Test of a Modified Infrared-Only ABI Cloud Mask Algorithm for AHI Radiance Observations

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ABSTRACT

Assimilation of infrared channel radiances from geostationary imagers requires an algorithm that can separate cloudy radiances from clear-sky ones. An infrared-only cloud mask (CM) algorithm has been developed using the Advanced Himawari Imager (AHI) radiance observations. It consists of a new CM test for optically thin clouds, two modified Advanced Baseline Imager (ABI) CM tests, and seven other ABI CM tests. These 10 CM tests are used to generate composite CMs for AHI data, which are validated by using the Moderate Resolution Imaging Spectroradiometer (MODIS) CMs. It is shown that the probability of correct typing (PCT) of the new CM algorithm over ocean and over land is 89.73% and 90.30%, respectively and that the corresponding leakage rates (LR) are 6.11% and 4.21%, respectively. The new infrared-only CM algorithm achieves a higher PCT and a lower false-alarm rate (FAR) over ocean than does the Clouds from the Advanced Very High Resolution Radiometer (AVHRR) Extended System (CLAVR-x), which uses not only the infrared channels but also visible and near-infrared channels. A slightly higher FAR of 7.92% and LR of 6.18% occurred over land during daytime. This result requires further investigation.

1. Introduction

Himawari-8 is the first in the new generation of Japanese geostationary meteorological satellites (GMS). It was successfully launched on 7 October 2014 and became operational in July of 2015 (Bessho et al. 2016). Himawari-8 carries the Advanced Himawari Imager (AHI), which has much higher spectral, temporal, and spatial resolutions to give a better description of the atmospheric state than did all earlier geostationary imagers, such as the Multifunctional Transport Satellite (MTSAT) imagers on board the second generation of Japanese GMS (Miyamura 2007), the Spinning Enhanced Visible and Infrared Imager (SEVIRI) on board the Meteosat Second Generation satellites (Schmetz et al. 2002), the Geostationary Operational Environmental Satellite (GOES) imagers (Menzel and Purdom 1994; Schmit et al. 2001), the Visible and Infrared Spin Scan Radiometer on board the Chinese Fengyun-2 series (Zhang et al. 2006), and the Very High Resolution Radiometer (VHRR) on board the Indian Kalpana-1 and Indian National Satellite System (INSAT)-3 series (Singh et al. 2011). It is anticipated that AHI radiance measurements will contribute significantly to an improved retrieval accuracy of most of the geophysical parameters (e.g., outgoing longwave radiation, quantitative precipitation estimation, sea surface temperature, and atmospheric motion vectors) and forecast skill of fast-evolving severe-weather systems through data assimilation in numerical weather prediction (NWP) systems.

Infrared Imager observations are functions of atmospheric temperature, water vapor, cloud, composition, surface temperature, and surface emissivity. Unlike microwave radiances, infrared radiation observations...
cannot penetrate clouds except for optically thin clouds (e.g., cirrus). Model simulations of geostationary-imager radiances by forward radiative transfer models are the most accurate in clear-sky conditions. Therefore, applications of geostationary-imager-radiance observations in NWP systems have been limited to infrared channels in clear-sky conditions. The direct assimilation of radiance measurements from geostationary imagers can be traced back to Kelly et al. (1996) and became operational at the European Centre for Medium-Range Weather Forecasts (ECMWF) in 2002 (Köpken et al. 2004). In the past two decades, a number of studies showed that geostationary-imager-radiance assimilation in global and regional weather forecast systems produced a slightly positive impact on the forecast skill. Midtropospheric humidity and geopotential-height forecasts over tropical regions were improved by assimilating Meteosat-7/8 SEVIRI or Kalpana-1 VHRR water vapor channels in the ECMWF model when compared with a control case in which only conventional observations were assimilated (Munro et al. 2004; Köpken et al. 2004; Szyndel et al. 2005; Singh et al. 2011, 2016). By assimilating infrared radiances from GOES-11/12 imagers into the Advanced Research version of the Weather Research and Forecasting Model, a preconvective environment was more accurately described in model initial conditions, resulting in improved quantitative precipitation forecasts near the Gulf Coast (Zou et al. 2011, 2015).

A quality control that removes the cloud-affected radiances from all of the satellite radiances ingested in NWP systems is required for clear-sky-radiance assimilation. This in turn requires a cloud mask (CM) algorithm. In the past, different CM algorithms were developed for the Advanced Very High Resolution Radiometer (AVHRR) on board NOAA Polar-Orbiting Operational Environmental Satellites (POES; Stowe et al. 1999), the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the NASA Earth Observing System Aqua and Terra (Ackerman et al. 2006), the SEVIRI (Hocking et al. 2010), the INSAT-3D imager (Ojha et al. 2016), and the Advanced Baseline Imager (ABI) to be on board GOES-R (Heidinger and Straka 2013). These CM algorithms are based on spectral differences, spatial variability, and temporal coherency of measured radiances in visible, near-infrared, and infrared channels. In general, a CM algorithm consists of several CM tests that use a corresponding set of thresholds to distinguish clear pixels from cloudy ones. The thresholds are generated from a training dataset and either are constant or depend on surface type and/or time. Moreover, the AVHRR CM of the latest version, the Clouds from AVHRR Extended System (CLAVR-x) technique, employs a naïve Bayesian method (Heidinger et al. 2012). A total of 12 Bayesian classifiers are computed for different surface types such as deep water, shallow water, unfrozen land, frozen land, Arctic, Antarctic, and desert. The CLAVR-x CM now supports nearly all of the operational geostationary imagers, including the AHI. These CM algorithms were developed mainly for use by the National Weather Service and in climate monitoring (Ackerman et al. 2006).

The geostationary-imager-radiance assimilation using the National Centers for Environmental Prediction (NCEP) Gridpoint Statistical Interpolation (GSI) analysis system requires an efficient CM algorithm to be embedded in the data assimilation system, instead of a CM that is generated by an offline algorithm. The CM must be frequently generated as the data assimilation cycle advances. Besides, since visible and near-infrared channels are not included in the GSI analysis system, the CM tests involving visible channels cannot be implemented. From these considerations, an infrared-only CM algorithm is developed and tested for cloud detection in this study. It is composed of a new CM test for optically thin clouds, two modified

<table>
<thead>
<tr>
<th>Channel no.</th>
<th>Central wavelength (μm)</th>
<th>Weighting-function peak (hPa)</th>
<th>Used in AHI CM</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>3.85</td>
<td>Surface</td>
<td>Yes</td>
</tr>
<tr>
<td>8</td>
<td>6.25</td>
<td>350</td>
<td>No</td>
</tr>
<tr>
<td>9</td>
<td>6.95</td>
<td>450</td>
<td>Yes if channel 10 is not available</td>
</tr>
<tr>
<td>10</td>
<td>7.35</td>
<td>600</td>
<td>Yes</td>
</tr>
<tr>
<td>11</td>
<td>8.60</td>
<td>Surface</td>
<td>No</td>
</tr>
<tr>
<td>12</td>
<td>9.63</td>
<td>40</td>
<td>No</td>
</tr>
<tr>
<td>13</td>
<td>10.45</td>
<td>Surface</td>
<td>No</td>
</tr>
<tr>
<td>14</td>
<td>11.20</td>
<td>Surface</td>
<td>Yes</td>
</tr>
<tr>
<td>15</td>
<td>12.35</td>
<td>Surface</td>
<td>Yes</td>
</tr>
<tr>
<td>16</td>
<td>13.30</td>
<td>990</td>
<td>No</td>
</tr>
</tbody>
</table>
ABI CM tests, and seven ABI CM tests (Heidinger and Straka 2013). The AHI pixels would be ultimately determined to be cloudy when at least one CM test flags them as cloudy. The modified CM algorithm aims at removing all cloud-contaminated pixels by sacrificing some clear pixels. Moreover, since visible and near-infrared channels are eliminated from the previous algorithm, the same set of CM tests could work throughout the day, irrespective of day and night.

This paper is organized as follows: Section 2 provides a brief description of data as well as a fast radiative transfer model that are employed in this study. The 10 CM tests employed in the modified CM algorithm are described in section 3. Numerical results including the performance and a validation of 10 CM tests are presented in section 4. A summary and conclusions are given in section 5.

2. A brief description of observations and model simulations

AHI provides spatially and temporally continuous observations with 6 visible and near-infrared channels and 10 infrared channels. The spatial resolutions for visible, near-infrared, and infrared channels are 0.5, 1,
and 2 km, respectively, and the time interval between two full-disk scans is 10 min. The infrared channels have central wavelengths ranging from 3.85 to 13.3 μm and weighting-function peak levels ranging from the surface to around 40 hPa (Table 1). Figure 1 shows the images of AHI channels 7, 14, 15, and 10 at 1500 UTC 22 September 2015 within and around Typhoon Dujuan. The brightness temperatures in the central dense overcast (CDO) near the typhoon center and deep convective clouds within typhoon rainbands are nearly 100 K lower than those in clear streaks for all three surface-sensitive channels (Figs. 1a–c). Channel 10 is sensitive to water vapor in the low troposphere, and its brightness temperatures are lower than those of the three surface channels (Fig. 1d). The spatial patterns of observed brightness temperatures are highly correlated among different channels. Although channels 7, 14, and 15 are all surface sensitive, large differences between shortwave surface channel 7 and thermal infrared surface channels 14 and 15 are found in the neighborhood of CDO and deep convective clouds in the typhoon rainband (Figs. 2a,b). The characteristic features of the spatial distributions of the differences between channels 14 and 15 or
channels 14 and 10 are very different from those between channels 7 and 14 (or 15). These spectral differences for different cloud types and cloud variability form the foundation of the CM algorithms (see section 3).

Model simulations of clear-sky brightness temperatures for AHI infrared channels that are required in the modified CM algorithm are calculated by the Radiative Transfer for TIROS Operational Vertical Sounder (RTTOV), version 11.2 (Saunders et al. 1999). The threedimensional temperature, water vapor, pressure, and ozone mixing ratio as well as the two-dimensional surface skin temperature, surface wind speed, and surface wind direction from the ECMWF analyses at 6-h interval are used as input to RTTOV. The ECMWF analyses have a horizontal resolution of 0.25° × 0.25°, 91 vertical levels, and a model top around 0.01 hPa. The satellite and solar geometries were calculated according to the local time, longitude, and latitude. The necessary coefficient files that serve as input to RTTOV were made on the basis of AHI spectral response functions updated in September of 2013 by JMA (http://www.data.jma.go.jp/mscweb/en/himawari89/space_segment/spsg_ahi.html). Model simulations were first generated with RTTOV at the ECMWF analysis grids and then bilinearly interpolated to the center of the AHI fields of view.

For validation purposes, the CM results from the official NASA Goddard MODIS CM website (via http://modis-atmos.gsfc.nasa.gov/MOD35_L2/index.html), known as MYD35, are used as the “truth.” The MYD35 is of widely accepted quality (Ackerman et al. 2006) and was commonly used for evaluating the performance of new CM algorithms. It provides a 4-category CM (i.e., cloudy, uncertain, probably clear, and confidently clear) at a spatial resolution of 1 km. In this study, probably clear and confidently clear are both regarded as clear. Because MODIS and AHI operate under different sampling schemes, only AHI fields of view within which MYD35 has a 100% clear fraction or 100% cloudy fraction are retained for the comparison between MYD35 and the modified CM algorithm proposed in this study.

Ten CM tests are employed in this study (Table 2): relative thermal contrast test (RTCT), emissivity at

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**Table 2. The abbreviations and mathematical formulas of the 10 CM tests employed in this study.**

<table>
<thead>
<tr>
<th>Name</th>
<th>Condition for cloudy pixels</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTCT</td>
<td>$(O_{ch14}^{max} - O_{ch14}) - 3\sigma_{ch14} &gt; e_{RTCT}$</td>
<td>Adopted from ABI CM</td>
</tr>
<tr>
<td>ETROP</td>
<td>$\frac{I_{11.2\mu m}(O_{ch14}) - I_{11.2\mu m}(B_{ch14})}{I_{11.2\mu m}(B_{top}) - I_{11.2\mu m}(B_{ch14})} &gt; e_{ETROP}$</td>
<td>Adopted from ABI CM</td>
</tr>
<tr>
<td>PFMFT</td>
<td>$(O_{ch14} - O_{ch14})(B_{ch14} - B_{ch15})(O_{ch14} - 260) &gt; e_{PFMFT}$</td>
<td>Adopted from ABI CM</td>
</tr>
<tr>
<td>NFMFT</td>
<td>$(B_{ch14} - B_{ch15}) - (O_{ch14} - O_{ch15}) &gt; e_{NFMFT}$</td>
<td>Adopted from ABI CM</td>
</tr>
<tr>
<td>RFMFT</td>
<td>$</td>
<td>O_{ch14} - O_{ch15} - (O_{ch14}^{NWC} - O_{ch15}^{NWC})</td>
</tr>
<tr>
<td>CIRH2O</td>
<td>$\rho(O_{ch14}, O_{ch15}) &gt; e_{CIRH2O}$</td>
<td>Adopted from ABI CM</td>
</tr>
<tr>
<td>M-EMISS4</td>
<td>$\frac{I_{1.5\mu m}(O_{ch7}) - I_{3.7\mu m}(B_{ch7})}{I_{1.5\mu m}(B_{ch7})} &gt; e_{M-EMISS4}$ (nonglint area)</td>
<td>Modified on the basis of ABI CM</td>
</tr>
<tr>
<td>M-ULST</td>
<td>$\frac{I_{1.5\mu m}(O_{ch7}) - I_{3.7\mu m}(B_{ch7})}{I_{1.5\mu m}(B_{ch14})} &gt; e_{M-ULST}$ (only nighttime)</td>
<td>Modified on the basis of ABI CM</td>
</tr>
<tr>
<td>N-OTC</td>
<td>$O_{ch15} - O_{ch15} &gt; e_{N-OTC}$</td>
<td>Newly added</td>
</tr>
<tr>
<td>TEMPIR</td>
<td>$O_{ch14}^{10\mu m} - O_{ch14} &gt; e_{TEMPIR}$</td>
<td>Adopted from ABI CM</td>
</tr>
</tbody>
</table>
tropopause test (ETROP), positive 14 minus 15 test (PFMFT), negative 14 minus 15 test (NFMFT), relative 14 minus 15 test (RFMFT), cirrus water vapor test (CIRH₂O), modified 4-μm emissivity test (M-EMISS4), modified uniform low stratus test (M-ULST), new optically thin cloud test (N-OTC), and temporal infrared test (TEMPIR). All of the CM tests except N-OTC were adopted from the ABI CM algorithm (Heidinger and Straka 2013). Because the spectral response functions of AHI and ABI infrared channels are almost the same, the thresholds for these CM tests are taken directly from the ABI CM algorithm. N-OTC is a new CM test added for detecting optically thin clouds. To minimize the number of pixels in fog and stratus clouds being identified as clear, EMISS4 and ULST were slightly modified in this study. Brief descriptions of these 10 CM tests are given in the following sections.

a. The 9 ABI CM tests

1) RELATIVE THERMAL CONTRAST TEST

RTCT is based on an assumption that the pixels with a relatively large spatial variation of channel-14 brightness temperatures are likely to be cloudy. The following formula is applied to identify cloudy pixels:

\[
(O_{\text{max}}^{\text{ch14}} - O_{\text{ch14}}) - 3\gamma \sigma_z > e_{\text{RTCT}},
\]

where \(O_{\text{ch14}}\) is the observed channel-14 brightness temperature, \(O_{\text{max}}^{\text{ch14}}\) is the maximum channel-14 brightness temperature.

Table 3. Sensitive experiments that show the effects of 0.5-K uncertainty in \(B_{\text{ch7}}\) or \(B_{\text{ch14}}\) on \([I_3\gamma_{\text{um}}(B_{\text{ch7}})]/[I_3\gamma_{\text{um}}(B_{\text{ch14}})]\). The \(B_{\text{ch7}}\) and \(B_{\text{ch14}}\) in control experiments are calculated with the surface temperature \(T_{\text{sfc}}\) given that the surface emissivities at channels 7 and 14 are 0.97 and 0.99, respectively.

<table>
<thead>
<tr>
<th>(B_{\text{ch7}})</th>
<th>(B_{\text{ch14}})</th>
<th>(I_3\gamma_{\text{um}}(B_{\text{ch7}})/I_3\gamma_{\text{um}}(B_{\text{ch14}}))</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>289.31 K</td>
<td>289.35 K</td>
<td>0.998</td>
<td>Control experiment</td>
</tr>
<tr>
<td>289.31 ± 0.5 K</td>
<td>289.35 K</td>
<td>0.998 ± 0.022</td>
<td>0.5-K uncertainty in (B_{\text{ch7}})</td>
</tr>
<tr>
<td>289.31 K</td>
<td>289.35 ± 0.5 K</td>
<td>0.998 ± 0.022</td>
<td>0.5-K uncertainty in (B_{\text{ch14}})</td>
</tr>
<tr>
<td>279.35 K</td>
<td>279.39 K</td>
<td>0.998</td>
<td>Control experiment</td>
</tr>
<tr>
<td>279.35 ± 0.5 K</td>
<td>279.39 K</td>
<td>0.998 ± 0.024</td>
<td>0.5-K uncertainty in (B_{\text{ch7}})</td>
</tr>
<tr>
<td>279.35 K</td>
<td>279.39 ± 0.5 K</td>
<td>0.998 ± 0.024</td>
<td>0.5-K uncertainty in (B_{\text{ch14}})</td>
</tr>
</tbody>
</table>
temperature in a $3 \times 3$ pixel box surrounding the target pixel, $\sigma_z$ is the standard deviation of terrain heights in this pixel box, and $\gamma$ represents the lapse rate (this and the following formulas are repeated in Table 2). A constant value of $7 \text{ K km}^{-1}$ is given to $\gamma$. Here, $\varepsilon_{\text{RTCT}}$ is the threshold for RTCT.

2) EMISSIVITY AT TROPOPAUSE TEST

ETROP assumes that the observed channel-14 brightness temperatures are much colder than those from model simulations under clear-sky conditions in the presence of cloud. Unlike the gross tests that are traditionally employed in other CM algorithms (e.g., Hocking et al. 2010), however, which work directly on the observed brightness temperature minus the simulated brightness temperature, ETROP operates on the tropopause-relative emissivity. A pixel is determined to be cloudy if

$$\frac{I_{1.2\mu m}(O_{\text{ch14}}) - I_{1.2\mu m}(B_{\text{ch14}})}{I_{1.2\mu m}(T_{\text{trop}}) - I_{1.2\mu m}(B_{\text{ch14}})} > e_{\text{ETROP}},$$

where $I_{1.2\mu m}(T)$ represents the radiance at temperature $T$ and 1.2-$\mu$m wavelength that is computed by the Planck function, $B_{\text{ch14}}$ is the simulated channel-14 brightness temperature under clear-sky conditions, and $T_{\text{trop}}$ is the tropopause temperature. The $e_{\text{ETROP}}$ is the threshold for ETROP.

3) POSITIVE FOURTEEN MINUS FIFTEEN TEST

The water vapor continuum absorption would generate a positive value of the brightness temperature difference between channels 14 and 15 ($O_{\text{ch14}} - O_{\text{ch15}}$) under clear-sky conditions. However, $O_{\text{ch14}} - O_{\text{ch15}}$ would be elevated if semitransparent cloud is present. Therefore, relatively large values of $O_{\text{ch14}} - O_{\text{ch15}}$ can be used to detect the semitransparent cloudy pixels. The formula used in PFMFT is

$$(O_{\text{ch14}} - O_{\text{ch15}}) - (B_{\text{ch14}} - B_{\text{ch15}}) \left(\frac{O_{\text{ch14}} - 260}{B_{\text{ch14}} - 260}\right) > e_{\text{PFMFT}},$$

where $B_{\text{ch14}}$ and $B_{\text{ch15}}$ are model-simulated brightness temperatures of channels 14 and 15 under clear-sky conditions, respectively. The term

<table>
<thead>
<tr>
<th>CM test</th>
<th>Ocean</th>
<th>Land</th>
<th>Snow</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTCT</td>
<td>3.2</td>
<td>4.1</td>
<td>—</td>
</tr>
<tr>
<td>ETROP</td>
<td>0.1</td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>PFMFT</td>
<td>0.8</td>
<td>2.5</td>
<td>1.0</td>
</tr>
<tr>
<td>NFMFT</td>
<td>1.0</td>
<td>2.0</td>
<td>5.0</td>
</tr>
<tr>
<td>RFMFT</td>
<td>0.7</td>
<td>1.0</td>
<td>—</td>
</tr>
<tr>
<td>CIRH2O</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>M-EMISS4 Nonl. area</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>M-EMISS4 Glint area</td>
<td>2.86</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>M-ULST</td>
<td>0.05</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>N-OTC Daytime</td>
<td>15</td>
<td>21</td>
<td>10</td>
</tr>
<tr>
<td>N-OTC Nighttime</td>
<td>11</td>
<td>15</td>
<td>4.5</td>
</tr>
<tr>
<td>TEMPIR</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
</tbody>
</table>

FIG. 4. (a) CLAVR-x cloud types: clear (labeled clr; cyan), fog (yellow), water (light green), supercooled water (labeled scwt; green), opaque ice (labeled op_ice; forest green), cirrus (orange), overlapping (labeled overlap; blue), and overshooting (labeled oversht; red); (b) cloudy pixels detected by N-OTC only (red), by both N-OTC and the other nine CM tests (blue), and by the other nine CM tests but not by N-OTC (gray) within and around Typhoon Dujuan at 1500 UTC 22 Sep 2015.
serves to eliminate the impact of clear-sky water vapor continuum absorption and is effective only when $O_{ch14} > 270$ K and $B_{ch14} > 270$ K. The $\varepsilon_{PFMFT}$ is the threshold for PFMFT.

4) NEGATIVE FOURTEEN MINUS FIFTEEN TEST

Opaque clouds residing above the bulk of water vapor can generate values of $O_{ch14} - O_{ch15}$ that are less than clear-sky estimates. From this consideration, a pixel is deemed cloudy if

$$ (B_{ch14} - B_{ch15}) \left( \frac{O_{ch14} - 260}{B_{ch14} - 260} \right) > \varepsilon_{NFMFT}, \quad (4) $$

where $\varepsilon_{NFMFT}$ is the threshold for NFMFT.

5) RELATIVE FOURTEEN MINUS FIFTEEN TEST

Previous studies showed that the values of $O_{ch14} - O_{ch15}$ vary with cloud thicknesses. Because the cloud thicknesses are not uniform, significant differences
in the values of $O_{\text{ch}14} - O_{\text{ch}15}$ between a cloudy pixel and its neighboring warm center (NWC) may exist. The NWC is defined as the warmest pixel in a $21 \times 21$ pixel box surrounding the target pixel and represents the optically thinnest pixel in the local area. A large deviation of $O_{\text{ch}14} - O_{\text{ch}15}$ at the targeted pixel from those at the NWC suggests an existence of clouds. The formula used in RFMFT for detecting cloudy pixels is

$$\| (O_{\text{ch}14} - O_{\text{ch}15}) - (O_{\text{ch}14}^{\text{NWC}} - O_{\text{ch}15}^{\text{NWC}}) \| > \varepsilon_{\text{RFMFT}},$$

where $\|$ represents the absolute value and $O_{\text{ch}14}^{\text{NWC}}$ and $O_{\text{ch}15}^{\text{NWC}}$ are brightness temperature observations of channels 14 and 15 at the NWC. The $\varepsilon_{\text{RFMFT}}$ is the threshold for RFMFT.

6) **CIRRUS WATER VAPOR TEST**

Spatial variations arising from surface features and water vapor variability are different, whereas spatial variations due to upper-tropospheric clouds are apparent and correlated in infrared window channels and water vapor channels. Therefore, the spatial correlations between the window channel 14 and water vapor channel 10...
are used for detecting upper-tropospheric clouds. In mathematical terms, a pixel is flagged as cloudy if

\[ \rho(O_{\text{ch14}}, O_{\text{ch10}}) > e_{\text{CIRH2O}}, \]  

where \( \rho(O_{\text{ch14}}, O_{\text{ch10}}) \) represents the Pearson correlation coefficient of brightness temperatures between channels 10 and channel 14 for each pixel over a 5 \times 5 pixel box. The \( e_{\text{CIRH2O}} \) is the threshold for CIRH2O.

7) 4-\( \mu \)m EMISSIVITY TEST

The emissivity in the 4-\( \mu \)m region (channel 7) is sensitive to clouds. This property can be used to detect clouds. EMISS4 compares the observed 4-\( \mu \)m emissivity to the expected emissivity of clear sky. The emissivity values are calculated as

\[ \text{Emis} = \frac{T_{\text{obs}}}{T_{\text{emiss}}}. \]

where \( T_{\text{obs}} \) is the observed brightness temperature and \( T_{\text{emiss}} \) is the emissivity.

FIG. 6. (a) Cloudy pixels detected inclusively by each of the 10 CM tests, and (b) cloudy pixels detected exclusively by one of the 10 CM tests but not by the other nine for AHI full-disk data at nighttime, 1500 UTC 22 Sep 2015.
with an estimated emissivity under clear-sky conditions. The EMISS4 formula is

\[
\frac{I_{3.9\mu m}(O_{ch7}) - I_{3.9\mu m}(B_{ch7})}{I_{3.9\mu m}(O_{ch14}) - I_{3.9\mu m}(B_{ch14})} > e_{EMISS4}^{*}, \tag{7}
\]

where \(I_{3.9\mu m}(T)\) represents the radiance at temperature \(T\) and 3.9-\(\mu\)m wavelength that is computed by the Planck function. The term \([I_{3.9\mu m}(O_{ch7})]/[I_{3.9\mu m}(O_{ch14})]\) is the observed 4-\(\mu\)m emissivity, and \([I_{3.9\mu m}(B_{ch7})]/[I_{3.9\mu m}(B_{ch14})]\) is an estimate under clear-sky conditions. Here, \(e_{EMISS4}^{*}\) is the threshold for EMISS4. The clear-sky-radiance simulation of channel 7 \([I_{3.9\mu m}(B_{ch7})]\) must include the effects of solar reflectance during daytime. Otherwise, a correction is needed that is based on the solar viewing geometry and the atmospheric transmittance.

8) UNIFORM LOW STRATUS TEST

Different from other cloud types, the uniform low stratus clouds are less emissive than the surface in channel 7. On the basis of this consideration, a pixel is flagged as fog or stratus if

\[
\frac{I_{3.9\mu m}(B_{ch7}) - I_{3.9\mu m}(O_{ch7})}{I_{3.9\mu m}(B_{ch14}) - I_{3.9\mu m}(O_{ch14})} > e_{ULST}^{*}, \tag{8}
\]

where \(e_{ULST}^{*}\) is the threshold for ULST. ULST is only applied during nighttime because the uncertainty in the reflected solar radiation is larger than the radiance difference between low-level cloud and the surface during daytime.

9) TEMPORAL INFRARED TEST

Pixels at cloud edges could be detected by an obvious cooling of channel-14 brightness temperatures as the clouds move to previously clear regions. Because the temporal resolution of AHI is 10 min, the formula used in TEMPIR is

\[
O_{10min}^{ch14} - O_{ch14} > e_{TEMPIR}, \tag{9}
\]

where \(O_{10min}^{ch14}\) represents the channel-14 brightness temperature observations taken 10 min earlier than \(O_{ch14}\). The \(e_{TEMPIR}\) is the threshold for TEMPIR.

b. One new and two modified CM tests

1) M-EMISS

The contribution of the reflected sunlight to a radiance observation is difficult to account for with Eq. (7). Thus, EMISS4 is not applied to sun-glint areas in the ABI algorithm, where a sun-glint area is defined by pixels with sun-glint angles of less than 40° over ocean. Nevertheless, this study exploits a new procedure for detecting clouds over a sun-glint area. Brightness temperatures of channel 7 over cloudy areas are lower than those of model simulations under clear-sky conditions. From this consideration, a pixel is flagged as cloudy if

\[
O_{ch7} - B_{ch7} < \mu - 3\sigma, \tag{10}
\]

where \(\mu\) and \(\sigma\) represent the bias and standard deviation of brightness temperature differences of channel 7 between AHI observations and model simulations in clear-sky conditions. On the basis of a previous study in which

![Fig. 7. As in Fig. 6, but for daytime, 0300 UTC 22 Sep 2015.](https://example.com/fig7.png)
the AHI data bias is estimated using RTTOV (Zou et al. 2016), $\mu$ and $\sigma$ are set to 0.26 and 1.04 K, respectively. Figure 3 shows an area populated with cloudy pixels identified by Eq. (10) over a sun-glint area located to the west of Australia at 0900 UTC 15 December 2015.

Another modification is made to EMISS4 over land. The original EMISS4 threshold for land in the ABI CM algorithm was 0.46. It is significantly larger than that for ocean (0.1) or a snow-covered surface (0.3), resulting in many cloudy pixels being identified as clear. In this study, the EMISS4 threshold for land is changed to a smaller value of 0.2. M-EMISS4 is the same as EMISS4 in the ABI algorithm except for the addition of the abovementioned two modifications.

2) M-ULST

M-ULST is the same as ULST in the ABI algorithm but with a change in the threshold over ocean. The ULST thresholds in the original ABI CM algorithm were 0.12, 0.1, and 0.12 for ocean, land, and snow-covered surfaces, respectively. The thresholds are determined by the uncertainty of $[I_{3.9\mu m}(B_{ch7})]/[I_{3.9\mu m}(B_{ch14})]$ and $[I_{3.9\mu m}(O_{ch7})]/[I_{3.9\mu m}(O_{ch14})]$. According to a set of sensitive experiments shown in Table 3, however, the uncertainty of $[I_{3.9\mu m}(B_{ch7})]/[I_{3.9\mu m}(B_{ch14})]$ is less than 0.024 for an uncertainty of 0.5 K in $B_{ch7}$ or $B_{ch14}$. Because model simulations by RTTOV are very accurate over ocean in clear-sky conditions (Sherlock 1999), the uncertainty of $B_{ch7}$ and $B_{ch14}$ can be even smaller than 0.024 for ocean pixels. This fact means that the ULST threshold for ocean surface can be more strict. To maximize the stratus and fog recognition over ocean, the ULST threshold of 0.12 is reduced to 0.05 in this study.

3) A NEW OPTICALLY THIN CLOUD TEST

N-OTC is a new CM test added for detection of optically thin clouds. Surface radiation has a larger impact on channel 7 than on channel 15, and thus the brightness temperatures of channel 7 are significantly higher than those of channel 15 in the presence of thin clouds. A pixel is flagged as cloudy by N-OTC if

$$O_{ch7} - O_{ch15} > \varepsilon_{N-OTC}.$$  

During daytime, solar radiation reflected from clouds will increase the brightness temperatures of channel 7. Therefore, the threshold of N-OTC ($\varepsilon_{N-OTC}$) during daytime is larger than during nighttime (Table 4).

Figure 4 gives a nighttime example of thin cloud pixels identified by N-OTC. According to the CLAVR-x cloud types at 1500 UTC 22 September 2015 (Fig. 4a), Typhoon Dujuan was characterized by optically thick overshooting and ice clouds near the center, widespread optically thin clouds (cirrus and fog) and overlapped clouds farther away from the center. The differences of brightness temperature between channels 7 and 15 (Fig. 2b) in regions with optically thick clouds (e.g., CDO, overshooting, and overlapping) are as small as in clear-sky conditions but are large in regions with optically thin clouds (cirrus and fog). Therefore, these optically thin cloudy pixels are successfully flagged as cloudy by the nighttime N-OTC ($O_{ch7} - O_{ch15} > 11$ K). Furthermore, cloudy pixels in the regions declared as fog by the CLAVR-x cloud-type algorithm are detected by N-OTC but are missed by all other nine CM tests (Fig. 4b). Note that the fogs in Fig. 4a are probably thin cirrus clouds because AHI pixels in those
fog regions are not cloudy according to M-ULST (see Fig. 5).

4. Performances and validation of 10 CM tests

a. Comparison among 10 CM tests

Spatial distributions of the test metrics employed by the 10 CM tests within and around Typhoon Dujuan at 1500 UTC 22 September 2015 are provided in Fig. 5. Thresholds for the 10 CM tests (Table 4) are indicated by the values shown between cyan and green. A pixel with a CM test value that is greater than its threshold is identified as cloudy by this test. A pixel would be finally determined as cloudy if at least one CM test flags this pixel as cloudy. The performance of each CM test can be examined from Fig. 5. RTCT examines the spatial

![Spatial distributions of correctly (green) and falsely (blue) detected cloudy pixels and correctly (cyan) and falsely (red) detected clear pixels detected by (a) the modified ABI CM and (b) CLAVR-x algorithms at 1500 UTC 22 Sep 2015 as validated by the MYD35 CM results within a temporal window of ±1 h. Only AHI pixels within which MYD35 has a 100% clear fraction or 100% cloudy fraction are included.](http://journals.ametsoc.org/jamc/article-pdf/55/11/2529/3586721/jamc-d-16-0254_1.pdf)

**TABLE 5.** Values of PCT, FAR, LR, and HSS of the modified ABI CM algorithm calculated using full-disk AHI data on 22–24 Sep and 15–17 Dec 2015 as well as on 20–22 Mar and 5–7 Jun 2016. The MYD35 CM results are used as the truth.

<table>
<thead>
<tr>
<th></th>
<th>Ocean</th>
<th>Land</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Day</td>
<td>Night</td>
<td>All day</td>
</tr>
<tr>
<td>Sample no. (×10^6)</td>
<td>35.67</td>
<td>33.42</td>
<td>69.09</td>
</tr>
<tr>
<td>PCT (%)</td>
<td>89.96</td>
<td>89.49</td>
<td>89.73</td>
</tr>
<tr>
<td>FAR (%)</td>
<td>4.73</td>
<td>3.55</td>
<td>4.16</td>
</tr>
<tr>
<td>LR (%)</td>
<td>5.31</td>
<td>6.96</td>
<td>6.11</td>
</tr>
<tr>
<td>HSS</td>
<td>0.770</td>
<td>0.739</td>
<td>0.756</td>
</tr>
</tbody>
</table>
variation of cloud-top brightness temperatures. Only pixels with relatively rough cloud tops are marked as cloudy, while the CDO and other uniform clouds are still marked as clear. As the most widely used CM test, ETROP could screen out the majority of the cloudy pixels. It is effective in convective clouds such as CDO and spiral cloud bands. PFMFT is designed for detecting semitransparent clouds and thus fails to identify CDO. In contrast, NFMFT is for detecting opaque clouds and thus only captures CDO and deep convective clouds embedded in the spiral bands. RFMFT is based on an assumption that the thicknesses within clouds are not uniform. As a result, the performance of RFMFT is more or less similar to that of RTCT. CIRH2O detects upper-tropospheric clouds and successfully captured relatively thick cirrus clouds. M-EMISS4 finds most convective clouds and overlapped clouds but missed all of the thin cirrus, low stratus, and fogs. Conversely, M-ULST can only detect low stratus and fogs. The newly added N-OTC succeeded in the detection of cirrus, especially very thin cirrus. TEMPIR screens out all of the pixels located at cloud edges.
The percentage of cloudy pixels detected inclusively by each of the 10 CM tests is shown in Fig. 6a. Note that all of the pixels from the full-disk scan at 1500 UTC 22 September 2015 are included in the statistics. It can be seen that ETROP screens out 74.10% of cloudy pixels while M-ULST only screens out 9.52%. The percentage of cloudy pixels detected exclusively by one but not detected by the other nine of the 10 CM tests is provided in Fig. 6b. It is seen that 4.50% of cloudy pixels are detected only by RFMFT, 3.25% are detected only by M-ULST, and 2.29% are detected only by N-OTC. Cloudy pixels detected by M-ULST and N-OTC are only 9.52% and 31.64%, respectively. This is reasonable because M-ULST and N-OTC are designed for detecting specific clouds such as stratus and cirrus. It is worth pointing out that every CM test detected exclusively some cloudy pixels. Therefore, every CM test is useful and plays an indispensable role for cloud detection.

When the daytime scan at 0300 UTC 22 September 2015 is analyzed (Fig. 7), M-EMISS4 detects the most cloudy pixels and N-OTC detects the secondmost cloudy pixels. These two CM tests involve AHI channel 7, which is influenced by reflected solar radiation. Meanwhile, M-ULST is not executed during daytime, and therefore it detects 0% of cloudy pixels. The cloudy pixels detected exclusively by M-EMISS4 are 6.05%, which includes some cloudy pixels in the sun-glint area identified by the newly added cloud-detection test in Eq. (10). With the exception of M-ULST, all other CM tests detected some cloudy pixels exclusively.

\[ PCT = \frac{N(T_{\text{cld}} \cap E_{\text{cld}} + T_{\text{clr}} \cap E_{\text{clr}})}{N(T_{\text{cld}} + T_{\text{clr}})}, \]  
\[ \text{FAR} = \frac{N(T_{\text{clr}} \cap E_{\text{cld}})}{N(T_{\text{cld}} + T_{\text{clr}})}, \]  
\[ \text{LR} = \frac{N(T_{\text{cld}} \cap E_{\text{cld}})}{N(T_{\text{clr}} + T_{\text{clr}})}, \]  
\[ \text{HSS} = \frac{N(T_{\text{cld}})N(E_{\text{cld}}) + N(T_{\text{clr}})N(E_{\text{clr}})}{N(T_{\text{cld}} + T_{\text{clr}})^2} - \frac{N(T_{\text{cld}})N(E_{\text{clrd}}) + N(T_{\text{clr}})N(E_{\text{clrd}})}{N(T_{\text{cld}} + T_{\text{clr}})^2}, \]

where \( T_{\text{cld}} \) and \( T_{\text{clr}} \) represent the “true” cloudy and clear-sky pixels determined by the MYD35 CM algorithm, respectively, and \( E_{\text{cld}} \) and \( E_{\text{clr}} \) represent the cloudy and clear-sky pixels identified by the CM algorithm to be evaluated. A good CM algorithm should have high PCT and HSS along with low FAR and LR.

\[ \text{PCT} = 90.41\%, \text{FAR} = 2.79\%, \text{LR} = 6.80\%, \text{HSS} = 0.802. \]

A CM comparison can also be made between the modified infrared-only ABI CM algorithm and the CLAVR-x...
CM algorithm. Figure 8b presents the CM results generated by the CLAVR-x, which can be compared with Fig. 8a. Figure 9b provides a spatial distribution of correctly and falsely detected cloudy pixels and correctly and falsely detected clear pixels detected by the CLAVR-x as validated by the MYD35 CM results. The PCT, FAR, LR, and HSS of the CLAVR-x CM algorithm are 90.48%, 2.56%, 6.95%, and 0.804, respectively. The HSS for modified ABI CM and CLAVR-x CM are nearly equal. The LR for the modified ABI CM algorithm is slightly lower than that for the CLAVR-x CM algorithm, but the FAR is slightly higher. This means that fewer cloudy pixels would be flagged as clear by the modified ABI CM algorithm than by the CLAVR-x CM algorithm.

The average performance of the proposed CM algorithm intended for AHI radiance assimilation is evaluated for 12-day data in the AHI full disk on 22–24 September and 15–17 December 2015 as well as on 20–22 March and 5–7 June 2016 (Table 5 and Fig. 10). Data of different months are used so as to test the performance of the new CM algorithm in different seasons. The PCT over ocean is 89.73%, with an HSS of 0.756. The PCT over land is 85.91% during daytime and 92.59% during nighttime. The FAR and LR during daytime are considerably higher (7.92% and 6.18%, respectively) than those during nighttime (4.23% and 3.17%, respectively), resulting in an HSS of 0.713 during daytime and an HSS of 0.827 during nighttime. The high LR and FAR during daytime are...
associated with stratus and fog pixels (figure omitted). As mentioned before, the M-ULST designed specifically for stratus and fogs is not available during daytime, and thus the fogs and stratus could be missed. The proposed CM algorithm screens out as many cloud-contaminated pixels as possible by sacrificing some clear pixels.

As a comparison, the performance of CLAVR-x CM during the same period is also provided (Table 6 and Fig. 10). The PCT and HSS of the CLAVR-x CM algorithm over ocean are slightly worse than those of the modified ABI CM algorithm, but the performance of CLAVR-x CM over land is much better. The CLAVR-x CM algorithm does not have a low PCT, high FAR, and high LR as the modified ABI CM algorithm did during daytime. This is because the Bayesian classifiers in the CLAVR-x CM algorithm involve the visible and near-infrared channels that are useful in fog detection during daytime. When all of the pixels get involved, the CLAVR-x CM achieves an HSS of 0.767. In contrast, the modified ABI CM algorithm achieves an HSS of 0.766. Overall, the modified ABI CM algorithm performs reasonably well when compared with the CLAVR-x CM algorithm, although more channels are employed in the CLAVR-x CM algorithm.

Figure 11 provides an illustration of the observed brightness temperatures (Fig. 11a), the consistency of clear and cloudy pixels between the modified ABI CM and CLAVR-x algorithms (Fig. 11b), and the differences between the observations and model simulations (Figs. 11c,d) of AHI channel 13 at 1500 UTC 22 September 2015. It can be seen that cloudy pixels that are detected by the modified ABI CM algorithm over southern China are declared as clear by the CLAVR-x algorithm (blue in Fig. 11b). The modified ABI CM algorithm apparently finds some clear pixels at the CLAVR-x cloud edges, however. The bias and standard deviation of the differences of brightness temperatures at AHI channel 13 between observations and model simulations calculated over the clear-sky pixels determined by both the modified ABI CM and CLAVR-x algorithms, that is, over areas with cyan in Fig. 11b, are $-0.43$ and $1.72$ K. The biases calculated over all of the clear-sky pixels determined by the modified ABI CM and the CLAVR-x algorithms are $-0.62$ and $-1.45$ K, respectively. The standard deviations calculated over all of the clear-sky pixels determined by the modified ABI CM and the CLAVR-x algorithms are $2.07$ and $3.18$ K, respectively. In other words, the bias and standard deviations in clear-sky conditions estimated by the modified ABI CM are more accurate than those estimated by the CLAVR-x algorithm.

### 5. Summary and conclusions

An infrared-only CM algorithm was developed for AHI radiance observations in this study. It consists of a new CM test for detecting optically thin cirrus, two modified ABI CM tests, and seven unmodified ABI CM tests. Considering the facts that currently most of the NWP data assimilation systems assimilate the infrared radiance only from clear-sky regions and that most of the geophysical parameters (e.g., land and sea skin temperature; temperature and moisture profiles; total precipitable water) are retrieved from space-based observing systems under clear-sky conditions only, any improvement in the cloud-detection algorithm will have large implications in areas such as NWP and retrieval of geophysical parameters.

In an evaluation using MYD35 CM results, the modified ABI CM algorithm gives a PCT of 89.77%, a FAR of 4.25%, an LR of 5.98%, and an HSS of 0.766. The modified CM algorithm has a high FAR of 7.92% and LR of 6.18% over land during daytime. Except for this limitation, the new algorithm is competitive with the CLAVR-x CM algorithm, which involves more channels and more advanced techniques.

The proposed CM algorithm will be incorporated into the NCEP GSI analysis system. Besides cloud detection, an AHI data-thinning strategy will need to be investigated and completed as follow-on research. Impacts of AHI radiance assimilation on quantitative precipitation forecasts and forecasts of typhoon track and intensity could then be assessed in either global or regional NWP models.

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