A MODIS Dual Spectral Rain Algorithm

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ABSTRACT

The Moderate Resolution Imaging Spectroradiometer (MODIS) dual spectral rain algorithm (MODRA) is developed for rain retrievals over the northern midlatitudes. The reflectance of the MODIS water vapor absorption channel at 1.38 μm ($R_{1.38 \mu m}$) has a potential to represent the cloud-top height displayed by the brightness temperature (TB) of the MODIS channel at 11 μm, because of an excellent negative relationship (correlation coefficient $\sim -0.9$) between $R_{1.38 \mu m}$ and TB$_{11 \mu m}$ for optically thick clouds with reflectance ($R_{0.65 \mu m}$) greater than 0.75. With a training rainfall dataset from the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) aboard the same Aqua satellite platform, two MODIS channels ($R_{1.38 \mu m}$ and $R_{0.65 \mu m}$) are applied to form multiregression curves to estimate daytime rainfall. Results demonstrate that the instantaneous rain rates from MODRA, independent AMSR-E rainfall products, and surface rain gauge measurements are consistent. This study explores a new way to estimate rainfall from MODIS water vapor and cloud channels. The resulting technique could be applied to other similar satellite instruments for rain retrievals.

1. Introduction

Precipitation is a very important variable in earth science–related scientific investigations. Rainfall retrievals based on satellite measurements have been an active research area for several decades because the satellite observations can provide global coverage, especially over remote continental areas and oceans where traditional measurements by rain gauge and radar are not available. High temporal and spatial resolution rainfall estimates are desired for soil moisture budgets, verification and data assimilation in general circulation model simulations, and hydrologic applications. The accumulated rainfall estimations are required for precipitation climatological research (Huffman et al. 1997; Kidd 2001; Mark et al. 2001).

The methods for estimating precipitation from satellite observations have been evolving and improving for decades. The early rain retrieval algorithms with satellite visible (VIS) and infrared (IR) measurements applied statistical regression methods to derive relationships between IR–VIS measurements and rain rates (RRs; Lethbridge 1967). Several satellite rainfall estimates originated from geostationary satellite measurements such as National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellite (GOES), relying on IR observations at 10.5–12.6 μm (Adler and Mack 1984; Scofield 1987). Representative rain algorithms using IR measurements are the GOES precipitation index technique (GPI; Arkin and Meisner 1987), the convective–stratiform technique (CST) (Adler and Negri 1988), the operational GOES IR rainfall estimation technique (Auto-estimator; Vicente et al. 1998), and the GOES multispectral rainfall algorithm (GMSRA; Ba and Gruber 2001).

The underlying assumption of IR-based rain retrievals is that the colder cloud tops are associated with thicker precipitating clouds resulting in significant surface rainfall (Miller et al. 2001). The IR method is indirect, based on the physical features of cloud tops, which are affected by rain cloud movement (Adler et
Satellite-based passive microwave (PMW) measurements provide a physical relationship between the satellite observations and the surface rain rates. Rain retrieval with PMW emission channels (CHs) over the ocean is a more physically direct method based on the enhanced emissions by raindrops at lower microwave frequencies, while rain estimates over land are mainly based on the scattering of upwelling radiation by ice particles at higher microwave frequencies (Spencer et al. 1989; Ferraro and Marks 1995; Ferraro 1997; Kummerow et al. 2001; McCollum and Ferraro 2003). Satellite microwave sensors, including the Special Sensor Microwave Imager (SSM/I), the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) and precipitation radar (PR), the Advanced Microwave Sounding Unit (AMSU), and Advanced Microwave Scanning Radiometer for Earth Observing System (AMSRE), have been successfully applied in rain retrievals, such as the NOAA National Environmental Satellite, Data, and Information Service (NESDIS) SSM/I-based rain algorithm (Ferraro 1997; Ferraro and Li 2002), the TMI-based Goddard Profiling (GPROF) rain algorithm (Kummerow et al. 1996, 2001; McCollum and Ferraro 2003; Olson et al. 2006; Yang et al. 2006), the NESDIS AMSU-B rainfall algorithm (Ferraro et al. 2000, 2005; Weng et al. 2003), and the TRMM PR rain algorithm (Iguchi et al. 2000). Results from many precipitation intercomparison projects demonstrate that rain retrievals from PMW measurements are superior to rain estimates from IR and/or VIS measurements (Ebert et al. 1996; Ebert and Manton 1998; Smith et al. 1998; Adler et al. 2001; Miller et al. 2001; Kidd et al. 2003; Tapiador et al. 2004; Yang and Smith 2005; Yang et al. 2006).

The combination of the better sampling of IR–VIS-based rain algorithms and the high quality of PMW-based rain algorithms is an alternative choice for rain retrievals. Several approaches of combining IR–VIS and PMW measurements for rain estimates have been developed, such as neural network approaches (Bellerby et al. 2000; Tapiador et al. 2004), the precipitation estimation from remotely sensed information using artificial neural networks (Hsu et al. 1999; Sorooshian et al. 2000), threshold-matched precipitation index for the Global Precipitation Climatology Project (GPCP) 1° daily rain products and 3-hourly 0.25° grid rain products (Huffman et al. 1997, 2001, 2007), regression function method (Miller et al. 2001), cumulative histogram matching technique (e.g., Kidd et al. 2003), and the Climate Prediction Center morphing method (e.g., CMORPH; Joyce et al. 2004). More detailed discussions on numerous techniques utilized in satellite IR–VIS- and PMW-based rain retrievals can be found in Barrett and Beaumont (1994), Kidd (2001), and Yang (2004).

This study presents an approach using two Moderate Resolution Imaging Spectroradiometer (MODIS) channels for rain retrievals, referred to as the MODIS dual spectral rain algorithm (MODRA). The selection processes of two MODIS channels for rain retrievals and analyses based on relationships between brightness temperature (TB) of the MODIS channel 31 (TB31, μm) and other channels for optically thick clouds have been described in detail. The daytime cloud height—obtained from the reflectance R measured at 1.38 μm, R1.38 μm—and cloud optical thickness—obtained from R measured at 0.65 μm, R0.65 μm—are eventually selected to derive MODRA instantaneous rain rates. A limited AMSR-E rain dataset is then used to train the MODRA. MODRA rain rates are finally evaluated with independent AMSR-E rainfall products and surface rain gauge measurements for four summer months in east China.

2. Datasets

The daytime MODIS, AMSR-E, and rain gauge measurements for May–September 2005 are used in this study. MODIS is the primary instrument onboard the National Aeronautics and Space Administration Earth Observing System (NASA EOS) sun synchronous Aqua satellite (1330 local time ascending node) with 36 spectral bands (see Table 1) ranging in wavelength from 0.4 to 14.4 μm. The spatial resolution of band 1–2 is 250 m at nadir, 500 m for bands 3–7, and 1 km for the remaining 29 bands (Kaufman et al. 1998; Barnes et al. 1998). As a medium-resolution multispectral, and cross-track scanning radiometer, it measures the physical properties of the atmosphere and biological and physical properties over ocean and land (Kaufman et al. 1998; Mace et al. 2005).

The MODIS 1B datasets were obtained from four China Meteorological Administration (CMA) meteorological satellite data receiving stations. The MODIS measurements at shortwave bands (0.405–1.390 μm) were converted to R corrected for the cosine of the solar zenith angle, while the infrared data (3.660–14.385 μm) were converted to TB.

The AMSR-E PMW aboard the same Aqua satellite measures radiation at 6 polarized frequencies (6.9, 10.6,
18.7, 23.8, 36.5, and 89 GHz). The spatial resolution at the surface varies from approximately 5 km at 89 GHz to 60 km at 6.9 GHz (Njoku et al. 2003). AMSR-E provides global coverage of precipitation rate, cloud water, water vapor, sea surface winds, sea surface temperature, ice, snow, and soil moisture (Njoku et al. 2003; Wilheit et al. 2003; Kelly et al. 2003). The AMSR-E official rainfall products were obtained from the National Snow and Ice Data Center (NSIDC; see online at http://nsidc.org/data/docs/daac/ae_rain_l2b_gd.html). The level-2B swath product (AE_Rain) contains instantaneous rain rates and rain types (convective versus stratiform) at a spatial resolution of 5.4 km (Adler et al. 2005). The GPROF algorithm generates rain rates and rain types (Kummerow et al. 2001; Wilheit et al. 2003; Adler et al. 2005; Olson et al. 2006; Yang et al. 2006). The MODIS measurements and AMSR-E rainfall products were resampled at a 0.05° grid scale in order to retain more information from AMSR-E rainfall products.

Surface rainfall from gauge measurements was collected at hourly intervals from 2700 automatic meteorological stations in China operated by CMA. The raw rain gauge datasets were processed for preliminary quality control. Additional quality control procedures were conducted to screen out obviously bad data points. These procedures include checking consistencies of rain measurements at any automatic meteorological station with the surface observations of weather phenomena, the coincident MODIS images, and the 6-hourly rainfall from nearby independent traditional rain gauge measurements. For example, some stations often report a heavy rain rate of 80 mm h⁻¹ while no rain was reported according to the surface observations of weather phenomenon. These kinds of data points were eliminated from the rain gauge datasets. The hourly rain gauge datasets and satellite rainfall datasets were finally grouped separately at different grid scales for evaluating the MODRA rain retrievals. Figure 1 presents the distribution of the automatic rain gauge stations in east China.

3. Selection of MODIS spectra

The cloud-top temperature plays a very important role in IR-related rain retrieval algorithms. Since MODIS has 36 spectral channels, it is worthwhile to explore whether any new channels could be used to represent the cloud-top height. It is reasonable to assume that the attention should be first on the cloud and water vapor channels because of their association with rain processes. It is our inference that the cloud-top temperature such as \( TB_{11 \mu m} \) could be used to assist in the se-
section of MODIS channels for rain retrievals. Two cases are presented to illustrate how to select MODIS spectra for optically thick clouds defined as $R_{0.65\ \mu m} \geq 0.75$.

Table 1 shows correlation coefficients (Corr) for case 1 between MODIS channel 31 and other channels on 22 August 2005. The reflectance of MODIS water vapor channels 18, 19, and 26 ($R_{0.936\ \mu m}, R_{0.94\ \mu m}$, and $R_{1.38\ \mu m}$) and MODIS TB$_{11\ \mu m}$ has a very good negative relationship with correlation coefficients ranging from $-0.80$ to $-0.94$ (i.e., the MODIS near-IR channels are able to depict the cloud-top height). The TBs of other infrared channels such as channels 20–25 and 27–36 have an excellent positive relationship to TB$_{11\ \mu m}$ with correlation coefficients greater than 0.98. However, there is no relationship between MODIS $R_{0.65\ \mu m}$ and TB$_{11\ \mu m}$ so that channel $R_{0.65\ \mu m}$ is an independent parameter to represent another feature of clouds [i.e., the cloud optical thickness (Rosenfeld and Gutman 1994)].

The MODIS near-IR channels were originally designed for detecting water vapor and cirrus clouds because they are within/around the 0.94- and 1.38-$\mu m$ water vapor absorption bands (Gao and Goetz 1990; Gao et al. 1993; Kaufman and Gao 1992; King et al. 1992). The potential application of the 1.38-$\mu m$ band in detecting cirrus clouds was initially noticed by Gao et al. (1993). The reflectance thresholds were used in MODIS to detect thin cirrus clouds in the upper troposphere (Ackerman et al. 1997). With sufficient atmospheric water vapor present in the beam path, no upwelling radiance reflected from the earth’s surface would reach the satellite. High clouds appear bright with a large 1.38-$\mu m$ reflectance when relatively little moisture is located in the upper troposphere, while reflectance from low- to midlevel clouds is partially attenuated by water vapor absorption (Ackerman et al. 1997).

Early studies on the 0.94-$\mu m$ water vapor band were primarily focused on how to derive the column water amount (Gao and Goetz 1990; Kaufman and Gao 1992; King et al. 1992). The underlying physics is that solar radiation at the 0.94-$\mu m$ band is partially absorbed by atmospheric water vapor. The MODIS near-infrared total precipitable water product (Gao and Kaufman 1998) consists of the column water vapor amounts over global clear land areas and column water vapor above clouds over both land and ocean.

When clouds are present, MODIS channels in 0.8–2.5-$\mu m$ bands provide the absorption information due to water vapor above and within clouds (Gao and Kaufman 1998). An example of the cumulus and cirrus cloud spectra over water surfaces measured with the NASA/JPL Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) instrument from an aircraft at 20-km altitude illustrates that the peak absorption at 0.94- and 1.38-$\mu m$ water vapor bands for cirrus spectra is much smaller than that for cumulus spectra, because cirrus clouds are located at much higher altitudes than cumulus clouds (Gao and Kaufman 1998; i.e., reflectance of the 0.94- and 1.38-$\mu m$ channels for high clouds is larger than that for low clouds).

The scatterplots (Fig. 2) for case 1 on 22 August 2005 between MODIS TB$_{11\ \mu m}$ and $R_{0.936\ \mu m}, R_{0.94\ \mu m}$, and $R_{1.38\ \mu m}$ show that the potential application of MODIS water vapor channels $R_{0.936\ \mu m}, R_{0.94\ \mu m}$, and $R_{1.38\ \mu m}$ in depicting cloud-top height is consistent with the previously published literature. However, it is also evident that $R_{0.94\ \mu m}$ saturates around 0.83 while the effect of saturation is not obvious at $R_{0.936\ \mu m}$, suggesting different sensor sensitivities for these two channels. The clear cutoff at 0.1 for $R_{0.936\ \mu m}$ and at 0.2 for $R_{0.94\ \mu m}$ indicates that both $R_{0.936\ \mu m}$ and $R_{0.94\ \mu m}$ do not well represent warm clouds or weak raining clouds. In addition, the large spread distributions between $R_{0.94\ \mu m}$ and TB$_{11\ \mu m}$ and between $R_{0.936\ \mu m}$ and TB$_{11\ \mu m}$ indicate that $R_{0.936\ \mu m}$ and $R_{0.94\ \mu m}$ do not correlate well with TB$_{11\ \mu m}$, while the distribution of $R_{1.38\ \mu m}$ from almost 0 to 0.72 corresponds well with TB$_{11\ \mu m}$. Therefore, $R_{1.38\ \mu m}$ could be an alternative choice to replace TB$_{11\ \mu m}$ in rain retrievals.

Figure 3 presents the scatterplots for another case between MODIS channel 31 (TB$_{11\ \mu m}$) and the other 35 channels on 23 July 2005. It shows that the water vapor channels and TB$_{11\ \mu m}$ have good relationships with the best correlation at channel $R_{1.38\ \mu m}$. Therefore, the MODIS channel $R_{1.38\ \mu m}$ is selected as the primary variable in rain retrievals.
Although other temperature channels have excellent relations to $\text{TB}_{11\,\mu m}$, they are not our choices because they do not significantly differ from $\text{TB}_{11\,\mu m}$. We explore different variables other than the temperature channels for rain retrievals. To improve rain retrievals, additional cloud information would be helpful in the retrieval processes. Figure 3 also illustrates that the remaining channels do not have good relationships with $\text{TB}_{11\,\mu m}$, so that these channels can be considered independent of $\text{TB}_{11\,\mu m}$. Detailed analyses of these plots demonstrate that $R_{0.65\,\mu m}$ has a nearly uniform distribution in the $R_{0.65\,\mu m}$–$\text{TB}_{11\,\mu m}$ plane. This feature is much better than for other channels. In addition, $R_{0.65\,\mu m}$ and $R_{1.38\,\mu m}$ have a small correlation coefficient (0.06) so that $R_{0.65\,\mu m}$ is also independent of $R_{1.38\,\mu m}$. Because two independent cloud variables could provide more cloud information than a single one, $R_{0.65\,\mu m}$ is selected as another important parameter in rain retrievals using the MODIS measurements. Similar results are found for other cases. In addition, consistent results are also evident with similar analyses conducted using NASA Terra MODIS datasets (1000 local time descending node).

4. Description of rain algorithm

The IR-based rain retrieval algorithms are generally based on the assumption that colder cloud-top temperature produces more surface rainfall (Scofield 1987; Arkin and Meisner 1987; Vicente et al. 1998; Ba and Gruber 2001). For example, analysis of surface rain gauge measurements and the Japanese Geostationary Meteorological Satellite (GMS) IR–VIS measurements indicate that convective thunderstorms are often characterized by very cold cloud-top IR temperature and very high visible reflectance, while weak precipitating clouds are often characterized by warm cloud-top IR temperature and low visible reflectance (Fan 2003). However, this type of rain rate–cloud-top TB relationship is not a linear function. Shown in Fig. 4 are scatterplots for five-day coincident AMSR-E rain rates and the MODIS $\text{TB}_{11\,\mu m}$ for different cloud conditions at $0.5^\circ$ grid scales. In general, the RR–TB relationship is consistent with published results. It is also evident that there is large variation of rain rates for any TB, especially for low TBs. In addition, the relationship between AMSR-E rain rates and the MODIS $\text{TB}_{11\,\mu m}$ is poor when $R_{0.65\,\mu m}$ is less than 0.85. It appears that the relations for MODIS $\text{TB}_{11\,\mu m}$ and AMSR-E rain rates are very different for different $R_{0.65\,\mu m}$ at $0.5^\circ$ grid scales. Therefore, results here demonstrate that it is impossible to apply a single rain rate–TB relationship to link the MODIS $\text{TB}_{11\,\mu m}$ to AMSR-E rain rates. Both the cloud-top height defined by $\text{TB}_{11\,\mu m}$ and the cloud optical thickness measured in $R_{0.65\,\mu m}$ would have to be used to estimate daytime rainfall. It is worthwhile to point out that $R_{0.65\,\mu m}$ is sometimes greater than 1 because the MODIS $R_{0.65\,\mu m}$ is a directional reflectance (i.e., it could be much larger in one direction than in other directions, so that it is not unusual to have
$R_{0.65 \mu m}$ greater than 1, especially for optically thick clouds; King and Curran 1980).

a. Rain screening technique

The major challenge in IR-based rain algorithms is how to distinguish nonprecipitating cirrus clouds from precipitating clouds. An empirical relationship developed by Adler and Negri (1988) has been widely used in IR rain retrievals to remove cirrus clouds by identifying the positions of the cloud spectra in the temperature/slope plane (Vicente et al. 1998; Ba and Gruber 2001). Ba and Gruber (2001) suggest that pixels with $R_{0.65 \mu m}$ less than 0.4 can be considered to be associated with nonprecipitating clouds.

Both thresholds of $R_{0.65 \mu m}$ and $R_{1.38 \mu m}$ for MODRA are proposed in this study. Since thin nonprecipitating cirrus are optically transparent, MODRA detects such cirrus using a more strict visible threshold of $R_{0.65 \mu m} < 0.75$ than that by Ba and Gruber (2001). This approach leads to a similar effect as the cirrus screening method of Adler and Negri (1988). The discussion in section 3

Fig. 3. Scatterplots of the MODIS CH 31 brightness temperature $T_{B_{11 \mu m}}$ (K) vs reflectance $R$ for the other MODIS 35 channels for the optically thick clouds on 23 Jul 2005. Each plot has 24 565 samples.

Fig. 4. Scatterplots of MODIS brightness temperature $T_{B_{11 \mu m}}$ (K) vs AMSR-E RR (mm h$^{-1}$) for optically thick clouds with various $R_{0.65 \mu m}$ at 0.5° grid scale during 26–30 May 2005: (a) $0.75 \leq R_{0.65 \mu m} < 0.80$, (b) $0.80 \leq R_{0.65 \mu m} < 0.85$, (c) $0.85 \leq R_{0.65 \mu m} < 0.90$, (d) $0.90 \leq R_{0.65 \mu m} < 0.95$, and (e) $0.95 \leq R_{0.65 \mu m} < 1.02$. 

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already demonstrates that $R_{1.38 \mu m}$ has the potential to depict the cloud-top height similar to TB$_{18 \mu m}$. Therefore, MODRA also applied the threshold of $R_{1.38 \mu m} \geq 0.12$, equivalent to TB$_{18 \mu m} \leq 265$ K, to identify precipitating clouds from nonraining clouds.

To evaluate this rain detection scheme, several statistical variables were applied to compare rain rates from AMSR-E and MODRA. They are the false-alarm ratio (FAR), the probability of detection (POD), and the Heidke skill score (Skill), defined by the following equations:

\[
\text{POD} = \frac{q_4}{q_3 + q_4},
\]

\[
\text{FAR} = \frac{q_2}{q_2 + q_4}, \quad \text{and}
\]

\[
\text{Skill} = \frac{2(q_1q_4 - q_2q_3)}{q_2^2 + q_4^2 + 2q_1q_4 + (q_2 + q_3)(q_1 + q_4)},
\]

where $q_1$ represents the matched numbers of no rain from both AMSR-E and MODRA, $q_2$ is the matched numbers of no rain from AMSR-E and rain from MODRA, $q_3$ is the matched numbers of rain from AMSR-E and no rain from MODRA, and $q_4$ is the matched numbers of rain from both AMSR-E and MODRA. The POD and FAR vary from 0 to 1; the Skill varies from 1 (perfect skill) to −1 (perfect negative skill) and a Skill of 0 represents a bad performance. An ideal algorithm would lead to POD, FAR, and Skill as 1, 0, and 1, respectively. These variables have been widely used for evaluation of the algorithm's ability to detect rainfall (Ebert and Manton 1998; Ba and Gruber 2001; Kidd et al. 2003; Tapiador et al. 2004).

b. Algorithm

The surface rainfall and satellite IR measurements do not have a linear relationship. Direct rain retrievals based on IR measurements with a linear rain-IR equation would not provide a satisfactory performance. Several rain algorithms using nonlinear rain-IR relationships were developed and results demonstrated that improved performances in rain retrievals were evident (Hsu et al. 1999; Bellerby et al. 2000; Tapiador et al. 2004; Ba and Gruber 2001; Fan 2003).

The multiregression curves of AMSR-E rain rates and MODIS $R_{0.05 \mu m}$ and $R_{1.38 \mu m}$ are shown in Fig. 5. Table 2 lists the related regression equations generated by calibration against the AMSR-E instantaneous rain-rate datasets for three days of May 2005. These multiregression curves present the primary feature of rain rates in the $R_{0.05 \mu m}$ and $R_{1.38 \mu m}$ domain. This feature agrees with Fig. 4 and the statistics of rain gauge data against IR–VIS measurements (Fan 2003). It is evident that any single regression equation would not be able to depict the complex relationship between MODIS $R_{1.38 \mu m}$ and $R_{0.05 \mu m}$ and AMSR-E rain rates.

MODRA is evaluated by comparing its rain rates with surface rain gauge measurements and AMSR-E rain rates over east China. The standard statistical variables used in the processes are mean rain gauge or AMSR-E rainfall (RR), mean MODRA rainfall (RR), bias, root-mean-square error (rmse), and correlation coefficient (Ba and Gruber 2001; Vicente et al. 1998); that is,

\[
\text{RR} = \frac{\sum_{i=1}^{N} RR_{i}}{N} \quad \text{and} \quad \overline{\text{RR}} = \frac{\sum_{i=1}^{N} RR_{i}}{N},
\]

\[
\text{bias} = \overline{\text{RR}} - \text{RR},
\]

\[
\text{rmse} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (RR_{i} - \text{RR})^2},
\]

Table 2. The RR (mm h$^{-1}$) regression equations for AMSR-E RR as a function of $R_{1.38 \mu m}$ for different $R_{0.05 \mu m}$ in east China.

<table>
<thead>
<tr>
<th>$R_{0.05 \mu m}$</th>
<th>Rain-rate regression equation</th>
</tr>
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<tbody>
<tr>
<td>0.75–0.80</td>
<td>RR = −0.032RR$<em>{1.38 \mu m}$ + 0.3764RR$</em>{1.38 \mu m}$ + 0.0036</td>
</tr>
<tr>
<td>0.80–0.85</td>
<td>RR = 3.3826RR$<em>{1.38 \mu m}$ − 1.0428RR$</em>{1.38 \mu m}$ + 0.4244</td>
</tr>
<tr>
<td>0.85–0.90</td>
<td>RR = 5.4427RR$<em>{1.38 \mu m}$ − 0.3140RR$</em>{1.38 \mu m}$ + 0.75</td>
</tr>
<tr>
<td>0.90–0.95</td>
<td>RR = 7.8356RR$<em>{1.38 \mu m}$ + 1.2678RR$</em>{1.38 \mu m}$ + 0.9</td>
</tr>
<tr>
<td>0.95–1.00</td>
<td>RR = 11.261RR$<em>{1.38 \mu m}$ + 3.7027RR$</em>{1.38 \mu m}$ + 1.25</td>
</tr>
<tr>
<td>1.00–1.05</td>
<td>RR = 14.019RR$<em>{1.38 \mu m}$ + 6.9906RR$</em>{1.38 \mu m}$ + 1.5</td>
</tr>
<tr>
<td>1.05–1.10</td>
<td>RR = 17.010RR$<em>{1.38 \mu m}$ + 11.132RR$</em>{1.38 \mu m}$ + 1.7</td>
</tr>
<tr>
<td>≥1.1</td>
<td>RR = 20.934RR$<em>{1.38 \mu m}$ + 16.126RR$</em>{1.38 \mu m}$ + 1.9</td>
</tr>
</tbody>
</table>
where $N$ is the total data points used in the statistical study. The evaluations of MODRA rain retrievals were conducted at different spatial and temporal scales in east China.

5. Evaluation of MODRA rain retrievals

a. Comparison with AMSR-E rain products

Six cases over east China were selected for comparison of instantaneous rain rates from MODRA and AMSR-E at various spatial resolutions. At $0.1^\circ \times 0.1^\circ$, $0.5^\circ \times 0.5^\circ$, $1^\circ \times 1^\circ$, and $2.5^\circ \times 2.5^\circ$ grid scales, the MODRA rain rates were averaged for each grid and compared with the coincident AMSR-E rain rates processed in the same way. Their scatterplots at different spatial scales for the six cases are presented in Figs. 6–7. The widespread distribution of the matched rain rates with a large rmse at a $0.1^\circ \times 0.1^\circ$ grid scale is expected. It leads to a much better intercomparison at large grid scales since the spatial averaging generally improves statistics. It is also evident that MODRA underestimates rain rates (when compared with the AMSR-E) with a bias of up to 0.06 mm h$^{-1}$ for four cases, while overestimating rain rates with a bias of up to 0.06 mm h$^{-1}$ for two cases (see Table 3).

The detailed intercomparison results are summarized in Table 3. It is evident that the values of these statistic variables differ from case to case, however, in general FAR and rmse decrease while the correlation coefficient, POD, and Skill increase with spatial averages increased from $0.1^\circ \times 0.1^\circ$ to $2.5^\circ \times 2.5^\circ$ grid scales. For example, FAR is less than 0.13 for five cases and POD is greater than 0.93 for four cases at a $2.5^\circ$ grid scale. The results are consistent with those reported by Vicente et al. (1998) from comparison of the GOES-based 3-hourly rainfall and the gauge-adjusted radar rainfall at different spatial scales.

The skill score ranges from 0.38 to 0.84 for these cases, which is generally consistent with the results from previously published results. Bellerby et al. (2000) presented a Skill of 0.77–0.92 for instantaneous TRMM PR rain rates, while Joyce et al. (2004) reported a Skill of 0.4–0.65 for daily rainfall at a $0.25^\circ$ grid scale against surface rain gauge measurements. The mean biases change only slightly for different spatial resolutions, which is similar to those in Vicente et al. (1998) and Bellerby et al. (2000). The averaged key statistics for the six cases from Table 3 are shown in Table 4. The percentage changes of these statistical variables clearly indicate impacts of the spatial averaging on satellite-based rain retrievals. Here the change of percentage presents the change rate from one previous higher grid scale to the current grid scale. Results show that the statistics improved dramatically from $0.1^\circ \times 0.1^\circ$ to $0.5^\circ \times 0.5^\circ$ grid scales as we expected. The basic characteristics of MODRA are consistent with many published studies (Ebert and Manton 1998; Bellerby et al. 2000; Yang et al. 2006). The analyses indicate the confidence of MODRA in rain retrievals.

An additional intercomparison of instantaneous rain rates for two cases was also conducted (Fig. 8). The left panels show MODIS images while the middle and right panels present the MODRA and AMSR-E rain maps for the two cases of 23 July and 22 August 2005. It is evident that MODRA and AMSR-E exhibit a very similar pattern of rainfall distributions, especially the locations of convective rain cells. However, differences also exist (e.g., MODRA produces more areas of small rain rates, which are probably related to warm rain clouds detected by the low threshold of $R_{1.38 \mu m}$). The AMSR-E rain retrievals over land are mainly based on the scattering signals of the PMW high-frequency measurements so that they would not be able to detect the small rain rates associated with warm rain clouds because of the lack of ice particles (Kummerow et al. 2001; Olson et al. 2006).

The MODRA rain rates for these two cases are further checked against the closest hourly surface rain gauge measurements (Fig. 9). There are similar rain patterns and magnitudes between the MODRA rain rates and the gauge measurements, except for a few strong convective cells where the retrievals are relatively larger. For comparison, rain rates from a simple TB$_{11 \mu m}$-only rain algorithm based on Vicente et al. (1998) are also shown in Fig. 9. This TB$_{11 \mu m}$-only based rain algorithm is governed by

$$RR = 1.1183 \times 10^{11} \exp(-3.6382 \times 10^{-2} \times T^{1.2}),$$  (7)

where RR is in millimeters per hour and $T$ is the cloud-top brightness temperature in kelvin. It is obvious that this TB$_{11 \mu m}$ based algorithm overestimates rain rates without further corrections applied in the operational GOES IR rain estimations for the environmental moisture, cloud growth, and cloud-top structure (Vicente et al. 1998), although it has a similar rain pattern. Therefore, the MODRA appears superior to the TB$_{11 \mu m}$-only rain algorithm for these two cases. However, we do not claim that the IR-based rain retrievals are not accurate; instead, we just demonstrate that the new approach with two cloud property channels in MODRA is reasonable.

Figure 10 presents the intercomparison of MODRA and AMSR-E rain rates from 20 May to 20 September 2005 for six $2.5^\circ \times 2.5^\circ$ grids. The correlation coefficient
ranges from 0.75 to 0.88 with rmse varying from 0.70 to 1.45. These statistics suggest that MODRA rain retrievals are comparable to the AMSR-E estimates at a 2.5° × 2.5° spatial resolution. Miller et al. (2001) indicates that continental rain estimates based on passive microwave scattering signals are physically more akin to IR-based rain retrievals because rain estimates over land using PMW scattering measurements are mainly based on the scattering effects of ice particles, not raindrops near the surface. Note that the samples used in the intercomparison are smaller than actual days because of the fact that there were mismatched AMSR-E
and MODIS granules in east China and some MODIS granules at daytime were missing during the time period.

b. Comparison with rain gauge measurements

The Aqua satellite is a polar-orbiting satellite, observing east China only 2 times per day: once at daytime and again at nighttime. The MODRA rain estimates are based on MODIS IR–VIS data at daytime, and so it is not applicable to compare rain rates from MODRA and surface rain gauge measurements at 6-h, daily, or monthly time scales. In addition, comparisons with rain gauges at high spatial resolutions such as a $0.1^{\circ} \times 0.1^{\circ}$ grid would lead to poor statistical results, and the spatial accumulation of satellite-based rain estimates could improve the statistical analysis with rain gauges (Tapia-dor et al. 2004; Bellerby et al. 2000). Ferraro and Li (2002) also indicate that the errors for instantaneous

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**Fig. 7.** As in Fig. 6, but for (left) 7 Aug, (middle) 22 Aug, and (right) 2 Sep 2005.
SSM/I rain rates at 0.5°, 1°, and 2.5° boxes are approximately 150%, 100%, and 70% of the mean gauge rain rates, respectively. Therefore, the preliminary evaluation of MODRA rain retrievals against surface rain gauge measurements is conducted for instantaneous rain rates at a 2.5° × 2.5° grid scale.

Figure 11 shows the comparison of rain rates for six 2.5° × 2.5° grids from 20 May to 20 September 2005. The correlation coefficient ranges from 0.44 to 0.79 while rmse varies from 1.08 to 1.91. The differences are obvious especially where MODRA shows significant rainfall, while the gauge suggests very weak rainfall. By

<table>
<thead>
<tr>
<th>Selected study areas</th>
<th>Samples</th>
<th>RR (mm h⁻¹)</th>
<th>Bias (mm h⁻¹)</th>
<th>Rmse (mm h⁻¹)</th>
<th>Corr</th>
<th>FAR</th>
<th>POD</th>
<th>Skill</th>
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<tr>
<td>25°–41°N, 103°–122°E</td>
<td>22 May 2006</td>
<td>39 204</td>
<td>0.089</td>
<td>-0.012</td>
<td>0.496</td>
<td>0.70</td>
<td>0.47</td>
<td>0.68</td>
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<tr>
<td>17°–40°N, 95°–115°E</td>
<td>17 Jun 2005</td>
<td>46 098</td>
<td>0.230</td>
<td>0.044</td>
<td>0.960</td>
<td>0.68</td>
<td>0.51</td>
<td>0.76</td>
</tr>
<tr>
<td>18°–44°N, 100°–122°E</td>
<td>23 Jul 2005</td>
<td>56 062</td>
<td>0.194</td>
<td>-0.013</td>
<td>0.900</td>
<td>0.62</td>
<td>0.51</td>
<td>0.76</td>
</tr>
<tr>
<td>22°–41°N, 109°–122°E</td>
<td>7 Aug 2005</td>
<td>22 755</td>
<td>0.289</td>
<td>-0.060</td>
<td>0.910</td>
<td>0.82</td>
<td>0.25</td>
<td>0.77</td>
</tr>
<tr>
<td>18°–42°N, 96°–117°E</td>
<td>22 Aug 2005</td>
<td>38 892</td>
<td>0.147</td>
<td>0.059</td>
<td>0.909</td>
<td>0.55</td>
<td>0.66</td>
<td>0.70</td>
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<tr>
<td>24°–39°N, 104°–121°E</td>
<td>2 Sep 2005</td>
<td>32 200</td>
<td>0.180</td>
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<td>0.464</td>
<td>0.72</td>
<td>0.35</td>
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<th>Bias (mm h⁻¹)</th>
<th>Rmse (mm h⁻¹)</th>
<th>Corr</th>
<th>FAR</th>
<th>POD</th>
<th>Skill</th>
</tr>
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<tbody>
<tr>
<td>0.1° × 0.1°</td>
<td>0.087</td>
<td>-0.012</td>
<td>0.240</td>
<td>0.86</td>
<td>0.40</td>
<td>0.83</td>
<td>0.63</td>
</tr>
<tr>
<td>0.5° × 0.5°</td>
<td>0.087</td>
<td>-0.012</td>
<td>0.148</td>
<td>0.89</td>
<td>0.32</td>
<td>0.81</td>
<td>0.62</td>
</tr>
<tr>
<td>1° × 1°</td>
<td>0.092</td>
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<td>0.403</td>
<td>0.87</td>
<td>0.28</td>
<td>0.93</td>
<td>0.62</td>
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<tr>
<td>2.5° × 2.5°</td>
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<td>0.93</td>
<td>0.04</td>
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<th>1° × 1°</th>
<th>2.5° × 2.5°</th>
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<tr>
<td>RR (mm h⁻¹)</td>
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<td>0.148</td>
<td>0.240</td>
<td>0.960</td>
</tr>
<tr>
<td>Bias (mm h⁻¹)</td>
<td>-0.012</td>
<td>-0.013</td>
<td>-0.012</td>
<td>-0.017</td>
</tr>
<tr>
<td>Rmse (mm h⁻¹)</td>
<td>0.403</td>
<td>0.403</td>
<td>0.403</td>
<td>0.403</td>
</tr>
<tr>
<td>Corr</td>
<td>0.86</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89</td>
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<tr>
<td>FAR</td>
<td>0.32</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
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<tr>
<td>POD</td>
<td>0.81</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
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<tr>
<td>Skill</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
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</tbody>
</table>

Table 3: Intercomparison of instantaneous RR from MODIS and AMSR-E at various spatial scales for six selected study areas. Sample size, mean AMSR-E RR, bias, rmse, Corr, FAR, POD, and Skill are listed.
the same token, a comparison between AMSR-E and surface rain gauge rain rates for the same cases is presented in Fig. 12. The correlation coefficient varies from 0.31 to 0.75 and the rmse ranges from 1.14 to 2.26. A comparison of Figs. 11 and 12 suggests that MODRA rain retrievals outperform AMSR-E rain estimates over east China for this summer season, possibly because of the fact that some light rainfall from warm rain clouds

<table>
<thead>
<tr>
<th>Statistical variables</th>
<th>Grid scales</th>
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<tr>
<td></td>
<td>$0.1^\circ \times 0.1^\circ$</td>
</tr>
<tr>
<td></td>
<td>Magnitude</td>
</tr>
<tr>
<td>Bias (mm h$^{-1}$)</td>
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<td>Rmse (mm h$^{-1}$)</td>
<td>0.622</td>
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<tr>
<td>Corr</td>
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</tr>
<tr>
<td>FAR</td>
<td>0.45</td>
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<tr>
<td>POD</td>
<td>0.72</td>
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<td>Skill</td>
<td>0.56</td>
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A comparison of Figs. 11 and 12 suggests that MODRA rain retrievals outperform AMSR-E rain estimates over east China for this summer season, possibly because of the fact that some light rainfall from warm rain clouds
was missed by the AMSR-E rain algorithm while MODRA could detect more warm cloud rainfall. However, we cannot make a general conclusion that MODRA is better than the AMSR-E rain algorithm over land because more detailed evaluations of rain estimates from MODRA and independent measurements for longer times and different seasons are needed.
Tapiador et al. (2004) pointed out that the correlation coefficients for the best case of satellite instantaneous estimates using a neural networks–based fusion technique were 0.75 and 0.4 against the interpolated and noninterpolated gauge measurements at a 0.1° × 0.1° grid scale, respectively. Bellerby et al. (2000) gave the correlation coefficients of 0.46–0.6 for similar analyses at a 0.12° × 0.12° grid scale. It is apparent that the

Fig. 10. Intercomparison of instantaneous RR (mm h⁻¹) from MODRA and AMSR-E for 20 May–20 Sep 2005 at six selected 2.5° × 2.5° grids. The basic statistics are shown in the left corner of each plot.

Fig. 11. As in Fig. 10, but for MODRA RR and surface rain gauge measurements.
statistics in this study are not as good as some of the published results. The relatively poor correlation and large rmse could primarily be caused by the time mismatching of the MODRA instantaneous rain retrievals and rain gauge hourly measurements. Tapiador et al. (2004) reported several issues affecting SSM/I rain estimates that also challenge MODRA rain retrievals. Because of the inhomogeneity property of rainfall, a rain gauge recording rainfall during the satellite overpass might measure no rainfall a few minutes later, and vice versa. In addition, a rain gauge value is a point measurement while satellite-based rain retrieval is a mean rain estimate over an area (the footprint of a satellite pixel). The small local convective cell rainfall could be missed by rain gauge observations while satellite measurements might be able to detect it. These kinds of mismatching in time and space could increase the false alarms and errors of satellite-based rain estimation. Another problem is that the satellite instruments measure the radiative signals of rainfall in the atmospheric column while rain gauges measure only surface rainfall that is affected by evaporation. We understand that surface rain gauge measurements may not be the best choice to evaluate the satellite-based instantaneous rain estimates; however, independent rain gauge measurements are still valid assets in evaluating satellite rain retrievals.

6. Discussion and conclusions

A MODIS-based rain algorithm called MODRA has been developed using the Aqua MODIS IR–VIS measurements with the selected training AMSR-E rain datasets. Because the Aqua satellite provides both passive microwave and 36-channel IR–VIS measurements, AMSR-E rain products are the best training datasets for using MODIS IR–VIS measurements in rain retrievals. MODRA is evaluated against independent AMSR-E rain products and the surface rain measurements from a dense rain gauge network in east China. MODRA (currently only for daytime) applied two MODIS spectra (R_{0.65 μm} and R_{1.38 μm}) measurements to construct its rain retrievals. The selection of these two channels is based on carefully detailed analyses of MODIS IR–VIS measurements. We demonstrate that a good relationship exists between brightness temperature T_{B11 μm} and vapor channel R_{1.38 μm} for optically thick clouds. In addition, MODIS channel R_{0.65 μm} is independent from channel R_{1.38 μm}. Therefore, the two independent MODIS channels provide better information than any one of them separately in rain retrievals.

The MODRA rain retrievals are derived from a lookup table consisting of eight regression equations as a function of MODIS R_{1.38 μm} and R_{0.65 μm}. Evaluation of MODRA instantaneous rainfall shows correlation...
coefficients of 0.75–0.96 for different cases with respect to independent AMSR-E rain rates at a 2.5° × 2.5° grid resolution. Intercomparisons with the surface dense rain gauge measurements over east China for summer (May–September) illustrate correlation coefficients varying from 0.44 to 0.79. In addition, results indicate that the statistics between MODRA and gauge rain rates are better than between AMSR-E and gauge rain rates. It appears that the differences are partially due to the capability of MODRA in detecting warm rain clouds while the AMSR-E rain algorithm has difficulty in identifying warm rain clouds over land because the AMSR-E rain algorithm primarily utilizes the scattering signals in PMW high-frequency channels. The results demonstrate that MODRA daytime rain retrievals over land are reasonable when compared with published studies; however, further evaluation studies are needed for different regions and seasons with more independent rain estimates. Since the TRMM PR rain product is one of the most accurate precipitation products from satellite measurements, it would be helpful to compare MODRA rain rates with coincident TRMM PR rain rates, especially for warm rain situations. The rainfall datasets for the International Precipitation Working Group (IPWG) project (Ebert et al. 2007) can be further applied to evaluate MODRA rain retrievals. These kinds of studies are important steps in order to establish the reliability of the MODRA rain algorithm and to further improve MODRA. With the limited evaluation analyses, MODRA for daytime rain retrievals is comparable to the AMSR-E rain algorithm over land. It also appears that MODRA leads to better rain estimates for warm rain clouds. The development of MODRA explores a promising approach for optimistically applying available resources of satellite measurements in satellite rain retrievals. Bellerby et al. (2000) indicated that additional information on rain clouds from independent channel measurements would improve satellite rain estimates. Therefore, we should apply as many more independent parameters as necessary in rain retrievals. MODRA has been developed with two independent variables in this study. Because of MODIS multiple channels, it is possible to discriminate raining clouds more accurately and to identify other variables based on MODIS multiple channel measurements, such as the differences of two channels that could depict cloud optical thickness at nighttime so that a nighttime rain algorithm from MODIS measurements could possibly be established.

The demand for high-quality precipitation measurements at fine temporal–spatial scales is strong. Rainfall products utilizing multiple satellite measurements would have more impacts on earth science–related applications. Thus, exploring the possibility of using different satellite measurements in rain retrievals is a step in the right direction. The methodology developed in this study could be applied to geostationary satellites and future satellite projects. A study extending this method to the Chinese Feng Yun geostationary satellites for estimating daytime 12-h rainfall is in progress.

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