Impacts of Partly Cloudy Pixels on Shortwave Broadband Irradiance Computations[✉]

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ABSTRACT

Because of the limitation of the spatial resolution of satellite sensors, satellite pixels identified as cloudy are often partly cloudy. For the first time, this study demonstrates the bias in shortwave (SW) broadband irradiances for partly cloudy pixels when the cloud optical depths are retrieved with an overcast and homogeneous assumption, and subsequently, the retrieved values are used for the irradiance computations. The sign of the SW irradiance bias is mainly a function of viewing geometry of the cloud retrieval. The bias in top-of-atmosphere (TOA) upward SW irradiances is positive for small viewing zenith angles (VZAs) $< \sim 60^\circ$ and negative for large VZAs $> \sim 60^\circ$. For a given solar zenith angle and viewing geometry, the magnitude of the bias increases with the cloud optical depth and reaches a maximum at the cloud fraction between 0.2 and 0.8. The sign of the SW surface net irradiance bias is opposite of the sign of TOA upward irradiance bias, with a similar magnitude. As a result, the bias in absorbed SW irradiances by the atmosphere is smaller than the biases in both TOA and surface irradiances. The monthly mean biases in SW irradiances due to partly cloudy pixels are $< 1.5 \text{ W m}^{-2}$ when cloud properties are derived from Moderate Resolution Imaging Spectroradiometer (MODIS) aboard *Aqua*.

1. Introduction

Earlier studies pointed out that partly cloudy pixels can cause significant biases in satellite cloud retrievals (Coakley et al. 2005; Kato et al. 2006; Marshak et al. 2006; Di Girolamo et al. 2010; Boeke et al. 2016; Zhang et al. 2016) when cloud optical thickness and particle size are retrieved with an overcast assumption. This is closely related to the fact that the relationship between cloud properties and spectral channel reflectances used for the retrievals is not linear. For example, the visible-channel reflectance, often used in cloud retrievals with passive sensors, rapidly increases with the cloud optical

depth for smaller cloud optical depths, but the reflectance slowly increases for larger cloud optical depths. As a result, when the pixel is partly cloudy, the cloud optical depth retrieved from the pixel-mean reflectance is not necessarily the same as the pixel-mean cloud optical depth; in most cases, the retrieved cloud optical depth is smaller than the area-weighted mean cloud optical depth including clear and cloudy areas.

Even though the cloud optical depth retrieved from a partly cloudy pixel is biased, a visible-channel reflectance can be reproduced well when the retrieved cloud optical depth is used in the reflectance computation (e.g., Ham et al. 2009). This is simply because the cloud optical depth is biased such that it gives the observed visible-channel reflectance. However, as shown in this study, the bias in channels other than the visible channel can be large, when the relationship between the cloud optical depth and the target channel reflectance is significantly different from the relationship between the cloud optical depth and the visible-channel reflectance.

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Generally, the relationship is different from the visible-channel reflectance when a different spectral range or the albedo (or irradiance) is used. Because Earth's radiation budget is often estimated from cloud properties retrieved from narrowband channels, how the different relationship impacts irradiance computation needs to be addressed.

In this study, we will demonstrate that shortwave (SW) broadband irradiances are biased for partly cloudy pixels when the cloud optical depths are retrieved with the overcast and homogeneous assumption, and the retrieved optical depths are subsequently used in irradiance computations. We will perform a sensitivity study to quantify SW broadband biases as a function of solar and viewing geometry, in-cloud optical depth (optical depth over the cloudy portion), and cloud fraction over the pixel. In addition, we will use Clouds and the Earth's Radiant Energy System (CERES; Wielicki et al. 1996) Single Scanner Footprint (SSF) product to examine biases with actual satellite cloud measurements. In the CERES SSF process, cloud properties are retrieved from each Moderate Resolution Imaging Spectroradiometer (MODIS; Salomonson et al. 1989) pixel with an assumption of a homogeneous and overcast cloud (Minnis et al. 2010, 2011a,b). This study quantifies the expected biases in SW irradiances when the MODIS pixels are partly cloudy. To estimate the fractional cloud coverage within MODIS pixels, we will use Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER; Yamaguchi et al. 1998) measurements. Finally, the monthly mean biases in computed SW irradiances will be estimated using realistic cloud fractions.

Section 2 describes satellite data and radiative transfer model used in this study. Section 3 examines biases in SW broadband computations from the sensitivity study with an idealized partly cloudy pixel. More realistic cloud fractions are considered in section 4 using ASTER and MODIS measurements, and SW broadband irradiances biases due to partly cloudy pixels will be quantified. Section 5 discusses the limitations and future applications of this study. A summary is provided in section 6.

2. Data and model

a. A radiative transfer model and generation of the lookup table

We use the ocean surface bidirectional reflectance distribution function (BRDF; Cox and Munk 1954; Koepke 1984) to compute the surface reflectance. The ocean reflectance includes contributions from the sunglint, white foam, and subsurface reflection. The contribution

from the white foam is parameterized as a function of wind speed. The subsurface reflection is parameterized as a function of the ocean chlorophyll concentration and salinity. In this study, we assume a wind speed of 5 m s^{-1} , a chlorophyll concentration of 0.01 mg m^{-3} , and a salinity of 34.3‰.

We use pressure, temperature, ozone, and water vapor profiles of midlatitude summer (MLS) standard atmosphere (McClatchey et al. 1972) to compute gaseous absorption and molecular scattering optical depths. The gas absorption optical depth is estimated by the correlated k -distribution method (Kato et al. 1999) and the Rayleigh scattering optical depth is computed by pressure (Fu and Liou 1993).

We compute cloud scattering parameters such as extinction efficiency, single scattering albedo, and phase function with Mie theory. This is based on the fact that most of broken/partly cloudy pixels appear in stratocumulus regions (section 4), and these clouds are liquid-phase clouds. Aerosol is ignored in the simulations.

We assume that the cloud effective particle radius is $10 \mu\text{m}$, and cloud-top and cloud-base heights are 2 and 1 km, respectively, for all clouds. The assumption of $10 \mu\text{m}$ is based on the fact that (i) the water clouds show a narrow distribution of particle size around $10 \mu\text{m}$ (Minnis et al. 2011b), and (ii) a visible channel reflectance is less sensitive to the particle size assumption due to weak cloud absorption. The impact of the particle size assumption is further discussed in section 5. As a consequence of the assumption of the cloud particle size and height, the top-of-atmosphere (TOA) reflectance depends only on the cloud optical depth.

All these wavelength-dependent properties are input to the Discrete Ordinate Radiative Transfer (DISORT) model (Stamnes et al. 1988) to simulate radiances and irradiances for clear and cloudy atmospheres. In the simulations, we use 40 streams. Computed radiances with 40 streams are almost identical to those with 129 streams (not shown), once corrections to the surface reflection directly transmitted to TOA (Kato et al. 2002) and a strong peak of cloud scattering (Nakajima and Tanaka 1988) are applied. We use 18 bands within the $0.18\text{--}4\text{-}\mu\text{m}$ region to compute broadband irradiances (Rose et al. 2006). Results of the 18 bands are averaged weighted by incoming solar irradiances of the 18 bands to compute SW broadband irradiances.

For the efficiency, all the radiances and irradiances are included in a lookup table (LUT) as a function of cloud optical depth, solar zenith angle (SZA), viewing zenith angle (VZA), and relative azimuth angle (RAA). The 27 values of cloud optical depths used in the lookup table are 0, 0.1, 0.2, 0.6, 1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16, 18, 20, 24, 28, 32, 36, 40, 50, 60, 80, and 100. Ten values of

SZA and VZA from 0° to 90° with an interval of 10° are used and 19 values of RAA from 0° to 180° with an interval of 10° are used. Radiances and irradiances are linearly interpolated for conditions that are not included in the LUT.

b. CERES SSF product

We use seasonal months (January, April, July, and October) of 2013 CERES *Aqua* level 2 addition 4A SSF product in this study. For each CERES footprint, this product provides clouds properties retrieved from MODIS radiances using CERES–MODIS cloud retrieval algorithm (Minnis et al. 2010, 2011a,b). Retrieved cloud properties include cloud phase, visible cloud optical depth, particle effective radius, and cloud-top and cloud-base heights. Note that the CERES–MODIS algorithm by CERES Science Team, which is used in this study, is different from MOD06/MYD06 cloud algorithm by MODIS Atmospheres Science Team (cf. Platnick et al. 2017). Comparison studies showed that cloud optical depths and effective radii derived from the two algorithms generally agree well (Stubenrauch et al. 2013; Minnis et al. 2016; Chiriaco et al. 2007). Larger differences exist, however, for optically thin clouds at cloud edges or clouds over polar regions (Minnis et al. 2016; Chiriaco et al. 2007).

In the CERES SSF algorithm, cloud properties retrieved at a MODIS resolution (i.e., 1 km) are grouped for up to two cloud types within a CERES footprint. Then the mean and standard deviation of cloud properties are computed for each cloud type, and these are kept in the CERES SSF product instead of 1-km resolution of cloud properties. The retrieved cloud properties are then used for SW irradiance computations in the downstream CERES products such as CERES synoptic cloud and radiation (SYN; Doelling et al. 2013; Rutan et al. 2015). The operational CERES SYN processing considers a gamma distribution of cloud optical depths using the mean and standard deviations of cloud optical depths for each cloud type (Kato et al. 2001, 2005). Assuming that the gamma distribution captures well the actual MODIS cloud optical depth variability within a cloud type, SW biases still occur if MODIS pixels are partly cloudy, as we show in section 3. Therefore, in section 4, we quantify those kinds of SW biases due to partly cloudy MODIS pixels.

In the CERES SSF product, the CERES viewing zenith angle is less than 67° ($VZA < 67^\circ$) when the CERES is in the cross-track scan mode (ASDC 2016). This is because only CERES footprints that overlap with the MODIS imager swath are useful and are retained (Loeb et al. 2007). Excluding large VZA affects the TOA and surface irradiance biases as we show in sections 3 and 4.

Note also that MODIS and CERES instruments are aboard on the same platform (i.e., *Aqua*), and thus VZAs of these two instruments are very similar when the CERES instrument is operated in the cross-track mode, which is used in this study. Therefore, we assume that MODIS VZAs are the same as CERES VZAs, and we use CERES VZAs for both CERES and MODIS VZAs.

c. Advanced Spaceborne Thermal Emission and Reflection Radiometer product

We use high-resolution of ASTER (Yamaguchi et al. 1998) measurements to examine the cloud fraction over a MODIS pixel scale (~ 1 km). The ASTER measurements have been used in earlier studies (Zhao and Di Girolamo 2006; Werner et al. 2016, 2018) to resolve cloud properties within a MODIS pixel size. ASTER aboard *Terra* has 14 channels covering an ultraviolet to thermal spectral range with a 15-, 30-, or 90-m spatial resolution, depending on the channel. We extract visible and near-infrared (VNIR2; 0.63 – $0.69 \mu\text{m}$) channel reflectances at a 15-m resolution from ASTER L1T V003 product for this study (NASA LP DAAC 2015; Meyer et al. 2015). Because the ASTER instrument was designed for terrain measurements such as vegetation, soil, and land elevation, ASTER images over land or coastal regions are only archived based on the prioritization map (Yamaguchi et al. 1998). Therefore, it is not possible to obtain high-resolution ASTER images over global ocean areas. Instead, we select ocean areas from images over coastal regions. The digital counts from 0 to 255 provided from ASTER L1T product are converted into TOA radiances using high, middle, and low gain values provided in the corresponding metafile. Then the TOA reflectances are obtained as the ratios of radiances to incoming solar irradiances (Thome et al. 2001). Consecutively, we apply the LUT computed at 0.60 – $0.69 \mu\text{m}$ (section 2a) to ASTER VNIR2 reflectances (0.63 – $0.69 \mu\text{m}$) and retrieve cloud optical depths. The slight spectral differences between the ASTER VNIR2 band and LUT should be negligible because cloud scattering parameters are almost constant over 0.60 – $0.69 \mu\text{m}$.

Once the cloud optical depth is retrieved, we apply a threshold of cloud optical depth to classify the pixel as either clear or cloudy at the ASTER 15-m resolution. Note that aerosol is ignored in the cloud retrieval, meaning that, if present, aerosol can cause the false detection of clouds. To prevent aerosol layers identified as clouds, a relatively high threshold of cloud optical depth as 0.5 is applied for the cloud detection. Note also that there are uncertainties related to assumptions of cloud phase, cloud altitude, and aerosol in the cloud optical depth retrieval, and these also affect the cloud detection. The impacts of cloud optical depth

FIG. 1. Visible channel (0.60–0.69 μm) reflectance (black line) and SW broadband (0.18–4.0 μm) albedo (red line) as a function of cloud optical depth. SZA is 60° . The visible reflectance is computed for (a) VZA = 80° and RAA = 90° and (b) VZA = 10° and RAA = 90° . RAA = 0° is defined as a forward scattering direction and RAA = 180° is defined as a backward scattering direction. The DISORT model with 40 streams is used for the computations.

uncertainties and the threshold of cloud optical depth are discussed in section 4b.

3. Understanding SW irradiance biases in case of partly cloudy pixels

a. SW broadband biases in a simple case

The TOA bidirectional reflectance factor at a given SZA, VZA, and RAA, hereinafter a reflectance, increases nonlinearly with an increasing cloud optical depth. The visible-channel reflectance R_{vis} is defined as

$$R_{\text{vis}}(\theta_s, \theta_v, \phi_r, \tau) = \pi I_{\text{vis,TOA}}^\uparrow(\theta_s, \theta_v, \phi_r, \tau) / F_{\text{vis,TOA}}^\downarrow(\theta_s), \quad (1)$$

where $I_{\text{vis,TOA}}^\uparrow$ is the TOA upward radiance at the SZA (θ_s), VZA (θ_v), and RAA (ϕ_r); τ is the cloud optical depth; and $F_{\text{vis,TOA}}^\downarrow$ is the incoming solar irradiance for the visible channel. Figure 1a shows the visible reflectance at $\theta_s = 60^\circ$, $\theta_v = 80^\circ$, and $\phi_r = 90^\circ$. The spectral range of the visible channel used in Fig. 1 is 0.60–0.69 μm , which is comparable to MODIS band 1 used for cloud optical depth retrievals. Suppose that a pixel consists of 50% cloudy and 50% clear portions. If the optical depth for the cloudy portion is 5, the corresponding visible reflectance is $R_{\text{vis}}(\tau = 5)$, while the reflectance for the clear portion is $R_{\text{vis}}(\tau = 0)$. The measured pixel-mean visible reflectance would be the average of these two reflectances, that is, $0.5[R_{\text{vis}}(\tau = 0) + R_{\text{vis}}(\tau = 5)]$. If the pixel-mean visible reflectance is used to retrieve a cloud

optical depth with an assumption of a homogeneous overcast cloud, the retrieved optical depth τ_{ret} would be smaller than the area-weighted mean of cloud optical depth for the entire pixel [$2.5 = 0.5(5 + 0)$], due to the nonlinearity of the visible reflectance with respect to cloud optical depth. This is well known as a *plane-parallel bias* ($\Delta\tau = \tau_{\text{ret}} - \tau_{\text{true}}$) in the retrieved cloud optical depth for the inhomogeneous cloudy pixel. It is expected that the magnitude of $\Delta\tau$ depends on the shape of the visible reflectance as a function of cloud optical depth; as the shape of the visible reflectance is more linear with respect to the cloud optical depth, $\Delta\tau$ gets smaller. Despite the bias in the retrieved cloud optical depth $\Delta\tau$, if we use the retrieved cloud optical depth τ_{ret} in computing the reflectance at the visible channel, the computed reflectance would be $0.5[R_{\text{vis}}(\tau = 0) + R_{\text{vis}}(\tau = 5)]$. Therefore, there is no apparent bias in the computed visible reflectance compared with the observed reflectance.

However, if we consider a different channel, which has a different shape of reflectance as a function of τ from the shape of the visible-channel reflectance, the bias in the computed reflectance remains. This can be a problem when estimating radiation budget in terms of SW broadband irradiances using cloud parameters retrieved from a visible channel. Let us consider SW broadband albedo α_{SW} , defined as $\alpha_{\text{SW}} = F_{\text{SWTOA}}^{\uparrow}/F_{\text{SWTOA}}^{\downarrow}$, where $F_{\text{SWTOA}}^{\uparrow}$ is the upward TOA SW irradiance and $F_{\text{SWTOA}}^{\downarrow}$ is the incoming solar broadband irradiance. In Fig. 1a, the SW albedo function (red line) is more linear compared to the visible-channel reflectance over the cloud optical depth. In this case, the computed SW albedo from τ_{ret} [i.e., $\alpha_{\text{SW}}(\tau_{\text{ret}})$] is smaller than the true pixel-mean albedo $\{0.5[\alpha_{\text{SW}}(\tau = 0) + \alpha_{\text{SW}}(\tau = 5)]\}$.

The retrieved optical depth bias $\Delta\tau$ depends on the viewing geometry. For example, In Fig. 1b, when a different viewing geometry ($\theta_v = 10^\circ$ and $\phi_r = 90^\circ$) from Fig. 1a is used, the shape of the visible reflectance is closer to linear, and the retrieved cloud optical depth is closer to the area-weighted mean of cloud optical depth [$2.5 = 0.5(5 + 0)$]. As a result, $\Delta\tau$ in Fig. 1b is much smaller than $\Delta\tau$ in Fig. 1a. However, the smaller $\Delta\tau$ does not necessarily mean that the bias in SW albedo computations is smaller when τ_{ret} is used for the albedo computation. In Fig. 1b, the computed SW albedo is positively biased when the cloud optical depth is retrieved at $\theta_v = 10^\circ$ and $\phi_r = 90^\circ$. Therefore, it is concluded that the main reasons for the SW albedo biases are the different shapes of visible channel reflectance and SW albedo as a function of τ .

Based on the examples shown in Fig. 1, the bias in the computed SW albedo $\Delta\alpha_{\text{SW}}$ for the partly cloudy pixels can be expressed as

$$\Delta\alpha_{\text{SW}} = \alpha_{\text{SW}}(\tau_{\text{ret}}) - [(1 - f_c)\alpha_{\text{SW}}(0) + f_c\alpha_{\text{SW}}(\tau_c)], \quad (2)$$

where τ_{ret} is the cloud optical depth retrieved from the visible channel with an assumption of a homogeneous overcast cloud, τ_c is the in-cloud optical depth, and f_c is the fractional cloud coverage within a pixel. Note that the SW albedo and irradiance are functions of the SZA (θ_s) but the notation is omitted in all equations. The in-cloud optical depth τ_c is related to the retrieved cloud optical depth τ_{ret} as

$$R_{\text{vis}}(\theta_s, \theta_v, \phi_r, \tau_{\text{ret}}) = [(1 - f_c)R_{\text{vis}}(\theta_s, \theta_v, \phi_r, 0) + f_c R_{\text{vis}}(\theta_s, \theta_v, \phi_r, \tau_c)]. \quad (3)$$

In a similar way to Eq. (2), the bias in the SW TOA upward irradiances is defined as

$$\Delta F_{\text{SWTOA}}^{\uparrow} = F_{\text{SWTOA}}^{\uparrow}(\tau_{\text{ret}}) - [(1 - f_c)F_{\text{SWTOA}}^{\uparrow}(0) + f_c F_{\text{SWTOA}}^{\uparrow}(\tau_c)]. \quad (4)$$

Note that $\Delta F_{\text{SWTOA}}^{\uparrow} = F_{\text{SWTOA}}^{\downarrow} \Delta\alpha_{\text{SW}}$. In addition, we define the SW surface net irradiance F_{SWSFC} as the difference between downward and upward irradiances ($F_{\text{SWSFC}} = F_{\text{SWSFC}}^{\downarrow} - F_{\text{SWSFC}}^{\uparrow}$), and define F_{SWATM} as the absorbed irradiance by atmosphere as $F_{\text{SWATM}} = F_{\text{SWTOA}}^{\downarrow} - F_{\text{SWTOA}}^{\uparrow} - F_{\text{SWSFC}}^{\downarrow} + F_{\text{SWSFC}}^{\uparrow}$. Then F_{SWTOA} , F_{SWATM} , and F_{SWSFC} are related by the equation,

$$-F_{\text{SWTOA}}^{\downarrow} + F_{\text{SWTOA}}^{\uparrow} + F_{\text{SWATM}} + F_{\text{SWSFC}} = 0. \quad (5)$$

As in Eq. (4), the biases in F_{SWATM} and F_{SWSFC} are defined as

$$\Delta F_{\text{SWATM}} = F_{\text{SWATM}}(\tau_{\text{ret}}) - [(1 - f_c)F_{\text{SWATM}}(0) + f_c F_{\text{SWATM}}(\tau_c)], \quad (6)$$

$$\Delta F_{\text{SWSFC}} = F_{\text{SWSFC}}(\tau_{\text{ret}}) - [(1 - f_c)F_{\text{SWSFC}}(0) + f_c F_{\text{SWSFC}}(\tau_c)]. \quad (7)$$

Combining Eqs. (4)–(7) yields

$$\Delta F_{\text{SWTOA}}^{\uparrow} + \Delta F_{\text{SWATM}} + \Delta F_{\text{SWSFC}} = 0, \quad (8)$$

because $\Delta F_{\text{SWTOA}}^{\downarrow} = 0$. It is again emphasized that all of $\Delta\alpha_{\text{SW}}$, $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} would be zero, if (i) the pixel is completely clear ($f_c = 0$) or overcast ($f_c = 1$), or (ii) the shapes of the visible channel reflectance and the SW albedo functions over τ are the same. In addition, as demonstrated in Figs. 1a and 1b, $\Delta\alpha_{\text{SW}}$ depends on the viewing geometry of the cloud optical depth retrieval and SZA. This is also true for all $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} . In the next section,

FIG. 2. Biases in computed SW broadband (a) TOA upward ($\Delta F_{\text{SWTOA}}^{\uparrow}$) (b) atmosphere-absorbed (ΔF_{SWATM}), and (c) surface net (ΔF_{SWSFC}) irradiances (W m^{-2}) when the pixel is 50% partly cloudy and in-cloud optical depth is 5. The surface net irradiance is defined as the downward minus upward surface irradiance. Biases are plotted as a function of VZA and RAA used to retrieve cloud optical depth. The RAA is given in the azimuthal axis of each panel, where RAA = 0° is defined as the forward direction. The VZA is given in the radial axis of each panel. Four different SZAs (left to right) 0°, 20°, 40°, and 60° are used. The cloud retrievals and SW broadband simulations are avoided at sunglint angles and these are given as white areas. The sunglint angle is defined when there is an inflection point in the visible reflectance with respect to the cloud optical depth. Note that the sum of (a), (b), and (c) equals zero according to Eq. (8). Thick solid lines in each panel are the zero contour line.

the signs and magnitudes of $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} will be examined with various conditions of SZAs, viewing geometries, and cloud fractions.

b. SW broadband biases depending on solar and viewing geometry, cloud fraction, and in-cloud optical depth

In Fig. 2, cloud retrievals with various SZAs and viewing geometries are used to understand the bias in SW TOA upward irradiances $\Delta F_{\text{SWTOA}}^{\uparrow}$ (Fig. 2a), absorbed irradiances by atmosphere ΔF_{SWATM} (Fig. 2b), and surface net irradiances ΔF_{SWSFC} (Fig. 2c) for partly

cloudy pixels. Similar to Fig. 1, we assume that all pixels are 50% partly cloudy with the in-cloud optical depth τ_c of 5. For the 50% cloudy pixel, the cloud optical depth τ_{ret} is retrieved from the visible-channel reflectance with the overcast assumption using Eq. (3), and then biases in SW TOA upward ($\Delta F_{\text{SWTOA}}^{\uparrow}$), atmosphere-absorbed (ΔF_{SWATM}), and surface net (ΔF_{SWSFC}) irradiances are computed using Eqs. (4), (6), and (7), respectively. These biases are plotted as a function of SZA and viewing geometry used in the cloud optical depth retrievals. The cloud retrievals are not performed for sunglint angles and these are given as

FIG. 3. Bias in computed SW broadband (left) TOA upward ($\Delta F_{\text{SWTOA}}^{\uparrow}$), (center) atmosphere-absorbed (ΔF_{SWATM}), and (right) surface net (ΔF_{SWSFC}) irradiances (W m^{-2}) at (a) SZA = 60°, VZA = 10°, and RAA = 90° and (b) SZA = 60°, VZA = 70°, and RAA = 90°.

white areas in Fig. 2. The sunglint angle is defined when there is an inflection point in the visible reflectance function with an increasing cloud optical depth.

Figure 2 shows that the magnitude of both $\Delta F_{\text{SWTOA}}^{\uparrow}$ and ΔF_{SWSFC} increases with an increasing SZA, even though the solar incoming irradiances $F_{\text{SWTOA}}^{\downarrow}$ decreases with SZA. Therefore, the impact of partly cloudy pixels becomes more significant for a larger SZA. In addition, when the SZA is 20°, 40°, or 60°, $\Delta F_{\text{SWTOA}}^{\uparrow}$ are likely to be positive when the VZA < 60° but negative when the VZA > 60°, although the specific VZA where the sign changes depending on the RAA. The sign of ΔF_{SWSFC} is opposite of the sign of $\Delta F_{\text{SWTOA}}^{\uparrow}$, and the magnitude is comparable between $\Delta F_{\text{SWTOA}}^{\uparrow}$ and ΔF_{SWSFC} . As a result, biases in $\Delta F_{\text{SWTOA}}^{\uparrow}$ and ΔF_{SWSFC} are largely canceled out when ΔF_{SWATM} is computed according to Eq. (8). As seen in Fig. 2b, ΔF_{SWATM} is about one order magnitude smaller than $\Delta F_{\text{SWTOA}}^{\uparrow}$ and ΔF_{SWSFC} .

Figure 3 shows $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} as a function of in-cloud optical depth τ_c and fractional cloud coverage within a pixel f_c at two sets of viewing and solar

geometries. The magnitude of $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} increases with τ_c because the larger τ_c means the larger optical depth contrast between clear and cloudy portions within a pixel. Moreover, the magnitude of $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} has a maximum when f_c is around 0.2–0.8, while $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} are zero for completely clear ($f_c = 0$) or overcast ($f_c = 1$) cases.

The results shown in Figs. 2 and 3 suggest that the SW irradiance biases due to partly cloudy pixels are functions of solar and viewing geometry, in-cloud optical depth, and fractional cloud coverage. Therefore, $\Delta F_{\text{SWTOA}}^{\uparrow}$ can be expressed as

$$\Delta F_{\text{SWTOA}}^{\uparrow} = \Delta F_{\text{SWTOA}}^{\uparrow}(\theta_s, \theta_v, \phi_r, \tau_c, f_c), \quad (9)$$

while similar expressions can be also used for ΔF_{SWATM} and ΔF_{SWSFC} . The sign of biases is predominantly determined by solar and viewing geometry (Fig. 2), while the specific magnitude of the biases is a function of the fractional cloud coverage f_c and in-cloud optical depth τ_c .

FIG. 4. (a) Retrieved cloud optical depths at a 15-m resolution from ASTER visible-channel reflectance observed at 0216 UTC 10 Jul 2013. (b) Cloud mask (purple = clear, red = cloudy) based on a threshold value of the cloud optical depth of 0.5. (c) Fractional cloud coverages at a $1 \text{ km} \times 1 \text{ km}$ area $f_{1\text{km} \leftarrow 15\text{m}}$ derived from (b), where the $1 \text{ km} \times 1 \text{ km}$ area is defined as a collection of 67×67 pixels at 15-m resolution.

(Fig. 3). Note that we do not consider variations of cloud properties within the cloudy area of the pixel. For example, even if the pixel is overcast ($f_c = 1$), the cloud optical depth within the pixel can have a distribution. This results in a bias in the computed SW irradiance if the mean cloud optical depth is used. However, once the minimum cloud optical depth within the pixel exceeds a certain threshold value, the dependence of the cloud reflectance on the cloud optical depth is nearly linear (see $\tau > 2.5$ in Fig. 1), and the biases would be negligible. For example, when the pixel is overcast and consists of two equal fractional coverages with cloud optical depths as 3 and 8, respectively, $\Delta F_{\text{SWTOA}}^\uparrow$ is smaller than 5 W m^{-2} for all solar and viewing geometries (not shown). The 5 W m^{-2} bias for $\Delta F_{\text{SWTOA}}^\uparrow$ is only 10%–20% of the bias shown in Fig. 2a. This suggests that the bias caused by neglecting cloud optical depth variations within the cloud portion is much smaller than that caused by assuming a homogeneous overcast cloud for a partly cloudy pixel. Therefore, the remaining part of this study mainly focuses on examining the bias for partly cloudy pixels with the assumption that cloud optical depth over the cloud portion is monodisperse.

4. Estimation of SW broadband biases due to partly cloudy MODIS pixels in CERES SSF product

In the previous section, we show that the SW broadband biases $\Delta F_{\text{SWTOA}}^\uparrow$, $\Delta F_{\text{SWATM}}^\uparrow$, and $\Delta F_{\text{SWSFC}}^\uparrow$ are functions of solar and viewing geometry θ_s , θ_v , and ϕ_r ; fractional cloud coverage f_c ; and in-cloud optical depth τ_c . In this section, we estimate SW irradiance biases when MODIS cloudy pixels are partly cloudy. To quantify, we use SZA,

viewing geometry, and the retrieved cloud optical depths τ_{ret} in CERES SSF product. In addition, we need cloud fractional coverages f_c within MODIS pixels in order to infer the in-cloud optical depth τ_c from τ_{ret} using Eq. (3).

To obtain f_c , we use 15-m resolution of ASTER measurements to resolve the cloud fraction within the MODIS pixel size. We then relate low-resolution and high-resolution of cloud fractions, that is, MODIS-scale-derived cloud fractional coverages over a CERES footprint and ASTER-scale-derived cloud fractional coverages over a MODIS pixel (f_c). An assumption here is that the high-resolution cloud fractions can be inferred from the low-resolution cloud fractions.

a. Cloud detection from ASTER measurements and computation of fractional cloud coverages within the MODIS pixel size

We retrieve the cloud optical depth from 15-m resolution of ASTER VNIR2 ($0.63\text{--}0.69 \mu\text{m}$) reflectances over ocean using the LUT generated in section 2a. For a given SZA and viewing geometry, LUT provides the visible-channel reflectance as a function of the cloud optical depth. Therefore, the cloud optical depth can be directly inferred from the measured ASTER reflectance. The retrieved cloud optical depths are shown in Fig. 4a for an example case. Using the threshold value of cloud optical depth of 0.5, ASTER pixels are classified as either clear or cloudy (Fig. 4b). Fractional cloud coverage within the 1-km MODIS size pixel is computed as

$$f_{1\text{km} \leftarrow 15\text{m}} = \frac{n_{\text{cldy}, 15\text{m}}}{n_{\text{tot}, 15\text{m}}} \bigg|_{1\text{km}}, \quad (10)$$

where $n_{\text{tot},15\text{m}}$ is the number of available 15-m resolution of pixels, and $n_{\text{cldy},15\text{m}}$ is the number of cloudy 15-m resolution of pixels in the $1\text{ km} \times 1\text{ km}$ area (Fig. 4c). The $1\text{ km} \times 1\text{ km}$ area is defined as a collection of 67×67 pixels at 15-m resolution. If the 15-m resolution of measurements is fine enough to resolve the cloud natural variability, $f_{1\text{km} \leftarrow 15\text{m}}$ can be regarded as a true fractional cloud coverage for the MODIS pixel size. In Fig. 4c, small values of $f_{1\text{km} \leftarrow 15\text{m}} < 0.8$ are seen at cloud boundary regions, while large values of $f_{1\text{km} \leftarrow 15\text{m}}$ as large as 1 are seen at the cloud-core regions. From what discussed in section 3, significant biases in SW broadband computations are expected at the cloud boundary regions, where $f_{1\text{km} \leftarrow 15\text{m}}$ is between 0.2 and 0.8.

b. Inference of fractional cloud coverages within a MODIS pixel size ($\sim 1\text{ km}$) from the cloud coverages at a CERES footprint size ($\sim 20\text{ km}$)

In this section, we statistically relate fractional cloud coverages over a MODIS pixel size derived with a 15-m resolution $f_{1\text{km} \leftarrow 15\text{m}}$ and fractional cloud coverages over a CERES footprint size derived with a 1-km resolution $f_{20\text{km} \leftarrow 1\text{km}}$. First, we generate pseudo-1-km resolution of pixels by averaging 67×67 ASTER pixels at 15-m resolution. Then a similar procedure as in the previous section is performed. That is, the averaged 1-km resolution of ASTER VNIR2 reflectances are used for cloud optical depth retrievals, and cloud pixels are identified with a cloud optical depth threshold of 0.5. Once cloudy pixels are identified at a 1-km resolution, $f_{20\text{km} \leftarrow 1\text{km}}$ is computed as

$$f_{20\text{km} \leftarrow 1\text{km}} = \frac{n_{\text{cldy},1\text{km}}}{n_{\text{tot},1\text{km}}} \bigg|_{20\text{km}}, \quad (11)$$

where $n_{\text{tot},1\text{km}}$ is the number of available 1-km-resolution pixels, and $n_{\text{cldy},1\text{km}}$ is the number of cloudy 1-km-resolution pixels in the $20\text{ km} \times 20\text{ km}$ area. The $20\text{ km} \times 20\text{ km}$ area is defined as a collection of 20×20 pixels at 1-km resolution, which is comparable to the size of a CERES footprint.

Figure 5 shows frequency distributions of $f_{1\text{km} \leftarrow 15\text{m}}$ obtained for 10 different ranges of $f_{20\text{km} \leftarrow 1\text{km}}$ using January and July data from 2012 to 2014 over the eastern Pacific (40°S – 10°N , 120°W – 70°E) and western Pacific (10°S – 30°N , 120° – 160°E) domains. In this process, the $20\text{ km} \times 20\text{ km}$ area is first classified by $f_{20\text{km} \leftarrow 1\text{km}}$, and then the frequency distribution of $f_{1\text{km} \leftarrow 15\text{m}}$ within the $20\text{ km} \times 20\text{ km}$ area is obtained using only cloudy pixels ($f_{1\text{km} \leftarrow 15\text{m}} > 0$). Then all available frequency distributions of $f_{1\text{km} \leftarrow 15\text{m}}$ are averaged for each range of $f_{20\text{km} \leftarrow 1\text{km}}$. If $f_{20\text{km} \leftarrow 1\text{km}}$ is smaller than 0.05, the $20\text{ km} \times 20\text{ km}$ area is regarded as clear and excluded in the computations. Figure 5 implies a high correlation between

FIG. 5. Normalized frequency (%) of $f_{1\text{km} \leftarrow 15\text{m}}$ [or $p(f_{1\text{km} \leftarrow 15\text{m}})$] for 10 different ranges of $f_{20\text{km} \leftarrow 1\text{km}}$ derived from ASTER measurements over the western Pacific (10°S – 30°N , 120° – 160°E) and the eastern Pacific (40°S – 10°N , 120°W – 70°E) in January and July of 2012–14. Parameter $f_{1\text{km} \leftarrow 15\text{m}}$ is the cloud fraction over a 1-km MODIS pixel size derived with a 15-m resolution, and $f_{20\text{km} \leftarrow 1\text{km}}$ is the cloud fraction over a 20-km CERES footprint size derived with a 1-km resolution. Exact values of $p(f_{1\text{km} \leftarrow 15\text{m}})$ are provided in Table 1.

MODIS-scale fractional cloud coverages $f_{1\text{km} \leftarrow 15\text{m}}$ and CERES-scale fractional cloud coverages $f_{20\text{km} \leftarrow 1\text{km}}$. For example, when $f_{20\text{km} \leftarrow 1\text{km}}$ is between 0.95 and 1.00 (red line of Fig. 5, Table 1), more than 95% of 1-km pixels are overcast ($f_{1\text{km} \leftarrow 15\text{m}} = 1$). In addition, when $f_{20\text{km} \leftarrow 1\text{km}}$ is between 0.05 and 0.15 (purple line of Fig. 5), only 3.2% of 1-km pixels are overcast ($f_{1\text{km} \leftarrow 15\text{m}} = 1$). Average values of $f_{1\text{km} \leftarrow 15\text{m}}$ for the 10 ranges of $f_{20\text{km} \leftarrow 1\text{km}}$ shown in Fig. 5 are 0.09, 0.16, 0.23, 0.33, 0.42, 0.52, 0.62, 0.72, 0.83, and 0.99, respectively, resulting a correlation between $f_{20\text{km} \leftarrow 1\text{km}}$ and $f_{1\text{km} \leftarrow 15\text{m}}$ around 0.99. The high correlation suggests that we can infer MODIS-scale fractional cloud coverages $f_{1\text{km} \leftarrow 15\text{m}}$ from CERES-scale fractional cloud coverages $f_{20\text{km} \leftarrow 1\text{km}}$.

It should be emphasized that the relationship between high-resolution ($f_{1\text{km} \leftarrow 15\text{m}}$) and low-resolution ($f_{20\text{km} \leftarrow 1\text{km}}$) fractional cloud coverages is derived from a single instrument (i.e., ASTER) and a consistent cloud mask algorithm. In obtaining the relation, the ASTER measurements are used for providing realistic spatial variability of cloud fractions. As a result, the relation between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$ is not affected by the uncertainties of the ASTER cloud mask algorithm itself. For example, there are uncertainties of the cloud mask algorithm related to the threshold of cloud optical depths. However, when the distributions of $f_{1\text{km} \leftarrow 15\text{m}}$ are derived with different thresholds of the cloud optical depth such as 0.3 or 0.4 (Fig. S1 in the online supplemental material), those are almost identical to distributions shown in Fig. 5. This confirms that the relation between high-resolution and low-resolution cloud fractions is not

TABLE 1. Probability (%) of $f_{1\text{km} \leftarrow 15\text{m}}$ for different ranges of $f_{20\text{km} \leftarrow 1\text{km}}$ in Fig. 5. Mean values of $f_{1\text{km} \leftarrow 15\text{m}}$ are given in the right column for the given range of $f_{20\text{km} \leftarrow 1\text{km}}$. When averaging $f_{1\text{km} \leftarrow 15\text{m}}$, zero values of $f_{1\text{km} \leftarrow 15\text{m}}$ are also included.

$f_{20\text{km} \leftarrow 1\text{km}}$	$p(f_{1\text{km} \leftarrow 15\text{m}})$										Mean $f_{1\text{km} \leftarrow 15\text{m}}$
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	
0.05–0.15	42.6	20.5	12.2	7.2	4.8	3.3	2.2	1.9	2.0	3.2	0.09
0.15–0.25	32.5	18.2	12.3	8.5	6.2	4.8	3.7	3.2	3.7	7.0	0.16
0.25–0.35	26.4	16.8	12.2	8.8	6.8	5.5	4.4	4.2	4.5	10.4	0.23
0.35–0.45	19.6	13.5	11.0	8.8	7.4	6.4	5.6	5.4	6.0	16.1	0.33
0.45–0.55	14.9	10.7	9.4	8.0	7.3	6.7	6.3	6.4	7.3	22.9	0.42
0.55–0.65	10.9	8.3	7.7	7.1	6.8	6.7	6.6	7.0	8.4	30.4	0.52
0.65–0.75	7.6	6.3	6.1	6.0	6.1	6.3	6.6	7.2	9.3	38.4	0.62
0.75–0.85	4.8	4.4	4.5	4.8	5.3	5.9	6.5	7.4	10.2	46.2	0.72
0.85–0.95	2.2	2.3	2.6	3.1	4.0	5.0	5.7	7.0	10.6	57.6	0.83
0.95–1.00	0.0	0.0	0.0	0.1	0.1	0.4	0.7	1.0	2.4	95.2	0.99

affected by the absolute accuracy of the cloud mask algorithm. Likewise, it is expected that uncertainties in other properties, such as aerosol, cloud phase, cloud particle size, or cloud-top/-base altitude made in the cloud mask have negligible effects on the derivation of the relation between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$. In addition, the distribution of $f_{1\text{km} \leftarrow 15\text{m}}$ remains very similar when different regions (the eastern or western Pacific) or different months (January or July) are considered (Fig. S2). Therefore, we apply the distributions of $f_{1\text{km} \leftarrow 15\text{m}}$ to other areas, even though those distributions are obtained from the specific regions of the globe.

c. Application of the relations between $f_{20\text{km} \leftarrow 1\text{km}}$ and $f_{1\text{km} \leftarrow 15\text{m}}$ to CERES measurements

We assume the fractional cloud coverages within MODIS pixels using the relations between $f_{20\text{km} \leftarrow 1\text{km}}$ and $f_{1\text{km} \leftarrow 15\text{m}}$ obtained in Fig. 5 and Table 1 in the following way. First, we use the cloud coverage over a CERES footprint, based on MODIS cloud mask with a 1-km resolution, as $f_{20\text{km} \leftarrow 1\text{km}}$. Note that CERES SSF product provides MODIS cloud coverages for up to two cloud types within a CERES footprint, that is, lower (f_{lower}) and upper (f_{upper}) clouds. Therefore, the sum of lower and upper clouds ($f_{\text{lower}} + f_{\text{upper}}$) is regarded as a total cloud fraction and used for $f_{20\text{km} \leftarrow 1\text{km}}$.

Second, we use the relationship from Fig. 5 and Table 1 to derive the probability of fractional cloud coverages within MODIS pixels, $p(f_{1\text{km} \leftarrow 15\text{m}})$ for the given $f_{20\text{km} \leftarrow 1\text{km}}$. For example, if $f_{20\text{km} \leftarrow 1\text{km}}$ is 0.5 for the CERES footprint, then about 14.9%, 10.7%, 9.4%, 8.0%, 7.3%, 6.7%, 6.3%, 6.4%, 7.3%, and 22.9% of cloudy MODIS pixels are assumed as $f_{1\text{km} \leftarrow 15\text{m}} = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$, and 1.0, respectively, as shown in Fig. 6. If both lower and upper cloud types exist within the CERES footprint, the distribution of $f_{1\text{km} \leftarrow 15\text{m}}$ is applied to both cloud types.

Third, we assume variations of cloud optical depth within each cloud type, using the mean $E(\tau_{\text{ret}})$ and

standard deviation $s(\tau_{\text{ret}})$ provided in CERES SSF product. Specifically, we construct a lognormal distribution as follows:

$$p_{\text{LN}}(\tau_{\text{ret}}) = \frac{1}{\sigma \tau_{\text{ret}} \sqrt{2\pi}} \exp \left[-\frac{(\ln \tau_{\text{ret}} - \mu)^2}{2\sigma^2} \right],$$

where

$$\mu = \ln[E(\tau_{\text{ret}})] - \frac{1}{2} \ln \left[1 + \frac{s(\tau_{\text{ret}})^2}{E(\tau_{\text{ret}})^2} \right] \quad \text{and}$$

$$\sigma^2 = \ln \left[1 + \frac{s(\tau_{\text{ret}})^2}{E(\tau_{\text{ret}})^2} \right], \quad (12)$$

where $p_{\text{LN}}(\tau_{\text{ret}})$ is the inferred cloud optical distribution within the cloud type of the CERES footprint. We have found that the lognormal and gamma distributions produce almost the same integration results, but the lognormal distribution is more numerically stable when $E(\tau_{\text{ret}})$ is very small, <1 (not shown). Note that MODIS cloud properties (e.g., τ_{ret}) are derived with the homogeneous overcast assumption. Therefore, if the MODIS pixel is actually partly cloudy (i.e., $f_{1\text{km} \leftarrow 15\text{m}} < 1$), the in-cloud optical depth τ_c should be larger than τ_{ret} . Fourth, therefore, τ_c is inferred by satisfying the following equation:

$$R_{\text{vis}}(\theta_s, \theta_v, \phi_r, \tau_{\text{ret}}) = (1 - f_{1\text{km} \leftarrow 15\text{m}}) R_{\text{vis}}(\theta_s, \theta_v, \phi_r, 0) + f_{1\text{km} \leftarrow 15\text{m}} R_{\text{vis}}(\theta_s, \theta_v, \phi_r, \tau_c), \quad (13)$$

where τ_{ret} is the cloud optical depth retrieved with an assumption of a homogeneous overcast cloud, which is provided in CERES SSF product, and τ_c is the in-cloud optical depth with a partly cloudy assumption based on $f_{1\text{km} \leftarrow 15\text{m}}$.

Fifth, once τ_c is obtained, we compute the bias in the SW TOA upward irradiances as

FIG. 6. A schematic showing an example how the cloud fractions over 1-km MODIS pixels $f_{1\text{km} \leftarrow 15\text{m}}$ are assumed when the cloud fraction over a CERES footprint derived with a 1-km resolution $f_{20\text{km} \leftarrow 1\text{km}} = 0.5$. (left) MODIS pixels are overcast with the cloud fraction over the CERES footprint of 0.5. (right) This is converted to the probability distribution of partly cloudy pixels for $f_{20\text{km} \leftarrow 1\text{km}} = 0.5$ using Table 1; that is, the occurrence of $f_{1\text{km} \leftarrow 15\text{m}} = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$, and 1.0 are, respectively, 14.9%, 10.7%, 9.4%, 8.0%, 7.3%, 6.7%, 6.3%, 6.4%, 7.3%, and 22.9%.

$$\Delta F_{\text{SWTOA,SSF}}^{\uparrow}(f_{1\text{km} \leftarrow 15\text{m}}, \tau_{\text{ret}}) = F_{\text{SWTOA}}^{\uparrow}(\tau_{\text{ret}}) - [(1 - f_{1\text{km} \leftarrow 15\text{m}})F_{\text{SWTOA}}^{\uparrow}(0) + f_{1\text{km} \leftarrow 15\text{m}}F_{\text{SWTOA}}^{\uparrow}(\tau_c)]. \quad (14)$$

Similar expressions can be also applied to compute $\Delta F_{\text{SWATM,SSF}}$ and $\Delta F_{\text{SWSFC,SSF}}$. To obtain the bias for the various cloud optical depths within the cloud type,

the above equation needs to be integrated using the probability density functions of $f_{1\text{km} \leftarrow 15\text{m}}[p(f_{1\text{km} \leftarrow 15\text{m}})]$ and $\tau_{\text{ret}}[p_{\text{LN}}(\tau_{\text{ret}})]$ as follows:

$$\begin{aligned} \Delta F_{\text{SWTOA,SSF,cldtype}}^{\uparrow} &= \int_{\tau_{\text{ret}}} \int_{f_{1\text{km} \leftarrow 15\text{m}}} [\Delta F_{\text{SWTOA,SSF}}^{\uparrow}(f_{1\text{km} \leftarrow 15\text{m}}, \tau_{\text{ret}}) p(f_{1\text{km} \leftarrow 15\text{m}}) p_{\text{LN}}(\tau_{\text{ret}})] df_{1\text{km} \leftarrow 15\text{m}} d\tau_{\text{ret}} \\ &\approx \frac{\tau_{\text{max}} - \tau_{\text{min}}}{2} \sum_{j=1}^5 \sum_{i=1}^{10} p(f_i) p_{\text{LN}}(\tau_j) w_j \Delta F_{\text{SWTOA,SSF}}^{\uparrow}(f_i, \tau_j), \end{aligned} \quad (15)$$

where $p(f_i)$ for $i = 1-10$ are 10 values of $p(f_{1\text{km} \leftarrow 15\text{m}})$ provided by Fig. 5 and Table 1 for the given range of $f_{20\text{km} \leftarrow 1\text{km}}$; $\tau_{\text{min}} = E(\tau_{\text{ret}}) - 4s(\tau_{\text{ret}})$; $\tau_{\text{max}} = E(\tau_{\text{ret}}) + 4s(\tau_{\text{ret}})$; $\tau_j = 0.5(\tau_{\text{max}} - \tau_{\text{min}})x_j + 0.5(\tau_{\text{max}} + \tau_{\text{min}})$; and x_j and w_j are j th terms of five-term Gaussian quadrature points and weights, respectively, where a similar approach was used in earlier studies (Barker 1996; Ham and Sohn 2010).

Sixth, the bias obtained for each cloud type in Eq. (15) is weighted by the area of the cloud type (f_{upper} and f_{lower}), and thus a total bias over the entire CERES footprint is estimated as

$$\begin{aligned} \Delta F_{\text{SWTOA,SSF}}^{\uparrow} &= f_{\text{upper}} \Delta F_{\text{SWTOA,SSF,upper}}^{\uparrow} \\ &\quad + f_{\text{lower}} \Delta F_{\text{SWTOA,SSF,lower}}^{\uparrow}. \end{aligned} \quad (16)$$

Finally, the estimated $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ represents the bias of SW TOA upward irradiance for a CERES footprint due to partly cloudy MODIS pixels. If the sign of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ is positive, the homogeneous overcast cloud assumption used for MODIS cloud retrievals cause a positive bias in the TOA SW upward irradiance computations.

FIG. 7. Monthly mean cloud fraction over a CERES footprint derived with a 1-km MODIS resolution $f_{20\text{km} \leftarrow 1\text{km}}$ taken from CERES SSF product for (a) January, (b) April, (c) July, and (d) October 2013.

Figure 7 shows the monthly average of $f_{20\text{km} \leftarrow 1\text{km}}$ from CERES SSF product, which represents the mean cloud fractional coverage within a CERES footprint based on MODIS observations. For the given $f_{20\text{km} \leftarrow 1\text{km}}$ of the CERES footprint, we follow the process described above to compute $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$, $\Delta F_{\text{SWATM,SSF}}^{\uparrow}$, and $\Delta F_{\text{SWSFC,SSF}}^{\uparrow}$ using Eqs. (12)–(16).

To demonstrate how the SW bias changes in different temporal averaging, we show hourly, daily, and monthly means of cloud properties and SW irradiance biases in Fig. 8. The hourly plots show smaller VZAs along the nadir and larger VZAs at the off-nadir angles (Fig. 8d). The VZA is a primary factor to determine the sign of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ (Fig. 8m), as also found in section 3a. For example, $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ is large positive along the nadir and near zero or slightly negative at off-nadir angles. In addition, the magnitude of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ is smaller when $f_{20\text{km} \leftarrow 1\text{km}}$ is close to 1 (Fig. 8g). When we obtain daily means of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$, the positive and negative biases of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ appear along the satellite paths, generating stripe patterns (Fig. 8n). However, the positive and negative biases are partially canceled in monthly means (Fig. 8o). The monthly means of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ tend to be positive, because the maximum VZAs are smaller than 67° (section 2b), and the mean VZAs are close to 30° (Fig. 8f), which are favorable conditions to have a positive $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$. In addition, the large magnitudes of

positive $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ are shown where $f_{20\text{km} \leftarrow 1\text{km}}$ is between 0.2 and 0.8 (Fig. 8i), in-cloud optical depth τ_c is large (Fig. 8l), and SZA is large (Fig. 8c).

In Figs. 9–11, monthly means of $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$, $\Delta F_{\text{SWATM,SSF}}^{\uparrow}$, and $\Delta F_{\text{SWSFC,SSF}}^{\uparrow}$ are provided for four seasonal months (January, April, July, and October). The difference between Figs. 8o and 9c is that we scale $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ in Fig. 9, based on diurnally averaged monthly mean solar incoming irradiances. This is because daytime CERES and MODIS observations are taken once a day at around 1330 local time (LT), and thus $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ from Eq. (16) are the biases in the instantaneous irradiances at around 1330 LT. Therefore, we scale $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$, $\Delta F_{\text{SWATM,SSF}}^{\uparrow}$, and $\Delta F_{\text{SWSFC,SSF}}^{\uparrow}$ using the ratio of the diurnally averaged solar incoming irradiances to the incoming solar irradiance at 1330 LT to plot Figs. 9–11. As a consequence of the scaling, the magnitude of the irradiance biases gets smaller by approximately a factor of 1/3 because the instantaneous solar incoming irradiances at 1330 LT are generally about 3 times larger than the diurnally averaged solar incoming irradiances.

In Fig. 9, the bias at TOA $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ is larger over 40° – 20° S and 20° – 40° N regions than the bias over other regions. These regions meet three conditions to make the bias larger: (i) $f_{20\text{km} \leftarrow 1\text{km}}$ is between 0.2 and 0.8 (Fig. 7), (ii) SZA is relatively larger, and (iii) the cloud optical depth is large. The biases in July are particularly

FIG. 8. (a)–(c) SZAs, (d)–(f) VZAs, (g)–(i) cloud fractional coverages within a CERES footprint based on a MODIS resolution $f_{20\text{km} \leftarrow 1\text{km}}$, (j)–(l) MODIS-retrieved cloud optical depths τ_{ret} , and (m)–(o) biases in SW TOA upward irradiance $\Delta F^1_{\text{SWTOA,SSF}}$ for the (left) hourly (0000 UTC 1 Jul 2013), (center) daily (1 Jul 2013), and (right) monthly (July 2013) periods.

larger than those in January. The main factor seems to be related to slight asymmetry of SZAs between the two hemispheres since the *Aqua* equatorial overpass time is 1330 LT and the satellite path is slightly off from the south–north direction due to the rotation of Earth. In Fig. 12a, distributions of SZAs are obtained for the 20°–40°N region in January and for the 40°–20°S region in July. The 40°–20°S region in July shows larger SZAs compared to the 20°–40°N region in January, contributing the larger SW biases $\Delta F^1_{\text{SWTOA,SSF}}$ in Figs. 9 and 12f. Besides the SZA differences, the 40°–20°S region in July shows slightly higher occurrences of partly cloudy pixels (Fig. 12d, smaller occurrences of $f_{20\text{km} \leftarrow 1\text{km}} = 1$) and slightly larger cloud optical depths (Fig. 12e), in comparison to the 20°–40°N region in January. In addition, the 20°–40°N region in January shows high occurrences at RAA = 60° and 120°, while the 40°S–20°N

region in July shows peaks at RAA = 70° and 110° (Fig. 12c). In Fig. 2, the larger SW biases occur along RAA = 90°, while smaller biases occur other RAA directions. Therefore, the different RAAs between January and July also contribute larger $\Delta F^1_{\text{SWTOA,SSF}}$ in July.

The sign of $\Delta F_{\text{SWATM,SSF}}$ is positive (Fig. 10) but the magnitude of $\Delta F_{\text{SWATM,SSF}}$ is much smaller than $\Delta F^1_{\text{SWTOA,SSF}}$ in Fig. 9, as expected based on Figs. 2 and 3. In contrast, the sign of $\Delta F_{\text{SWSFC,SSF}}$ is negative because the bias in net surface irradiances is mostly negative for VZAs < 67° (see Fig. 2c). Note that the sum of Figs. 9–11 yields zero according to Eq. (8).

5. Discussion

In this section, we discuss assumptions used in this study and their impacts on the results. The conversion of

FIG. 9. Monthly mean bias in SW TOA upward irradiances due to partly cloudy pixels over MODIS pixels $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ for (a) January, (b) April, (c) July, and (d) October 2013. Since CERES and MODIS observations occur once a day at around 1330 LT, the estimated biases are scaled using diurnally averaged solar incoming irradiances. Note that (c) is the same as Fig. 8o, except for the scaling is based on solar incoming irradiances.

the bias to the daily mean value in section 4c is strictly for the purpose of expressing the bias comparable to the daily mean value instead of instantaneous value. This is done by simply scaling the bias by the ratio of solar

insolation. Therefore, this study does not take into account the diurnal cycle of clouds or variations of SZA over the course of the day. Considering stratocumulus regions show strong diurnal variations, the impact of

FIG. 10. As in Fig. 9, but for SW atmosphere-absorbed irradiances $\Delta F_{\text{SWATM,SSF}}^{\uparrow}$.

FIG. 11. As in Fig. 9, but for SW surface net irradiances $\Delta F_{\text{SWSFC,SSF}}$.

partly cloudy pixels might be different once the diurnal cycle is taken into account. One possible way is to use cloud properties from geostationary satellites but we expect larger magnitudes of SW biases than the biases with MODIS by following reasons. First, the VZA is fixed for a given location in geostationary measurements. Because the large cancellation of SW biases come from the variation of VZAs (Figs. 8d,m), we expect larger SW biases due to fewer cancellation. Second, because the SW bias is larger for a larger SZA (Fig. 2), the inclusion of large SZAs, in the early morning and late evening, induces larger SW biases. Third, most of the geostationary satellites have larger pixel sizes (~ 4 km) than MODIS (~ 1 km), leading to a larger probability of partly cloudy pixels.

In this study, we assume cloud fractional coverages within MODIS pixels, based on the relationship between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$; we take $p(f_{1\text{km} \leftarrow 15\text{m}})$ for the given range of $f_{20\text{km} \leftarrow 1\text{km}}$ in Table 1. The relationship between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$ is shown to be reliable regardless of locations, seasons, and the threshold of cloud masking (section 4b). However, the relationship was obtained from large samplings of ASTER measurements. This means that there should be instantaneous deviations of $p(f_{1\text{km} \leftarrow 15\text{m}})$ from the mean distribution. This raises a question how the estimated SW biases $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} would be affected by the instantaneous error of the cloud fraction

$f_{1\text{km} \leftarrow 15\text{m}}$. From Fig. 3, it is shown that the cloud fraction f_c does not change the sign of SW biases $\Delta F_{\text{SWTOA}}^{\uparrow}$, ΔF_{SWATM} , and ΔF_{SWSFC} and it only affects the magnitudes of the SW biases. Therefore, the instantaneous errors of $p(f_{1\text{km} \leftarrow 15\text{m}})$ also generate instantaneous errors in SW biases. Considering the instantaneous errors of $p(f_{1\text{km} \leftarrow 15\text{m}})$ randomly occur and their mean is zero, it is also expected that the corresponding instantaneous errors of SW biases would be largely canceled out in the monthly means.

The relationship between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$, found in this study, can be used for identifying partly cloudy MODIS pixels and correcting the corresponding SW biases in the future CERES processing. In addition, we can also derive a similar relationship for the desired pixel size other than the MODIS pixel size. In this case, a different number of ASTER pixel averaging is needed in Eqs. (10) and (11).

In this study, one-dimensional (1D) radiative transfer model is used to examine SW biases due to partly cloudy pixels, while three-dimensional (3D) radiative effects are ignored (section 2a). Note that we took a spatial averaging to generate low-resolution cloud fractions from the high-resolution of ASTER measurements, and then we related the high-resolution cloud fractions to the low-resolution cloud fractions. Therefore, the 3D effects are included in both low- and high-resolution of cloud fractions. This means that the impact of the 3D

FIG. 12. Frequency distributions of (a) SZAs, (b) VZAs, (c) RAAs, (d) cloud fractional coverages within a CERES footprint based on a MODIS resolution $f_{20\text{km} \leftarrow 1\text{km}}$, (e) MODIS-derived cloud optical depths τ_{ret} , and (f) biases in SW TOA upward irradiance $\Delta F_{\text{SWTOA,SSF}}^{\uparrow}$ obtained for 20°–40°N ocean in January 2013 (blue lines) and 40°–20°S ocean in July 2013 (red lines). Only CERES footprints with $f_{20\text{km} \leftarrow 1\text{km}} > 0.05$ are used for the statistics.

effect on the relationship between $f_{1\text{km} \leftarrow 15\text{m}}$ and $f_{20\text{km} \leftarrow 1\text{km}}$ should be negligible because the 3D effects are largely canceled. However, it does not necessarily mean that the absolute impact of the 3D radiative effects is smaller than the SW biases due to partly cloudy pixels. According to the earlier study with MODIS measurements (Ham et al. 2014), the 3D effects on the cloud retrievals are significant at a MODIS pixel scale, and they depend on the solar and viewing geometry. Therefore, a further study is needed to combine the SW biases due to 3D radiative effects and partly cloudy pixels.

In addition, we fix the cloud particle effective radius at $10\text{ }\mu\text{m}$ as a typical value in MODIS measurements (Minnis et al. 2011b). When different particle size is assumed, the estimates in SW biases $\Delta F_{\text{SWTOA}}^{\uparrow}$, $\Delta F_{\text{SWATM}}^{\uparrow}$, and $\Delta F_{\text{SWSFC}}^{\uparrow}$ can be different. For example, if we use $20\text{-}\mu\text{m}$ particle size instead of $10\text{-}\mu\text{m}$, $\Delta F_{\text{SWTOA}}^{\uparrow}$, $\Delta F_{\text{SWATM}}^{\uparrow}$, and $\Delta F_{\text{SWSFC}}^{\uparrow}$ in Fig. 3 can be changed up to 4 W m^{-2} (17%), 2 W m^{-2} (< 33%), 6 W m^{-2} (13%), respectively, while the sign of changes can be positive or negatives depending on the viewing geometry. When the new LUT with the particle size of $20\text{ }\mu\text{m}$ is applied to compute monthly means of $\Delta F_{\text{SWTOA}}^{\uparrow}$, $\Delta F_{\text{SWATM}}^{\uparrow}$, and $\Delta F_{\text{SWSFC}}^{\uparrow}$ as in Figs. 9–11, the changes in monthly means

are very small, $< 0.04\text{ W m}^{-2}$. This indicates that the assumed particle size has a relatively small impact on the estimation of monthly mean SW biases. However, our study does not consider a coupling of the retrieval errors in cloud optical depth and effective radius in case of partly cloudy pixels as in Zhang et al. (2016), and a further study is required to examine the coupling effect.

6. Summary

When the pixel is partly cloudy and the cloud optical depth is retrieved with an assumption of a homogeneous and overcast cloud, the retrieved cloud optical depth is biased due to the nonlinearity of the visible-channel reflectance with respect to the cloud optical depth. We demonstrate that the partial coverage of the pixel further leads to a bias in the computed SW broadband irradiance. The SW bias is a function of solar zenith angle (SZA), viewing zenith angle (VZA), relative azimuth angle (RAA), fractional cloud coverage within a pixel f_c , and in-cloud optical depth τ_c . The sign of the bias is mostly determined by the VZA. For a given SZA and viewing geometry, the bias in irradiances increases with the in-cloud optical depth τ_c , and the bias has a

maximum when the fractional cloud coverage f_c is between 0.2 and 0.8. The bias in the surface net irradiance is with the opposite sign of the bias in the TOA upward irradiance, yielding a smaller bias in atmosphere-absorbed irradiance.

We quantify biases in computed SW irradiances when the MODIS pixels are partly cloudy. To assume the fractional cloud coverage within a MODIS pixel scale (below 1 km), high-resolution ASTER measurements are additionally used. The estimated biases in SW broadband TOA upward and surface net irradiances are up to 1.5 W m^{-2} , while regions with a relatively large SZAs, large in-cloud optical depths, and small values of $f_{20\text{km} \leftarrow 1\text{km}}$ tend to have large SW biases. The VZA range used in the CERES SSF product (less than 67°) contributes to the positive biases in TOA upward irradiances and negative biases in surface net irradiances.

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