particles. According to this conceptual model, raining cloud areas with higher rainfall intensities are characterized by higher thickness and larger particles. Optical thickness and effective particle radius, which can be retrieved from optical satellite data, can be taken as proxies for the geometrical cloud thickness and the cloud particle size. Because no operational technique is currently available to retrieve $\tau$ and $a_{eq}$ for water and ice clouds for every 15-min interval of MSG SEVIRI measurements, the original VIS0.6 and NIR1.6 reflectivities are used in lieu of $\tau$ and $a_{eq}$ in this study.

To investigate the relationship between the two data sets of different characteristics, various preprocessing steps are necessary. To minimize the problem of comparing continuously measured point data (rain gauge) with area-wide satellite data of snapshot-like character, the satellite data were spatially and temporally aggregated. The station data were only temporally aggregated. The spatial and temporal aggregation of the satellite data is done to minimize potential spatial and temporal offsets between the station data and the satellite data.

Analysis of the aggregated datasets reveals a relationship between the ground-based rainfall rate and the value combination of VIS0.6-NIR1.6 reflectivity. To investigate the relationship in more detail, a technique for rainfall-rate assignment as a function of the VIS0.6 and NIR1.6 reflectivity was proposed. The technique is applied and evaluated for two validation periods in May
2006 and October 2005, respectively. The results of the validation study confirm the stated relationship between ground-based rainfall rate and the sensor signal. Furthermore, it proved to be possible to assign the rainfall rate with good accuracy on a 6- and 12-h basis, which represents a clear improvement over existing IR retrievals that obtain comparable results on a monthly basis.

The results of the presented study corroborate the introduced conceptual model and show great potential for an improved rainfall-rate assignment based on satellite-based
cloud properties such as $\tau$ and $d_{st}$ in comparison with existing IR techniques. In this context, the spectral resolution provided by MSG SEVIRI offers the possibility for area-wide rainfall retrieval in near–real time and in a quasi-continuous manner.

The assumed physically based relationship between the optical and microphysical cloud properties and the ground-based rainfall rate was confirmed. However, further investigations are necessary to develop an operational retrieval technique, which should be based on a larger data basis to allow a more substantiated statement about the discovered relationship. A larger dataset used to calculate the mean rainfall rate as a function of the VIS$_{0.6}$ and NIR$_{1.6}$ reflectivities should reduce the averaging problems and the resulting underestimation of very high rainfall rates and overestimation of very low rainfall rates. In this context, the dataset should be temporally and spatially enlarged. As stated by Xie and Arkin (1995), Morisse et al. (1995), and Bell and Kundu (2003), a spatial densification of the station network can help to improve the retrieval technique. Such a dense network would support the assumption that the rainfall rate measured at the station is representative of the whole pixel.

Altogether, it can be stated that the introduced conceptual model provides a valid and stable basis for an improved satellite-based rainfall retrieval technique and that it reveals the great potential for area-wide rainfall detection in high spatial and temporal resolutions by means of MSG SEVIRI.

Acknowledgments. The authors are grateful to the German Weather Service for providing the ground-based precipitation dataset. The current study was funded by the German Ministry of Research and Education (BMBF) in the framework of the GLOWA-Danube project (G-D/2004/TP-10, precipitation/remote sensing) and by the German Research Council DFG (BE project (G-D/2004/TP-10, precipitation/remote sensing) in the framework of the GLOWA-Danube basin and its relationship to the rainfall over the Rift Valley lakes of East Africa during 1983–90 using the Meteosat infrared channel. J. Appl. Meteor., 37, 1250–1264.


Berliner Wetterkarte e.V., 2005: Berliner Wetterkarte. No. 54. [Available online at http://wkserv.met.fu-berlin.de/]


Platnick, S., 2001: A superposition technique for deriving mean PET.


