An algorithm for estimating downward shortwave radiation from GMS 5 visible imagery and its evaluation over China

Ning Lu, Ronggao Liu, Jiyuan Liu, and Shunlin Liang

1State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China.
2Graduate University of Chinese Academy of Sciences, Beijing, China.
3Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China.
4Department of Geography, University of Maryland, College Park, Maryland, USA.

Copyright 2010 by the American Geophysical Union. 0148-0227/10/2009JD013457

Received 28 October 2009; revised 20 May 2010; accepted 26 May 2010; published 16 September 2010.

[1] This paper presents an operational scheme to estimate downward shortwave radiation (DSR) over China from the visible-band top-of-atmosphere reflectance of the Geostationary Meteorological Satellite (GMS) 5 imagery. The proposed algorithm retrieves surface reflectance and atmospheric parameters directly from GMS 5 images by searching lookup tables, which are created by the radiative transfer model SBDART and consider the effects of water vapor absorption and surface altitude variations. Experiments show that the DSR retrieval is more sensitive to the selection of aerosol type and less to that of the cloud type. Uncertainty in the reflectance of a bright surface leads to a considerable DSR retrieval error (∼(6–9%)). The instantaneous retrieved DSR is evaluated by field measurements on the Tibetan Plateau, and the daily retrieved DSR is compared with one year’s ground-based measurements at 96 stations in China. The results show that the estimated DSR is in good agreement with ground measurements with a correlation coefficient of ∼0.9 and a bias of 1.5%. Root-mean square differences in the daily DSR are 17.7% for all-sky and 13.1% for clear-sky conditions. These results suggest that the proposed method applied to the GMS 5 satellite data can accurately estimate temporally and spatially continuous instantaneous and daily DSR. These DSR data sets will be useful for a wide range of applications.


1. Introduction

[2] The temporal and spatial distribution of downward shortwave radiation (DSR) at the surface is important in terms of the surface energy budget and a necessary input for models of land–surface processes. Such information is required for a wide range of applications, such as the hydrological cycle [Arnold et al., 1998; Bala et al., 2008], the global terrestrial net primary productivity estimation [Ruimy et al., 1994; Field et al., 1998], the climate model validation [Wild et al., 1995; Rinke et al., 1997], and the planning of solar energy utilization [Mondol et al., 2008].

[3] The spatial DSR can be interpolated from radiation observed by meteorological stations. However, only a few routinely operational meteorological stations observe global radiation, and their density is too low for accurate spatial interpolation. Especially in China, the spatial density of surface observations is inadequate. Surface observations are particularly sparse in the extended and low-populated region of northwestern China and even absent in inaccessible areas such as the Tibetan Plateau. Satellite remote sensing provides a practical approach to estimating spatially continuous DSR over a large region.

[4] The solar radiation reaching the top of the atmosphere (TOA) is nearly constant for a specific period. However, the amount of radiation (i.e., DSR) transferred through the atmosphere to the Earth’s surface depends on the composition of the atmosphere (e.g., the amounts of water vapor and ozone and the optical properties of cloud and aerosols), the path length that the radiation travels through the atmosphere which is determined by the solar zenith angle, and to some extent, the albedo of the surface, which constrains multiple reflections between the ground and atmosphere. Various methods have been developed to derive DSR data from satellite measurements with different temporal and spatial resolutions. Different DSR retrieval methods were reviewed by Pinker et al. [1995]. Generally, two main types of algorithms are used for calculating the DSR with a radiative transfer model from satellite data. One approach is that cloud, aerosol and other atmospheric parameters, which are determined from various sources, are used directly as input to the radiative transfer models [Halldore et al., 2005; Kim and Ramanathan, 2008]. Another approach is that a relationship between the TOA radiance/albedo and flux transmittance or incident DSR is established on the basis of...
an atmospheric radiative transfer model [Pinker et al., 2003; Liang et al., 2007]. Some popular surface solar radiation products derived from satellite observations include the Global Energy and Water cycle EXperiment–Surface Radiation Budget (GEWEX–SRB) 3-hourly products in a $1^\circ \times 1^\circ$ global grid, the Clouds and Earth’s Radiant Energy System (CERES) hourly and monthly surface flux data for each $1^\circ$ equal-angle region and the International Satellite Cloud Climatology Project–Flux Data (ISCCP–FD) with a resolution of 3 h and 280 km (equal-area map equivalent of $2.5^\circ$ latitude/longitude at the equator) [Wielicki et al., 1996; Raschke et al., 2006; Zhang et al., 2006].

[5] The geostationary satellite data can capture the diurnal cycle of DSR which is important for an accurate estimation of the daily total radiation [Laszlo et al., 2008]. The Geostationary Meteorological Satellite (GMS) program is a series of satellites operated by the Japan Meteorological Agency. GMS 1 to 5 have been in operation for about 30 years and can observe the whole of China. The GMS data set is preferred for DSR estimation over China in past decades owing to its diurnal frequency, long-term observation and particular spatial coverage.

[6] Previous studies on estimating the DSR from GMS 5 data mainly focused on the cloud cover [Kawamura et al., 1998; Tanahashi et al., 2001; Kawai and Kawamura, 2005]. However, the cloud attenuation coefficient is not universal. In addition, these studies gave less consideration to the role of aerosol absorption/reflection and surface altitude variation. In this paper, we describe an operational scheme to estimate downward flux at the surface using a lookup table approach from the TOA reflectance of the visible band acquired by the GMS 5 imager. This approach retrieves the surface reflectance and the atmospheric parameters directly from GMS 5 imagery, and the water vapor absorption and surface altitude are taken into account. The instantaneous and daily DSR over mainland China are estimated from GMS 5 images over the spatial range from an upper-left point of $55^\circ$N, $75^\circ$E to a lower-right point of $15^\circ$N, $137^\circ$E (Figure 1). The satellite-derived instantaneous DSR is evaluated using three in situ measurements on the Tibetan Plateau, and the daily DSR is validated using one year’s pyranometer measurements from 96 stations in China.

[7] The paper is organized as follows. The data, including those used for validation, are presented in Section 2. The algorithm description and the data processing are detailed in Section 3. After sensitivity analysis of the retrieved DSR results in Section 4, evaluation of the satellite-derived DSR

Figure 1. Locations of ground stations used in the validation of GMS 5 estimates of DSR. The GAME-Tibet stations from top to bottom are Anduo, MS3478 and Naqu. Ten stations of the CMA that serve as international exchange stations are labeled. SRTM30 DEM represents the surface elevation with a unit of meters.
using ground-based observations, and comparison with reanalysis data are discussed in Section 5. A summary is presented in Section 6.

2. Data

[8] GMS 5 was launched into a geostationary orbit above 0°N, 140°E in March 1995 and began operation in June 1995 as the successor to GMS 4. The characteristics of the GMS 5 satellite channels are summarized in Table 1. GMS 5 operationally provided images of East Asia with a cycle of one hour, and was switched over to GOES 9 in May, 2003 after exceeding its 5-year design life. In the distributed GMS 5 data archive, visible and infrared data have been resampled to a spatial resolution of 0.08°. Calibrations of GMS 5 data (e.g., cross-calibration of GMS 5 and NOAA 14 data) [Le Marshall et al., 1999] have been applied to account for the GMS 5 sensor degradation. Currently, the post-launch calibration tables in the distributed GMS 5 data sets are used to convert digital counts of visible and infrared data into TOA reflectance and brightness temperature data respectively [Tokuno et al., 1997; Tanahashi et al., 2003]. But the calibration coefficients obtained from only a part of the measurement period would lead to uncertainties in the rest of the degradation period. According to the relevant NOAA 14 calibration study [Deneke et al., 2005], an absolute uncertainty between 1% and 4% can be expected in this process.

[9] Cloud detection for each image was performed using the coupled Cloud Depiction and Forecast System model, which implements a hybrid, three-step procedure comprising temporal differencing, dynamic thresholding and spectral discrimination [d’Entremont and Gustafson, 2003]. Each step uses a different temporal, spatial, or spectral cloud signature, and therefore, the model can detect clouds on each image.

[10] Elevation data are the near-global elevation model Shuttle Radar Topography Mission (SRTM) 30 data set and have been averaged to the 0.08° latitude–longitude grids of the GMS 5 imagery.

[11] Hourly DSR data from three sites (Anduo, MS3478 and Naqu) were collected as part of GEWEX Asian Monsoon Experiments–Tibet (GAME–Tibet) in an intensive observation period (May–September 1998) [Koike et al., 1999]. The available measurements for June 1998 are used for validation. All station elevations are higher than 4000 m above mean sea level. The data were sampled every second and the average of each 30-min period was recorded. As discussed and evaluated by Yang et al. [2008], the GAME–Tibet radiation data set is regarded as the most reliable data for this region.

[12] The daily DSRs estimated from GMS 5 data are validated by the daily global radiation measured at ground stations. The daily global radiation is available from the China Meteorological Administration (CMA, http://cdc.cma.gov.cn), which currently operates an observation network of ground stations at various altitudes and having different land cover types in China (Figure 1). The DFY-4 thermoelectric pyranometer has a spectral response of 0.3–3.0 μm, sensitivity of 7–14 μV/W m², thermal effect of less than 5% and annual stability of 5% [China Meteorological Administration, 1996]. For the solar zenith angle less than 70°, the error caused by the pyranometer cosine effect is within 5% [Qiu, 2006]. There are usually 5% and 10% measurement errors in the daily global radiation when using first-class and second-class pyrometers [World Meteorological Organization, 1981], respectively. The CMA pyranometer is calibrated once every two years (after 1990) using international standard instruments. The calibration accuracy is 5%. However, the thermal cooling of the detectors would cause an important thermal offset in clear-sky than in cloudy conditions [Bush et al., 2000], which would lead to an erroneous calibration of pyranometers. As determined in previous quality control assessment of ground data, errors in radiation measuring instruments (DFY-4 thermoelectric pyranometer) at CMA stations do not exceed 5% after the year of 1990 [Shi et al., 2008].

3. Downward Shortwave Radiation Retrieval

3.1. Algorithm Description

[13] A diagram of the DSR retrieval process is presented in Figure 2, and the rationale of the mathematical derivation is given in Appendix A. The clear-sky and cloudy conditions of the GMS 5 data are first flagged by cloud detection in the image preprocessing procedure (Section 2). Under a clear-sky condition, the (narrowband) visible TOA reflectance is first converted to (broadband) shortwave TOA reflectance using spectral conversions. The spectral conversions are derived from linear regression of narrowband and broadband albedos obtained from radiative transfer simulations performed for a variety of realistic surface and atmospheric conditions. Several studies have demonstrated that the broadband albedo can be adequately predicted with knowledge of the narrowband albedo [e.g., Pinker and Ewing, 1986; Laszlo et al., 1988; Liang, 2001]. The radiative transfer model is used to derive a collection of spectral and broadband (shortwave; 0.3–3 μm) fluxes at the TOA in a controlled manner for varying amounts of aerosols, water vapor and clouds with various solar and viewing zenith angles. The Santa Barbara Discrete ordinates Atmospheric Radiative Transfer (SBDART) code [Ricchiazzi et al., 1998] is used for model simulation. The narrowband outgoing and incident fluxes are calculated by convoluting the spectral fluxes with the filtered response function of the GMS 5 visible channel (0.55–0.9 μm) approximated by a Gaussian
function. The narrowband and broadband albedos are derived as the ratios of the corresponding outgoing to incident fluxes. Different cloud types and atmospheric and surface conditions are set for each calculation. A set of simple linear regressions that simultaneously use albedos for the four surface types (ocean, vegetation, desert and snow) are determined in terms of different solar zenith angles [Laszlo et al., 1988].

The visible and shortwave TOA reflectance is converted to the surface narrowband and broadband reflectance, respectively, by the atmospheric correction [Pinker et al., 2003; Liang et al., 2006], and then the effect of illumination angle on the surface reflectance is corrected by the angular correction. For a number of days (one month in this study), the angular correction is performed for the same hours on each day to find the minimal surface reflectance by curve fitting (see Section 3.4 for details). The surface narrowband reflectance is used to simulate the TOA reflectance, while the surface broadband reflectance is used to derive the instantaneous downward shortwave flux (see equation A1 and A2 in Appendix A). Once the surface narrowband reflectance is given, the TOA reflectance for the GMS 5 visible band is then simulated by searching a lookup table with corresponding Sun–view geometries. Under the cloudy-sky condition, once the Sun–view geometry of the pixel is known, the TOA reflectances for different cloud optical depths of the two respective thermodynamic phases (water and ice) can be simulated using the first lookup table.

First, the observed TOA reflectance is compared with all simulated TOA reflectances to find the nearest simulated TOA reflectance, and the thermodynamic type of the nearest simulated reflectance is assigned to the pixel. Second, the cloud optical depth of the pixel is interpolated along the cloud optical depths of this thermodynamic type. Multilinear interpolation of the lookup table entries to the actual viewing geometry is employed in this step. No aerosol profile is

![Figure 2. Flowchart of the retrieval processing of surface radiative fluxes from a GMS 5 image. The rounded rectangles represent retrieved data, the shaded ovals represent satellite input, and the unshaded ovals represent auxiliary data.](image-url)
Table 2. Summary of Important Characteristics of the Lookup Table

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Value</th>
<th>$\omega$</th>
<th>$g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar zenith angle</td>
<td>0° to 80° at 5° increments</td>
<td></td>
<td></td>
</tr>
<tr>
<td>View zenith angle</td>
<td>0°, 15°, 30°, 45° and 65°</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative azimuth angle</td>
<td>0°, 30°, 60°, 90°, 120°, 150° and 180°</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Integrated water vapor</td>
<td>0.4, 0.8, 1.4, 3.0, 5.0 and 7.0 g/cm²</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface altitude</td>
<td>0.0, 1.0, 1.5, 2.5, 4.0 and 6.0 km</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerosol types</td>
<td>rural, urban, oceanic, tropospheric</td>
<td>0.9558</td>
<td>0.6891</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.7603</td>
<td>0.7240</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.9921</td>
<td>0.7567</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.9710</td>
<td>0.6770</td>
</tr>
<tr>
<td>Aerosol visibilities</td>
<td>5, 10, 20, 30, 50, 80 and 100km</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud types</td>
<td>water and ice</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud optical depths at 0.55 µm</td>
<td>5, 10, 20, 30, 50, 100, 150, 200, 250</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*aFor the aerosol type, $\omega$ and $g$ denote the single scattering angle and asymmetry factor, respectively.

3.3. Creation of Lookup Tables

Because SBDART online simulation is very time consuming, lookup tables are created to speed up the computation. Two lookup tables were created by integration with the GMS visible band spectral response function in two separate processes. The first table is used to convert surface narrowband reflectance to the simulated TOA reflectance, which is then compared with the observed TOA reflectance to find the atmospheric parameters; the second table is used to derive the instantaneous incident shortwave flux at the surface.

These lookup tables contain data for a range of discrete values (Table 2). Four aerosol types and two cloud types were used to create the lookup tables in the presented algorithm. For those more familiar with the aerosol optical depth (AOD) than aerosol visibility, they can be easily reciprocal-transformed with a function of the vertical profile of aerosol density defined in the SBDART model. For example, 5 and 100 km aerosol visibilities are equivalent to AODs of 1.15 and 0.04 respectively. An effective radius of 10 µm was used for the water cloud droplet size and that of 65 µm for the ice cloud droplet size. The assumed effective radii have been confirmed as typical values for midlatitude conditions [Han et al., 1994; Jensen et al., 1994]. The radius distribution is given by a modified gamma size distribution of effective variance 0.1 [Ricchiazzi et al., 1998]. The optical properties (extinction efficiency, single scattering albedo and asymmetry factor) for spherical water cloud droplets were calculated using Mie scattering in SBDART [Stephens et al., 1990], and the scattering parameters for spherical ice crystals of a single-size distribution were used for ice clouds. Nevertheless, this treatment of ice clouds is still simplistic. It is found that the ice particle effective size would lead to substantially large uncertainties in retrieval results even though the ice crystal shape may not lead to significant errors in DSR estimation [Zhang et al., 2002]. The possible effect of ice crystal effective size will be presented in the sensitivity analysis.

For DISORT calculation, the number of internal radiation streams is 40 because radiance predictions require more streams to fully resolve the angular dependence of the radiation field. The number of quadrature angles is the same as that of streams. The number of terms needed in an azimuthal series is equal to or less than that of streams, which depends on the azimuthal convergence. The extra number is truncated by a Cauchy criterion calculated in DISORT. The
4. Sensitivity Analysis

[22] The lookup table works only when the output is fairly linear with respect to the changes in independent variables and the interactive effects of different variables are weak [Liang et al., 2006]. To better assess the interactive effects and to determine the steps of different atmospheric input variables in the lookup table, a series of sensitivity studies were performed using the SBDART model. Six standard atmospheric profiles (tropical, midlatitude summer, midlatitude winter, subarctic summer, subarctic winter and the U.S. standard 1962) were first tested since they represent different gaseous (trace gas, water vapor and ozone) amounts and profiles. The dependence of the surface downward flux on the atmospheric profile is insignificant when column trace gas and water vapor amounts are kept constant [Gadhavi et al., 2008]. Therefore, only one atmospheric profile (midlatitude summer) is applied to generate the lookup table for a Lambertian surface. The integrated transmittances of water vapor and ozone over the shortwave

which the corrected surface reflectance is negative. Those observations with negative values are flagged as shadow and are excluded from the composite data. The minimal surface reflectance for a pixel during the given observational period is considered the clearest observation. Once the surface reflectances of the “clearest” observations are determined, those surface reflectances affected by “shadowing” can be interpolated.

[21] While the view angles of geostationary sensors are constant, the directional effects of surface reflectance depend only on the illumination angle, which changes during the course of the day (and season), and is described by the bidirectional reflectance distribution function. It is assumed that the surface characteristic at each image location does not change during a given observation period and that at least one observation exists under clear-sky conditions for each pixel during the same period. The bidirectional reflectance distribution function for each pixel is subsequently approximated by plotting the retrieved surface reflectance as a function of the diurnal observation time and extracting the lowest value in each observation period (Figure 3). After histogram analysis, a surface-reflectance threshold of 0.01 is chosen for GMS 5 data to reject undetected cloud-shadowed pixels. A similar threshold of 0.005 was chosen for Meteosat Second Generation data after checking the two modes of the histogram distribution [Popp et al., 2007]. A polynomial fitting procedure or a moving average method can be applied to the resulting background curve to compensate for minor inaccuracies. At the pixel for the Beijing station (Figure 3), the estimated surface reflectance increases with a decrease in the Sun zenith angle in the morning and decreases with an increase in the Sun zenith angle in the afternoon. For those land covers that have an opposite angular dependence, this method can also fit a curve to approximate the reflectance characteristics. Once the effect of the illumination angle is removed, the surface reflectance for each hour can be estimated from the fitted curve. For water surfaces, the glint effect of the Sun can be constrained by setting the glint cone angle at 30° and then those pixels with surface reflectance lower than 0.001 are excluded [Popp et al., 2007].

3.4. Estimation of Surface Reflectance

[19] Surface reflectance can be estimated from the minimum shortwave TOA albedo observed in a certain period. However, the approach of searching for the minimum surface reflectance in the visible channel to derive composite images is not applicable in the snow season because the observed reflectance over a snow surface may be even larger than that over clouds [Li et al., 2007]. In addition, it is difficult to account for the Sun–view geometry in the atmospheric correction for composite images. Instead, the minimum apparent surface reflectance is used to composite the most clear-sky data. This retrieved surface reflectance represents the minimum aerosol and atmospheric contribution under clear-sky conditions.

[20] Through atmospheric correction, the TOA reflectance is converted into the surface reflectance after masking the cloud area. The aerosol visibility (horizontal path) of 100 km is set as the background value for representing very clear atmospheric conditions. The TOA reflectance is corrected for the Sun–view geometry, gaseous absorption, Rayleigh scattering, and aerosol extinction. This method can effectively locate shadow observations (e.g., cloud shadows or observation with a solar zenith angle greater than 80°) for

Figure 3. Estimated surface reflectance as a function of the observation hour for the pixel above the CMA station of Beijing. Dots represent the surface reflectance estimated hourly during the observation period. Circles represent the determined minimal surface reflectance. The line is a polynomial fitting curve.

LOWTRAN–7 solar spectrum is specified as the extraterrestrial solar spectrum. The TOA downward radiation is calculated from the extraterrestrial solar spectrum by accounting for the variation in the Sun–Earth distance and the position of the Sun in the sky relative to the local vertical (solar zenith angle). Downward spectral fluxes in the shortwave range (0.3–3 μm) are integrated with a wavelength increment of about 5 nm in the visible and about 200 nm in the thermal infrared, which is a good compromise of resolution and computation time. The defined shortwave wavelength range from 0.3 to 3 μm corresponds to the default measuring range of the ground-based pyranometers.
Table 3. Ozone Concentration, Water Vapor Concentration, and Their Integrated Transmittances Over the Shortwave Region

<table>
<thead>
<tr>
<th>Column Ozone Amount (Dobson Unit)</th>
<th>Transmittance</th>
<th>SZA = 0°</th>
<th>SZA = 30°</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>7.4</td>
<td>0.999</td>
<td>0.999</td>
<td>0.999</td>
</tr>
<tr>
<td>43.4</td>
<td>0.998</td>
<td>0.997</td>
<td>0.997</td>
</tr>
<tr>
<td>104.2</td>
<td>0.995</td>
<td>0.994</td>
<td>0.994</td>
</tr>
<tr>
<td>152.1</td>
<td>0.993</td>
<td>0.992</td>
<td>0.992</td>
</tr>
<tr>
<td>264.7</td>
<td>0.989</td>
<td>0.987</td>
<td>0.987</td>
</tr>
<tr>
<td>609.9</td>
<td>0.977</td>
<td>0.975</td>
<td>0.975</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Column Water Vapor Amount (gm/cm²)</th>
<th>Transmittance</th>
<th>SZA = 0°</th>
<th>SZA = 30°</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>0.418</td>
<td>0.918</td>
<td>0.913</td>
<td>0.913</td>
</tr>
<tr>
<td>0.854</td>
<td>0.898</td>
<td>0.893</td>
<td>0.893</td>
</tr>
<tr>
<td>1.418</td>
<td>0.882</td>
<td>0.876</td>
<td>0.876</td>
</tr>
<tr>
<td>2.085</td>
<td>0.868</td>
<td>0.862</td>
<td>0.862</td>
</tr>
<tr>
<td>2.934</td>
<td>0.856</td>
<td>0.849</td>
<td>0.849</td>
</tr>
<tr>
<td>4.117</td>
<td>0.845</td>
<td>0.839</td>
<td>0.839</td>
</tr>
<tr>
<td>6.726</td>
<td>0.822</td>
<td>0.815</td>
<td>0.815</td>
</tr>
</tbody>
</table>

region at two solar incident angles and their concentrations are shown in Table 3. The atmospheric conditions are set as the midlatitude summer model with a rural aerosol and visibility of 50 km. Other atmospheric parameters (e.g., surface pressure) are set as constant in the model. The impact of ozone on downward shortwave flux at the surface clearly is quite small because the transmittance effect can be ignored. However, water vapor absorption has a significant effect on downward shortwave flux, although water vapor absorption might be neglected in the visible band [Liang et al., 2006]. When the water vapor concentration (\( WV > 0.5 \) g/cm²) increases by one unit in the standard atmospheric profile, the transmittance decreases by about 1.5%, which thereby reduces the downward shortwave flux at the surface by about 15–18 W/m². A sensitivity study for the cloud droplet effective radius and cloud optical depth (COD) shows that the impact of cloud cover on the surface downward flux depends significantly on the COD (Figure 4). The cloud height (see figure S1 in auxiliary materials), as well as the cloud droplet effective radius, has little impact on the surface downward flux when the COD is constant. Hence, a fixed cloud height (1–6 km for water clouds and 6–9 km for ice clouds) and effective droplet radius (10 µm for water and 65 µm for ice) are used. Zhang et al. [2002] found that the errors in surface radiation flux retrievals due to misinterpretation of the ice crystal effective size are from 35 to –50 W/m², and the errors diminish as the solar zenith angle decreases. In our analysis, a group of discrete values for the ice crystal effective radius (from 2 to 128 µm) were tested for a solar zenith angle of 30°. When the effective radius changes from 2 to 20 µm, the uncertainty in the instantaneous downward flux changes exponentially, with a maximum error of about 45 W/m². However, when the effective radius is greater than 20 µm, the DSR retrieval is not overly sensitive to the ice crystal effective radius (i.e., the error is no more than 4 W/m²) (see auxiliary material Figure S2).1

[23] Surface elevation is not negligible in DSR retrievals, although some algorithms only for low regions do not take this influence into account [Pinker et al., 2003; Liang et al., 2006; Denike et al., 2008]. The effect of variation in the surface elevation below 1000 m on DSR is insignificant. A 100 m change in surface elevation appears to change the retrieved DSR by 0.1%, while an increase in the surface elevation above 1000 m results in a nonlinear increase in the surface downward flux. There is a large variation of 2.41% in the retrieved DSR around 6000 m elevation.

[24] To evaluate the aerosol/cloud effects on the DSR retrievals obtained from GMS 5 data, we use different cloud types and aerosol types to represent atmospheric turbidity. It was found that selecting different aerosol types does not significantly affect the DSR retrieval in most cases. Figure 5 compares DSR estimated from GMS 5 imagery for three aerosol types (rural, urban, and tropospheric) and two cloud types (water and ice). Except for the comparison between rural and urban aerosols, the differences in DSR estimated for different aerosol/cloud combinations are small. For the case of rural versus urban aerosols with water clouds, the slope of 0.98 indicates either slight overestimation of the rural aerosol type for small DSR values or slight underestimation of the urban aerosol type, or the opposite situation for large DSR values (Figure 5a). The total root-mean square error is 15.24 W/m², and the mean bias is 0.33 W/m². The largest difference is about 70 W/m² when the incident shortwave radiation at the surface is low because of a turbid atmosphere (e.g., aerosol visibility of 5 km). This condition fits the observation that rural and urban aerosols have distinct characteristics and size distributions [Kaufman et al., 2002; Chung et al., 2005]. The urban aerosol with strong absorption has strong effects on the surface irradiance. The diagram shows the sensitivity of downward flux at the surface to surface altitude, cloud droplet effective radius and COD. The atmospheric condition is represented by a midlatitude summer model with rural aerosol type. Other input parameters remain constant (solar zenith angle (30°), column ozone amount (325 DU), water vapor concentration (2.9 g/cm²), aerosol visibility (50 km), optical thickness of the cloud layer (2) and surface albedo (0.05)).

---

1Auxiliary materials are available in the HTML. doi:10.1029/2009JD013457.
uncertainty in the amount of absorbing aerosol over China/South East Asia will affect the DSR retrieval [Krüger and Graßl, 2004; Hayasaka et al., 2006]. The same situation occurs in the case of ice clouds (Figure 5c). However, there is not much difference between rural and tropospheric aerosols (Figures 5b and 5d) or rural and oceanic aerosols (see auxiliary material Figure S3).

To examine the impact of surface reflectance, $r_s$, on DSR retrieved from GMS 5 data, $r_s$ is changed by ±10% for input to model simulation. When $r_s$ is low (<0.2), it has less effect on incident shortwave flux at the surface. A 10% change in $r_s$ appears to change the retrieved DSR by 0.5%. In the case of very high $r_s$ (>0.6; e.g., for snow on the ground), the average retrieved DSR increases by 6–9% as $r_s$ increases by 10–20%. This is mainly because an overestimation of $r_s$ generally leads to a lower aerosol/cloud optical depth, which further leads to a higher level of DSR. In addition, the retrieved DSR is much more sensitive to change in $r_s$ when the sky is extremely cloudy (e.g., COD > 100). The maximum absolute retrieval error in this study due to uncertainty in the snow surface is about 30 W/m² under cloudy skies. The average error is 3–7 W/m² when a normal variation of 0.2–0.4% in $r_s$ is considered [Wang et al., 2003].

5. Results and Discussion

5.1. Evaluation of Results on an Hourly Timescale

Figures 6a–6c show the results of comparison with ground observations in June 1998 recorded at the Naqu, Anduo, Ms3478 stations on the Tibetan Plateau, respectively, on hourly timescales. The ground observations are averaged over one hour and centered at the time of the satellite overpass on the hour. Satellite-derived fluxes are instantaneous values. The performances of GMS 5 estimation are evaluated using three indices: the mean bias error (bias), root-mean square error (rms), and coefficient of correlation between estimation and observation (r). The total
number of available observations is also given (n). The average root-mean square error on an hourly timescale in the analysis for these three stations was 76.6 W/m² and the corresponding bias was −8 W/m². The overall negative bias indicates underestimation of GMS 5 retrievals for the hourly shortwave fluxes at these three stations. The neglect of three-dimensional radiative effects and broken clouds in the model retrieval is a potentially significant contribution to the hourly DSR bias [Deneke et al., 2008]. Through visual interpretation of GMS 5 visible images, large errors for the Ms3478 station under cloud were noted in the local afternoon (points A, B and C in Figure 6c). In the comparison between the satellite estimate and the ground measurement, one of the major reasons for discrepancies is the different amounts of cloud in the different illumination and viewing paths [Liang et al., 2006]. The DSR measured by a pyranometer underneath broken cloud for the condition of a clear illumination path but cloudy viewing path can be much larger than the DSR retrieved from satellite observations even if the inversion is perfect. Considering the comparatively low pixel resolution of input images (~8 km), all cloudy pixels at the GMS 5 image resolution are expected to correspond to only partial cloud cover. This would result in large errors in retrieved cloud properties that propagate to radiative flux. The effects of the different spatial and temporal averaging scales on measurements need to be accounted for in the quantitative evaluation of retrieval performance, because the errors would be introduced by different averaging ranges. A detailed analysis of the spatial and temporal scaling properties of the DSR is another issue. Using a rough-estimate method for the sampling error proposed by Deneke et al. [2005], an increase in correlation from 0.86 to 0.94 and a decrease in root-mean square error from 125 to 70 W/m² can be found for longer averaging intervals (from 10 min to 80 min) and larger regional scales (from 1 × 1 to 5 × 5 satellite pixels). Initial results from a comparison between the averages of satellite and ground observations indicate that a one-hour interval is suitable for hourly evaluation because of the dependence on the average speed of cloud movement [Pinker et al., 2003]. Furthermore, Deneke et al. [2009] showed that a period of 40–80 min for averaging surface irradiance is optimal for a comparison with satellite retrievals.

Because the water vapor amount on the Tibetan Plateau should be low given that the annual evaporation is 1767–2079 mm and the mean annual precipitation is 360–534 mm [Xu et al., 2006], an inappropriately high water vapor absorption setting in the model is another source of the negative bias. Discrepancies between satellite products and in situ measurements, usually larger in highly variable (high-relief) terrain and smaller for non-variable (low-relief) terrain, have also been found to be spatially dependent over Tibet because of the elevation effect [Yang et al., 2006; 2008]. Figure 7 shows the monthly mean diurnal variations of hourly DSR at the three stations for June 1998. Although GMS 5 retrievals for the Tibetan Plateau have slight biases toward underestimating the monthly mean values of hourly shortwave fluxes, the results still indicate good agreement between model estimations and ground observations.

5.2. Evaluation of Results on a Daily Timescale

The retrieved daily DSR values are evaluated against ground observations distributed throughout China in the year 2000. Figure 8a presents a comparison under all-sky conditions with the 96 stations from January to December 2000. Corresponding statistical parameters from the linear regression analysis are also given. The average values for 34,948 pairs of satellite estimates and ground observations

![Figure 6](image-url)
are 165.21 and 164.27 W/m$^2$ respectively. The mean bias between satellite estimates and ground observations is 0.94 W/m$^2$ (0.6%) and the root-mean square error is 29.16 W/m$^2$ (17.7%) under an all-sky condition. This results are quite comparable to the results of Tanahashi et al. [2001] with almost zero bias and 12% root-mean square error and those of Kawai and Kawamura [2005] with −1.02 W/m$^2$ bias and 19.5% root-mean square error. The correlation coefficient for all measurement–retrieval pairs is 0.90. The slope of the linear least square fit is 0.8977 and the intercept is 16.76 W/m$^2$. The deviation of the slope from 1 may be attributed to the inappropriate assumptions of the aerosol model. For example, the amount of absorbing aerosol in mixed aerosol model may be less than its true value when the atmosphere becomes turbid. In such case, the DSR actually measured would be less than that estimated. A similar comparison for clear-sky conditions is shown in Figure 8b. Clear sky is determined on the basis of no cloud cover during the daytime. The atmospheric scattering effect is reduced for the clear-sky case. For clear sky, the average values for 20,775 pairs of satellite estimates and ground observations are 204.1 and 198.0 W/m$^2$ respectively. The mean bias is −6.08 W/m$^2$ (3.1%) and the root-mean square error is 25.93 W/m$^2$ (13.1%). These results suggest that GMS 5 estimations work well for various climate regions, land cover types and elevations, and that the algorithm has better performance in estimating daily DSR than hourly DSR.

[29] The differences between satellite-derived estimates and ground observations may be attributed to calibration dynamics of the satellite sensor, undetected cloud shadows, linear interpolation in table searching, uncertainty in determining surface reflectance, missing satellite observations during certain hours of the day, and errors in ground observations. The root-mean square error can be explained in terms of differences between the viewing geometry of the ground and satellite observations. It may also be due to inadequacy of the parallel-plane assumption in the radiative transfer calculations at large solar zenith angles. In addition,
the lookup tables with coarser Sun–view geometries may lead to discrepancies between satellite estimates and ground observations. Finer resolution lookup tables are used in the MODIS atmospheric correction, which consists of 22 solar and view zenith angles and 73 relative azimuth angles, and the interpolation error is reduced to 0.002 in reflectance units [Vermote and Kotchenova, 2008].

[10] To understand the relationship between retrieval biases and aerosols, the average daily bias between the GMS 5 estimate and ground observation for each station under a clear-sky condition was calculated; meanwhile, the average AOD corresponding to each station in the same year determined from MODIS Atmosphere Level-3 monthly products was selected and compared with the bias for the 96 CMA stations (Figure 9). The Pearson coefficient of correlation between the MODIS AOD and the bias is 0.57, which is significant ($p < 0.01$) at the 99% level of confidence. Despite variation due to complicated causes, there is a moderately related trend. With an increase in AOD, the bias value changes from negative to positive, meaning that the GMS 5 retrievals change from an underestimation to an overestimation. Since aerosol loading is underestimated when less absorptive aerosols are assumed in the present model parameters, these positive biases are believed to be mainly attributed to underestimations of the aerosol amount in the retrieval process, especially for aerosols in the sub-thin-cloud layer [Hayasaka et al., 2006].

5.3. Evaluation of Results on a Monthly Timescale

[11] For the months with lowest and highest Sun elevation (August and December 2000), Figure 10 shows the histogram of differences between daily DSR from GMS 5 retrieval and the ground measurements. The histogram is significantly wider in August than in December owing to the much higher mean DSR value. The large errors in February may be mainly due to errors in snow cover information and cloud detection over snow. A box plot that groups all retrieved and measured daily DSR by month is shown in Figure 11. The gray-filled boxes delimit the lower and upper quartiles of retrieved data and measurements in each month’s data set. The median is plotted as a black bar, and the monthly means are shown by gray lines. The range from the fifth to the 95th percentile maximum values is shown by the whiskers. Good agreement between retrieved data and measurements throughout the year is clearly visible, with an overall positive bias for the retrieval. This plot confirms visually that the GMS 5 retrieval is able to represent a seasonal cycle of DSR similar to that of the ground measurement.
5.4. Comparison With a Reanalysis DSR Product

A reanalysis DSR product of the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis 1 project was selected to compare with the DSR data estimated from GMS 5 observations. The spatial resolution of daily DSR data provided by NCEP/NCAR is about 180 km in a Gaussian grid system. The original NCEP/NCAR data (192 × 192 grids) were first cropped to correspond with the study region (34 × 21 grids). The GMS 5-derived DSR data were then resampled from 8 to 180 km using the method of the nearest neighbor to match the spatial resolution of NCEP/NCAR data for comparison. Normal probability density functions (NPDFs) of the daily DSR of GMS 5 and NCEP/NCAR data over China for the period from 1997 to 2003 are shown in Figure 12. The density of the reanalysis data set is lower on the left of 200 W/m$^2$ and higher on the right of 200 W/m$^2$ than that of GMS 5 DSR data. The NPDF peaks around 215 and 170 W/m$^2$ respectively. The NPDF for NCEP/NCAR reanalysis data does not fall to low levels (<100 W/m$^2$), which suggests that the NCEP/NCAR data may not capture the lower DSR conditions over mainland China. Meanwhile, Qin et al. [2006] suggested that satellite DSR data may not capture lower DSR conditions over oceans. In general, the NPDF normal distribution of NCEP/NCAR reanalysis data is more concentrated on higher magnitudes than the GMS 5 DSR data, which implies that over China, the NCEP/NCAR reanalysis product tends to provide daily DSR higher than the GMS 5 estimation. The differences between the daily DSR of NCEP/NCAR and GMS 5 (i.e., NCEP/NCAR data minus GMS 5 data) were calculated and their average in each year is presented in Figure 13 to examine the spatial characteristics. The difference ranges from −29 to +50 W/m$^2$. The NCEP/NCAR reanalysis DSR is higher over the mainland (red and yellow) and lower over tropical seas (blue) than satellite DSR. This corroborates the above observations that the daily DSR of NCEP/NCAR reanalysis data and that of GMS 5 data tend to be high over China and surrounding sea areas, respectively. Apart from the Tibetan Plateau and ocean regions, most of the mainland has differences around 15–30 W/m$^2$. This discrepancy can be explained in that the NCEP/NCAR 1 reanalysis DSR product overestimates over land as shown above in the NPDF analysis. The model physics employed in deriving reanalysis DSR solely from the model fields forced by data assimilation could also lead to this discrepancy [Kalnay et al., 1996]. The large positive differences (40–50 W/m$^2$) grouped on the Tibetan Plateau suggest that the NCEP/NCAR 1 reanalysis DSR product may overemphasize the height effect in high-mountain regions in its assimilation process. Another main source of overestimation throughout the Tibetan Plateau may be the numerical weather forecast models; even with strictly correct radiation physics, they can underestimate cloud generation and thus overestimate solar radiation. Furthermore, according to Weare [1997] and Qin et al. [2006], the negative differences concentrated in areas of tropical seas are probably attributed to the capability of GMS 5 to handle tropical convective clouds in geostationary satellite observations with high temporal and spatial resolutions. This capability has great potential for capturing cloud behavior in the cloudy tropical zones.

6. Summary

The GMS series from 1 to 5 has operated for about 30 years. With the long-term available record of GMS satellite data, GMS-estimated DSR will play an important role in the evaluation of the solar radiation budget. This paper presents an operational scheme that uses a lookup table approach, which considers water vapor absorption and surface elevation, to estimate diurnal variation in the surface-reaching shortwave flux and daily DSR over China from the GMS 5 visible band satellite data. This scheme can also...
apply to Multifunctional Transport Satellites (MTSAT), the successor to the GMS launched in 2005.

[34] The DSR estimates are validated against ground-based observations on hourly, daily and monthly scales. The average root-mean square error of the retrieved hourly DSR is 76.6 W/m² (14.4%), and the corresponding bias is −8 W/m² (1.5%). The overall negative bias indicates an underestimation in the GMS 5 retrieval of hourly shortwave fluxes on the Tibetan Plateau. The mean bias between satellite-retrieved and ground-measured daily DSR is 0.94 W/m² (0.6%). The root-mean square difference of 29.16 W/m² (17.7%) for all-sky conditions and 25.93 W/m² (13.1%) for clear sky indicate that cloud spatial and temporal variability contributes considerable uncertainty when comparing satellite estimates with ground observations.

[35] Experiments presented in this study demonstrate that the column water vapor amount has a strong absorption impact on incident shortwave flux at the surface. The magnitude of downward flux variation rises by about 6% with one unit (gm/cm²) change in the water vapor amount in the clear-sky situation. Clouds and the water vapor amount have significant effects on DSR in addition to those due to the surface elevation and Sun-view geometry. DSR estimation is more sensitive to the selection of the aerosol type and less to that of the cloud type. The uncertainty of bright surface reflectance leads to considerable DSR retrieval bias. The comparison with NCEP/NCAR 1 reanalysis DSR data shows that NCEP/NCAR reanalysis data may overestimate the daily DSR in high-elevation regions.

[36] The estimation of instantaneous and daily DSR from GMS 5 data may be further improved using lookup tables and surface elevations with finer resolutions and especially using better defined aerosol properties (e.g., single scattering albedo and size distribution) and the relative humidity of the atmospheric profile in the radiative transfer model. At a large Sun zenith angle, the uncertainty in cloud property retrieval increases greatly because of the increasing influence of three-dimensional cloud effects and the curvature of

Figure 13. Mean of daily DSR differences between the NCEP/NCAR 1 reanalysis product and GMS 5 product (i.e., NCEP/NCAR data minus GMS data). Note the high positive differences over the Tibetan Plateau and low negative differences over tropical oceans.
the Earth. Therefore, supplement information of the three-dimensional radiative effects of clouds, which can lead to significant biases in satellite-estimated radiative fluxes depending on the Sun–view geometry, is planned for the future. More sophisticated validation methods, including inter-comparisons among different remote sensing DSR products and comparisons with more in situ instantaneous measurements, will be evaluated in future work.

[37] The complete and highly resolved spatial coverage of GMS 5 estimations can serve as an excellent source of information on DSR in addition to the traditional network of ground measurements, particularly for regions with sparse surface observations in northwestern China such as the Tibetan Plateau. Such information is expected to benefit agriculture, water management, crop yield prediction, weather forecasting, climate research and the planning of solar power plants.

Appendix A

[38] Considering a parallel-plane atmosphere over a Lambertian surface, the TOA reflectance in the solar spectrum that reaches the GMS 5 instrument \( \rho_{\text{TOA}} \) and the downward spectral flux \( F(\mu_s) \) at the surface for a specified cosine of the solar zenith angle \( \mu_s \) can be expressed as [Kaufman et al., 1997; Liang et al., 2006]

\[
\rho_{\text{TOA}}(\mu_s, \phi, \theta) = \rho_0(\mu_s, \phi, \theta) + \frac{\rho_s(\mu_s, \phi, \theta)}{1 - \rho_0(\mu_s, \phi, \theta) S} T(\mu_s) T(\mu_s), \tag{A1}
\]

\[
F(\mu_s) = \mu_s E_0 T(\mu_s) \left( \frac{1}{1 - \rho_0(\mu_s, \phi, \theta) S} \right), \tag{A2}
\]

where \( \rho_0 \) is the atmospheric reflectance without being reflected by the surface, \( T(\mu_s) \) is the total transmittance from the TOA to the ground along the path of the incoming solar beam, \( T(\mu_s) \) is the total transmittance from the ground to the TOA in the viewing direction of the satellite, \( E_0 \) is the extraterrestrial solar irradiance at the TOA, \( \rho_s(\mu_s, \phi, \theta) \) is the surface reflectance with no atmosphere above, \( \phi \) is the reflectance of the atmosphere for isotropic light entering the base of the atmosphere, \( \mu_s \) is the cosine of the view zenith angle and \( \phi \) is the azimuthal difference between the solar and view zenith angles, and \( \mu_s E_0 T(\mu_s) \) is the downward flux without any contribution from the surface.

[39] These equations are only exact for the monochromatic case, thus their application to the solar spectral region is an approximation. In equations (A1) and (A2), the variables of path reflectance \( \rho_0 \), direct downward flux \( \mu_s E_0 T(\mu_s) \), total transmittance \( T(\mu) \), and atmospheric spherical albedo \( S \) are functions of the optical thickness, single scattering albedo, and phase function of the scatterers and absorbers in the atmosphere. These unknown variables can be determined using a radiative transfer model [Liang et al., 2006; Liu et al., 2007; Zheng et al., 2008]. Once these variables are determined, it is straightforward to calculate downward flux at the surface and TOA reflectance with any surface reflectance.

[40] Acknowledgments. This research was supported by the Chinese MOST 863 program 2007AA12Z158 and projects 2006BAC08B04 and 2009CB421100. We thank Kun Yang (Institute of Tibetan Plateau Research) for helpful suggestions and providing the GAME-Tibet validation data.

References


