Coupling sky images with three-dimensional radiative transfer models: a new method to estimate cloud optical depth

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Abstract

A method for retrieving cloud optical depth ($\tau_c$) using a ground-based sky imager (USI) is presented. The Radiance Red-Blue Ratio (RRBR) method is motivated from the analysis of simulated images of various $\tau_c$ produced by a 3-D Radiative Transfer Model (3DRTM). From these images the basic parameters affecting the radiance and RBR of a pixel are identified as the solar zenith angle ($\theta_0$), $\tau_c$, solar pixel angle/scattering angle ($\vartheta_s$), and pixel zenith angle/view angle ($\vartheta_z$). The effects of these parameters are described and the functions for radiance, $I(\tau_c, \theta_0, \vartheta_s, \vartheta_z)$ and the red-blue ratio, $\text{RBR}(\tau_c, \theta_0, \vartheta_s, \vartheta_z)$ are retrieved from the 3DRTM results. RBR, which is commonly used for cloud detection in sky images, provides non-unique solutions for $\tau_c$, where RBR increases with $\tau_c$ up to about $\tau_c = 1$ (depending on other parameters) and then decreases. Therefore, the RRBR algorithm uses the measured $I_{\text{meas}}(\vartheta_s, \vartheta_z)$, in addition to $\text{RBR}_{\text{meas}}(\vartheta_s, \vartheta_z)$ to obtain a unique solution for $\tau_c$. The RRBR method is applied to images taken by a USI at the Oklahoma Atmospheric Radiation Measurement program (ARM) site over the course of 220 days and validated against measurements from a microwave radiometer (MWR); output from the Min method for overcast skies, and $\tau_c$ retrieved by Beer’s law from direct normal irradiance (DNI) measurements. A $\tau_c$ RMSE of 5.6 between the Min method and the USI are observed. The MWR and USI have an RMSE of 2.3 which is well within the uncertainty of the MWR. An RMSE of 0.95 between the USI and DNI retrieved $\tau_c$ is observed. The procedure developed here provides a foundation to test and develop other cloud detection algorithms.

1 Introduction

Advances in solar photovoltaic (PV) technologies have paved the way for higher PV penetration but as we rely more heavily on solar energy it becomes ever more crucial to understand the characteristics of this energy source. Unlike fossil fuels, solar energy has an inherent variability that causes difficulty when integrating solar energy into the
Improving forecasting of the available solar irradiance will support management of the electric grid and electricity markets and therefore ensure a more economical integration of solar power (Mathiesen et al., 2013). Currently several different methods are used to forecast at different spatial and temporal resolutions including numerical weather prediction (e.g. Lorenz et al., 2009; Mathiesen et al., 2011), and satellite image-based forecasting (e.g. Hammer et al., 1999). For short term forecasting, whole-sky imagery has been used (e.g. Urquhart et al., 2013).

Physics-based solar forecasting using whole-sky imagery requires geolocating clouds in the sky images, estimating their optical depth, motion, and dynamics (Chow et al., 2011). To estimate cloud optical depth ($\tau_c$), the most advanced methods separate the image into clear sky, thin cloud and thick cloud and assign a $\tau_c$ to each of these groups. To distinguish thin and thick clouds, the red-blue ratio (RBR; or a function of RBR) has been used as the default method (Koehler et al., 1991; Shields et al., 1993; Chow et al., 2011; Ghonima et al., 2012; Roy et al., 2001). It is defined as the ratio of the signal from the red channel to the signal from the blue channel. The RBR method takes advantage of Rayleigh scattering being greater in the blue wavelengths than the red wavelengths. When Rayleigh scattering is the predominant form of scattering, such as in clear skies, the RBR for a given view angle is smaller than under cloud scattering. RBR successfully differentiates clear sky from thin clouds and to a more limited extent thick clouds, but the RBR has not been applied to differentiate $\tau_c$. It is also difficult to apply the RBR method in the circumsolar region as thick dark clouds have lower RBRs than clear sky (Chow et al., 2011). In fact we will demonstrate in this paper through radiative transfer modeling (Sect. 4) that RBR by itself is ineffective for differentiating $\tau_c$ even for homogeneous cloud layers.

Most current cloud detection methods are designed empirically using look-up tables and/or thresholds that are adjusted to “work” with a specific imager and cloud conditions (see Sect. 2). The present paper breaks new ground in that it attempts to improve our fundamental understanding of the impact of three-dimensional radiative transfer (3D-RT) and $\tau_c$ on the radiance and RBR of a given pixel in a sky image. To analyze
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2 Review of sky imager cloud detection methods and geometrical factors

Individual pixel cloud detection using the output image from sky imagers is based on either the radiance measurement or the ratio between radiance measurements for different wavelengths. Cloud detection algorithms using single channel radiance have found limited success (McGuff et al., 1989; Kegelmeyer et al., 1994) due to the similarities in radiance values between clear skies and thick clouds in the visible spectrum. More success has been obtained when cloud detection uses the ratio between radiance measurements at different wavelength bands. One such algorithm is the RBR method, which uses the ratio of camera measurement in the red channel to the blue channel to classify a pixel as cloudy or clear. Initially a fixed RBR threshold between clear sky and cloudy sky (Koehler et al., 1991) is used which led to successful identification of opaque clouds but consistently failed to distinguish between thin and clear skies. However, the ratio of observed RBR to the clear sky RBR is fairly constant between contrail cases and provided a good way to identify thin clouds (Koehler et al., 1991). This lead to the development of clear sky libraries (CSL; Shields et al., 1993; Chow et al., 2011) to express clear sky RBR value under any condition. CSL are constructed by binning pixel values from clear sky images into matrices as a function of solar zenith angle ($\theta_0$, Fig. 1), solar pixel angle/Scattering angle ($\vartheta_s$) and pixel zenith angle/view angle ($\vartheta_z$). Figure 1 demonstrates a diagram of the camera optics as well as solar and sky geometry. From the CSL it is then possible to simulate a clear sky
(Fig. 2a) for any given day, allowing the calculation of the ratio of measured RBR to clear sky RBR. A clear sky image reconstructed from the CSL, as well as the $\vartheta_{s}$ and the $\vartheta_{z}$ for an example image are illustrated in Fig. 2.

Gauchet et al. (2012) used a different approach to account for the directional effects in cloud detection, in which they segmented images into five zones, solar disk, circum-solar disk, extended circumsolar disk, main zone, sky horizon, and orographic horizon, each with its own radiance and red-blue difference (RBD) threshold separating clear sky, bright cloud, and dark cloud.

The red-blue difference (RBD, Heinle et al., 2010) uses the same principles as the RBR for cloud detection but attempts to eliminate the strong directional variability in the RBR due to variability in the radiance, $I_{\Delta\lambda}$, of the blue channel as seen in Eqs. (1, 2),

$$\text{RBR} = \frac{I_r}{I_b} = 1 + \frac{I_r - I_b}{I_b}, \quad (1)$$

$$\text{RBD} = I_r - I_b = I_b(RBR - 1), \quad (2)$$

where $I_r$ is the $I_{\Delta\lambda}$ in the red channel, and $I_b$ is the $I_{\Delta\lambda}$ in the blue channel. However, Ghonima et al. (2012) found minimal differences in performance between RBD and RBR retrieval with RBR outperforming RBD.

These approaches have led to improved accuracy of cloud detection, yet limited progress has been made to attempt to understand the phenomena that influence the performance of these various methods. Although a direct relationship with aerosol optical depth ($\tau_a$) and RBR is observed for small $\tau_a$, ($\tau_a < 0.3$; Ghonima et al., 2012) no direct relationship has been found between RBR, or other variables determined from sky imagers, and larger optical depths ($\tau$) such as those found typically in clouds which has limited sky imager cloud detection to a binary classification. The lack of research on $\tau_c$ classification also stems from the fact that $\tau_c$ are challenging to measure accurately and large spatio-temporal variability and 3-D effects of cloud scattering make it difficult to conduct controlled case studies. Instead, a 3-D radiative transfer model is
applied here to investigate the interrelationships between radiances, radiance ratios (RBR), and \( \tau_c \) and devise a method to detect \( \tau_c \).

3 Radiative transfer modeling of sky images and comparison to measurements

3.1 SHDOM model and input parameters

Because of the 3-D dependency of the sky radiance field, a 3D-RT model must be used to simulate sky images. SHDOM is an explicit 3D-RT model that uses discrete ordinates to integrate the radiative transfer equation spatially, while spherical harmonics are used to save memory when solving the source function. This method allows for better computational efficiency compared to other methods such as the Monte Carlo (MC) method when solving the whole sky radiance field. SHDOM is also found to be within 2–3 \% of the MC models as part of the Intercompparison of 3-D Radiation Codes (I3RC) which is close to the MC noise (Marshak et al., 2005; Cahalan et al., 2005). Because of its computational efficiency and accuracy, SHDOM is selected for this analysis. SHDOM radiative transfer calculations are performed for 161 overcast skies with homogeneous \( \tau_c \), ranging in \( \tau_c \) from 0 to 80 at solar zenith angles ranging from 21 to 70° and for wavelengths corresponding to the peaks of the USI camera’s red (620 nm), green (520 nm) and blue (450 nm) channels.

Yearly average Aerosol Robotic Network (AERONET) data from the ARM Southern Great Plains (SGP) site for the year of 2013 for aerosol effective radius, and refractive index is used to calculate the single scattering properties of the aerosols in the SHDOM simulation (Holben et al., 1998; Holben et al., 2001; Table 1). Background Rayleigh and aerosol optical depths are also obtained from yearly averages taken from the sun-tracking photometer at the ARM SGP site. A cloud droplet effective radius of 8 µm (Min et al., 2003), is used to obtain the single scattering properties of the clouds in the SHDOM simulations. Given the desired \( \tau_c \), LWC is computed as (Stephens et al.,
Cloud liquid water content \( LWC \) is assumed constant between a cloud base of 1 km and cloud top of 2 km.

The SHDOM output radiance field is used to reproduce a sky image that would be obtained through a fisheye lens with an equisolid angle projection (Miyamoto et al., 1964),

\[
    r' = 2f \sin \left( \frac{\vartheta_z}{2} \right) \tag{4}
\]

where \( f \) is the focal length, and \( r' \) is the distance from the principal point in the image plane. Since SHDOM outputs a radiance field the USI signal output in counts must be calibrated to radiance.

### 3.2 USI hardware and calibration of the signal to radiance

On 14 March 2013 we deployed two USIs (serial numbers 1.7 and 1.8) at the ARM SGP site. The instrument domes were cleaned weekly. Daytime images from the USIs were collected continuously every 30 s for 220 days. Since USI 1.8 was located closer (at 200 m distance) to the instruments used for validation, it is used for the analysis. The optical setup included a Sigma 4.5 mm fisheye lens, an IR filter, and an Allied Vision GE2040 CCD camera (Fig. 1). The fisheye lens creates an equisolid angle projection onto the CCD resulting in an image where the solid angle subtended on each CCD cell (pixel) is approximately constant. Custom apertures were inserted into the lens of both USIs with diameters of 700 and 1000 \( \mu \text{m} \) for USI 1.7 and 1.8, respectively. A Bayer color filter on the CCD separates pixels into red, green and blue pixels allowing for...
multispectral images. Three different images are taken at different exposure times and combined to create a high dynamic range (HDR) image (Urquhart et al., 2015). The signal measured by each pixel is related to the amount of photons that are transmitted through the optics and converted to a voltage. The signal measured can therefore be calibrated to estimate the irradiance, $E_{\Delta \lambda}$ at a wavelength band, incident on a pixel. The radiance $I_{\Delta \lambda}^{\text{meas}}$ observed by each pixel can then be calculated using

$$I_{\Delta \lambda}^{\text{meas}} = \frac{E_{\Delta \lambda}}{\Delta \Omega \Delta \lambda} = \frac{C_{1,\lambda} \cdot \nu}{\Delta t \cdot A_{\text{in}} \cdot \Delta \Omega \cdot \Delta \lambda} = C_{2,\lambda} \cdot \nu,$$

(5)

where $\nu$ is the camera measurement in counts at a given pixel, $C_{1,\lambda}$ (units of J/count) is a calibration factor between $\nu$ and $E_{\Delta \lambda}$, $C_{2,\lambda}$ (units of W m$^{-2}$ st$^{-1}$ nm$^{-1}$) is a calibration factor between $\nu$ and $I_{\Delta \lambda}^{\text{meas}}$, $A_{\text{in}}$ is the area of the pixel, $\Delta \Omega$ is the solid angle, and $\Delta \lambda$ is the wavelength band. Given the equisolid angle lense, $A_{\text{in}}$, $\Delta \Omega$ and $\Delta \lambda$ are constant across the image sensor, resulting in a linear relationship (ignoring optical errors, and camera sensor nonlinearities) between the camera’s signal $\nu$ and the radiance $I_{\Delta \lambda}$ at the pixel’s $\vartheta_z$ as

$$C_{2,\lambda} = \frac{I_{\Delta \lambda}(\vartheta_z, \vartheta_s)}{\nu(\vartheta_z, \vartheta_s)},$$

(6)

The calibration constant $C_{2,\lambda}$ is obtained as the average (denoted as overbar in Eq. 6) of 131 all overcast (cloud fraction (CF) is greater than 0.9) images on 98 different days. Overcast skies are preferred because the radiance is more homogeneous and since the more robust method by Min et al. (2003) could be applied to obtain the $\tau_c$ that is input to SHDOM. $C_{2,\lambda}$ values are $1.16 \times 10^{-4}$, $1.11 \times 10^{-4}$, and $9.69 \times 10^{-5}$ W m$^{-2}$ st$^{-1}$ nm$^{-1}$ for the red, green and blue channels, respectively.
3.3 Application to other imaging systems

Other ground imaging designs have also been developed (Seiz et al., 2007; Souza-Echer et al., 2006; Calbo et al., 2008; Cazorla et al., 2008; Heinle et al., 2010; Roman et al., 2012; Gauchet et al., 2012) with the most dissimilar design consisting of a downward pointing camera capturing the sky from a reflection off a spherical mirror (Pfister et al., 2003; Kassianov et al., 2005; Long et al., 2006; Mantelli et al., 2010; Martinez-Chico et al., 2011). Most ground imaging devices follow a relationship between the camera’s signal and radiance similar to Eq. (1) differing only in the wavelength region $\Delta\lambda$, calibration factors $C_1\lambda$, and $C_2\lambda$, and optical and sensor errors, with non-equisolid lens camera systems requiring $\Delta\Omega$, to be specified per pixel. Therefore the method presented here can be adapted easily to images from other sky imaging systems.

3.4 Comparison of real and synthetic (SHDOM) images and stray light correction

Example measured images and their SHDOM equivalent images are illustrated in Fig. 3. Differences between the clear sky image (Fig. 3a) and the synthetic image (Fig. 3b) highlight the impacts of stray light as well as the vertical smear stripe caused by the CCD sensor (Fig. 3c). The error observed in the solar disk is caused by errors in the geometrical calibration causing the solar location to be slightly different between the SHDOM and the USI image. The stray light is particularly strong in the circumsolar region causing enhancement of the red radiance of up to 30%. Stray light is caused by light from the direct beam being scattered through the optics (mainly the protective acrylic dome). This means that stray light is strongest for $\tau_c$ near 0 and should decrease to zero once clouds are thick enough to eliminate the direct beam. Particular optical reflections are observed as circular patterns throughout the image that are concentrated at the solar azimuth. While stray light patterns are often consistent for the same sun position, misalignments in the camera optics (e.g. during instrument maintenance) can lead to stray light changing under constant $\theta_s$, and $\theta_z$ making it difficult to implement a
general stray light correction, for example through a look-up table. Stray light leads to brighter pixel values than are expected, which in turn can lead to misclassifications of clear sky as thin clouds ($\tau_c < 3$). To mitigate some of the stray light effects the SHDOM results for clear sky ($\tau_c = 0$) are replaced by the measurements from the CSL to obtain the interpolant described in Sect. 5.

Figure 3d–f demonstrates USI images and a synthetic image from SHDOM for $\tau_c$ of 30. The majority of the sky ($\vartheta_z < 80^\circ$) red radiance differs by less than 5%. At $\tau_c = 30$ direction normal irradiance is absent and stray light is not present.

4 Impact of geometrical parameters and cloud optical depth on radiance and RBR

As described in Sect. 2 individual channel radiance and RBR are the most fundamental parameters for cloud detection in sky images. To obtain $\tau_c$, the functions $I_\lambda (\tau_c)$ and RBR($\tau_c$) must be parameterized. Furthermore, geometrical parameters ($\vartheta_z, \vartheta_s$), and solar position ($\theta_0$) have been found to affect RBR($\tau_c$) and $I_\lambda (\tau_c)$ (Shields et al., 1993) such that we must obtain RBR($\tau_c, \theta_0, \vartheta_s, \vartheta_z$) and $I_\lambda (\tau_c, \theta_0, \vartheta_s, \vartheta_z)$ to solve the inverse problem. With the aid of the SHDOM it is possible to analyze each of these parameters individually. In this section, we will discuss example cases under various $\vartheta_s$, $\vartheta_z$, and $\theta_0$ to demonstrate how each variable affects $I_\lambda$ and RBR.

4.1 Solar pixel angle

Figure 4a demonstrates for the red and blue channel that radiance decreases with increasing $\vartheta_s$ for non-thick clouds ($\tau_c < 30$). For thin clouds ($\tau_c = 1$) the radiance peaks in the solar region as a result of the forward scattering peak of the cloud phase function. As $\tau_c$ increases, radiance becomes constant with $\vartheta_s$.

Figure 4a shows that the blue radiance is larger than the red radiance under clear skies, except for very small $\vartheta_s$, while for cloudy skies the two radiances are more sim-
ilar. Therefore, most cloud detection methods assume that RBR is higher for clouds than for clear sky; however, Fig. 4b demonstrates that this is not always the case. At small $\vartheta_s$ ($\vartheta_s < 6^\circ$) the RBR of thick clouds is lower than that of clear sky. Moreover, as demonstrated by the $\tau_c = 1$ case thin clouds have a higher RBR at $\vartheta_s < 30^\circ$ than thick clouds. For $\tau_c \leq 10$ RBR increases as $\vartheta_s$ approaches the solar region. At higher $\tau_c$ ($\tau_c > 30$) RBR becomes constant over $\vartheta_s$. Note that all of the statements in Sect. 4 strictly only apply for the $\theta_0$ and $\vartheta_z$ shown in the figure, but Figs. 4–6 indicate that the conditions $\theta_0 = 60^\circ$, $\vartheta_s = 60^\circ$, $\vartheta_z = 60^\circ$ are representative for a wide range of conditions.

4.2 Sky imager zenith angle

Near the horizon (large $\vartheta_z$), diffuse irradiance is commonly observed to be enhanced. Horizon brightening is indeed observed for clear skies in Fig. 5a. As clouds become thicker the dependence of radiance on $\vartheta_z$ is inverted and radiance decreases with increasing $\vartheta_z$. The radiative transfer transitions into the diffusion regime, where it is only dependent on $\vartheta_z$. On the other hand the RBR dependence has a similar shape independent of the $\tau_c$ (Fig. 5b). Pixels near zenith have lower RBR than those near the horizon.

4.3 Solar zenith angle

The effects of $\theta_0$ are intuitive and consistent to what is observed during a sunset and therefore not graphically presented; the red and blue radiance is observed to decrease with increasing $\theta_0$. The decrease in radiance is caused by the decrease in extraterrestrial horizontal flux as $\theta_0$ increases. On the other hand, RBR is found to increase with increasing $\theta_0$, reflecting the increase in airmass with increasing $\theta_0$. Increased airmass causes more blue light to be scattered back into space than red light.
4.4 Cloud optical depth

Figure 6a illustrates the ambiguity that arises when attempting to differentiate cloud optical depth with radiance. Radiance reaches a peak at $\tau_c = 3.25$ and almost for the entire range of $\tau_c$ there are two $\tau_c$ that lead to the same radiance. Figure 6b on the other hand, demonstrates the ambiguity of $\tau_c$ detection using only RBR. SHDOM simulations demonstrate that as $\tau_c$ increases RBR increases until it reaches its maximum around $\tau_c = 2$ and then decreases until converging to a constant value for $\tau_c > 20$. This creates the following challenges: (i) RBR is insensitive to cloud $\tau_c$ for $\tau_c > 20$ and therefore thick clouds of different $\tau_c$ cannot be distinguished. (ii) There is ambiguity because of the non-monotonic behavior. For example, clouds with a $\tau_c$ of 1.5 have similar RBR values to clouds of $\tau_c > 20$. While (outside the solar region, see Fig. 4b) RBR is a useful differentiator between clouds and clear sky more information is needed to differentiate between different $\tau_c$.

Note that while Fig. 6a and b demonstrate the radiance and RBR for a section of the sky these curves change throughout the sky. The dependence is illustrated for a few geometric cases through the $\tau_c$ for which the peak in the red radiance is observed. In the circumsolar region red radiance peaks at $\tau_c \sim 0.75$ while clear sky has a higher radiance than thick clouds ($\tau_c > 5$). A similar trend is observed for RBR, where clear sky has a higher RBR than thick clouds ($\tau_c > 5$). Approaching $\vartheta_z = 0^\circ$ and on the opposite side of the sun ($\vartheta_s > 60^\circ$), the red radiance peaks at $\tau_c = 8.75$. Near the horizon ($\vartheta_z > 80^\circ$) the red radiance peaks again at lower $\tau_c = 1.25$.

In addition, Fig. 6a highlights one of the main challenges of ground based images compared to satellite based cloud detection. In satellite based $\tau_c$ detection, the measured radiance can be used to calculate $\tau_c$ (Nakajima et al., 1990) as the measured (upwelling) radiance monotonically increases with higher $\tau_c$. This same method cannot be used for ground based imagery as radiance increases for thin clouds peaks and then begins to decrease. This means that there can exist two $\tau_c$ that produce the same radiance. It is again important to also note that the curves in Fig. 6 depend on $\vartheta_s$ and...
\( \vartheta_z \). For example, near the horizon \((\vartheta_z > 80^\circ)\), the radiances are in fact highest for clear skies and decrease with increasing \( \tau_c \).

4.5 Expressing cloud optical depth through geometrical and solar parameters

Since it is currently computationally infeasible to use SHDOM to solve \( \tau_c (I_\lambda, \text{RBR}, \theta_0, \vartheta_s, \vartheta_z) \) in real-time \((\sim 10 \text{ s})\) as required for sky imager solar forecasting, the homogeneous cases described in Sect. 1 are used instead to create interpolants. As seen in Fig. 6a and b. \( \tau_c (I_\lambda, \theta_0, \vartheta_s, \vartheta_z) \) and \( \tau_c (\text{RBR}, \theta_0, \vartheta_s, \vartheta_z) \) are multivalued functions. Therefore two separate interpolants are created for each function. \( \tau_c (I_\lambda, \theta_0, \vartheta_s, \vartheta_z) \) is split into \( \tau_c \) that are higher than the peak radiance and \( \tau_c \) that are lower than the peak radiance. \( \tau_c (\text{RBR}, \theta_0, \vartheta_s, \vartheta_z) \) is similarly split into \( \tau_c \) that are higher than the peak RBR and \( \tau_c \) that are lower than the peak RBR. Section 5 will describe how these interpolants are used to find up to two \( \tau_c (I_\lambda^{\text{meas}}) \) (one for the higher and one for the lower branch of \( \tau_c \)) and how a unique \( \tau_c \) is obtained.

5 Radiance red blue ratio (RRBR) method for cloud optical depth measurement

We have shown that it is difficult to distinguish between different \( \tau_c \) by using RBR alone. As demonstrated in Fig. 6 radiance and RBR are non-monotonic functions of \( \tau_c \) with generally two \( \tau_c \) associated with the same radiance or RBR. However, for most cases, there is a unique \( \tau_c \) solution for a pair of RBR and radiance. The RRBR method attempts to obtain this solution by first solving \( \tau_c (I_\lambda, \theta_0, \vartheta_s, \vartheta_z) \) and then substituting the (usually two) \( \tau_c \) solutions into \( \text{RBR}(\tau_c, \theta_0, \vartheta_s, \vartheta_z) \) and identifying the correct \( \tau_c \) as the one with the smallest \( \text{abs}(\text{RBR}^{\text{meas}}(\vartheta_s, \vartheta_z) - \text{RBR}(\tau_c, \theta_0, \vartheta_s, \vartheta_z)) \), where \( \text{RBR}^{\text{meas}}(\vartheta_s, \vartheta_z) \) is the measured RBR. The algorithm for the RRBR method is described in Fig. 7. \( I_\lambda \) at a wavelength of 620 nm is used because its variations with \( \tau_c \) are larger than the other wavelengths. This larger dynamic range reduced the errors caused by instrument noise.
The algorithm begins by comparing \( I_{620}^{\text{meas}}(\vartheta_s, \vartheta_z) \) against \( \max(I_{620}(\tau_c, \theta_0, \vartheta_s, \vartheta_z)) \) (e.g., 0.19 W m\(^{-2}\) sr\(^{-1}\) nm\(^{-1}\) in Fig. 6a), where \( I_{620}^{\text{meas}}(\vartheta_s, \vartheta_z) \) is the measured radiance in the camera’s red channel. Heterogeneity in clouds can cause \( I_{620}^{\text{meas}}(\vartheta_s, \vartheta_z) \) to be larger than \( \max(I_{620}(\tau_c, \theta_0, \vartheta_s, \vartheta_z)) \); in this case as the pixel conditions fall outside the range of the method the algorithm reverts back to \( \tau_c \) assignment solely based on RBR. \( \tau_c(RBR, \theta_0, \vartheta_s, \vartheta_z) \) is used to find \( \tau_c \). If there are two solutions, then the \( \tau_c \) associated with the maximum red radiance is used as there is no way to differentiate between the multiple solutions.

If \( I_{620}^{\text{meas}}(\vartheta_s, \vartheta_z) \) is within the range of \( I_{620}(\tau_c, \theta_0, \vartheta_s, \vartheta_z) \), then \( \tau_c \) is calculated from \( \tau_c(I_{620}^{\text{meas}}, \theta_0, \vartheta_s, \vartheta_z) \). If only one solution is found the \( \tau_c \) is assigned based on \( \tau_c(I_{620}^{\text{meas}}, \theta_0, \vartheta_s, \vartheta_z) \) and RBR(\( \tau_c, \theta_0, \vartheta_s, \vartheta_z \)) is not considered. When two solutions are found, they are input into RBR(\( \tau_c, \theta_0, \vartheta_s, \vartheta_z \)) and the one closest to RBR(\( I_{620}^{\text{meas}}, \theta_0, \vartheta_s, \vartheta_z \)) is assigned. Note that since saturated pixel values near the sun exceed the dynamic range of the USI sensor, the RBR defaults to 1, the red radiance is unknown, and no \( \tau_c \) can be assigned.

An example \( \tau_c \) estimate is presented in Fig. 8. The darker clouds are correctly identified as higher \( \tau_c \), even though the RBR is lower than for the thinner clouds, for example for the clouds between the sun and the horizon. In the circumsolar region, the RBR is largest but the RRBR method correctly identifies a thinner cloud. The black points in Fig. 8b corresponds to undetermined \( \tau_c \) due to signal saturation. In practice one could interpolate across the saturated region, but we prefer showing the raw results in this paper.

Although the RRBR method is developed from overcast scenarios we also apply this method to broken clouds. Errors are caused by 3-D effects near cloud edges, but are minimal for areas of the clouds far from cloud edges, where clouds may be considered locally homogeneous. An additional source of error is the \( \tau_a \) used in the reference SHDOM simulations; higher actual \( \tau_a \) values than those in the simulations may lead to \( \tau_a \) being classified as \( \tau_c \), while smaller \( \tau_a \) lead to a reduced \( \tau_c \) estimate. This error is minimal since \( \tau_c \) is much larger than the variations in \( \tau_a \). Furthermore, this error is not
important for solar forecasting as – spectral effects aside – only the total atmospheric optical depth is of interest to estimate ground irradiance, not the exact differentiation between $\tau_a$ and $\tau_c$.

6 Validation

6.1 Cloud optical depth measurements for validation

The Min method (Min et al., 1996b, 2003) is designed to estimate $\tau_c$ for conditions with homogenous clouds using the measured atmospheric transmittance of global radiation (also referred to as clearness index). The atmospheric transmittance is obtained using a multifilter rotating shadowband radiometer (MFRSR) as,

$$T = \frac{\text{GHI}_{415}^{\text{nm}}}{\text{GHI}_0^{415\text{nm}}},$$

where GHI$^{415\text{nm}}$ is the global horizontal irradiance, and GHI$^{415\text{nm}}_0$ is the top of the atmosphere GHI, both at a wavelength of 415 nm. The MFRSR measurements at a wavelength of 415 nm is used in Eq. (7), to reduce effects of gaseous absorption. GHI$^0$ is adjusted from the true TOA GHI to remove $\tau_a$ influences on $T$, by applying Langley regression calibrations from the direct normal irradiance (DNI) on clear skies to the GHI (Harrison et al., 1994; Min et al., 1996b). A discrete ordinate radiative transfer model is applied to identify the $\tau_c$ corresponding to the measured $T$ (Min et al., 1996a). By default a cloud effective radius ($r_e$) of 8 µm is assumed in the Min method, but when liquid water path (LWP) values are available from a microwave radiometer (MWR), then $r_e$ is iteratively solved. $r_e$ is first solved for with Eq. (8) and used as an input in the discrete ordinate model, which provides a different $\tau_c$, which leads to a different $r_e$ and this process is repeated until the changes in $\tau_c$ are within a threshold value. Since the Min method uses GHI measurements to estimate $\tau_c$, the $\tau_c$ is representative of the sky hemisphere. At ARM Min $\tau_c$ is sampled and reported every 20 s.
\( \tau_c \) is also measured by a MWR. The MWR is a microwave receiver that detects the microwave emissions of the vapor and liquid water molecules. It measures cloud liquid water path (LWP) in the zenith direction within a field of view of 6° (Liljegren et al., 2000; Cadeddu et al., 2013). \( \tau_c \) can then be estimated as (Stephens et al., 1978)

\[
\tau_c \approx \frac{\int_{0}^{LWP} \text{LWC} \, dz}{\rho_l r_e} \approx \frac{3 \text{LWP}}{2 \rho_l r_e},
\]

(8)

where LWC is the cloud liquid water content and \( \rho_l \) is the density of liquid water. A \( r_e \) of 8 µm is assumed, as in the Min method. The MWR has an irregular timestep ranging between 20 to 40 s. The uncertainty in the LWP obtained from the MWR is \( \pm 0.03 \text{ mm} \) \((30 \text{ g m}^{-2}, \) Morris et al., 2006) which corresponds to a \( \tau_c \) of \( \pm 5.6 \) with Eq. (8).

### 6.2 Validation in overcast conditions with Min algorithm

Data from the Min algorithm is compared to the average \( \tau_c \) from an entire USI image. Since the Min method assumes overcast skies, only conditions with cloud fraction (CF) > 0.7 are used for this analysis yielding 5197 datapoints (about 43 h of data). The mean transmission of horizontally heterogeneous clouds is higher than the transmission of a uniform cloud with the same mean optical depth (Hinkelman et al., 2007). This is caused by the nonlinear relationship between \( \tau_c \) and radiance. To adjust the heterogeneous USI \( \tau_c \) retrieval to be consistent with the Min method, the average \( \tau_c \) from the USI image is taken as the geometric mean of the image,

\[
\tau_c = \exp\left(\log(\tau_c)\right)
\]

(9)

Figure 9 compares results from both methods. An \( R^2 \) of 0.93 reflects the high correlation between the two methods. The relative RMSE decreases as \( \tau_c \) increases as demonstrated in Table 2, with thin clouds \((\tau_c < 5)\) having an RMSE of 42.7 % and thick clouds \((\tau_c > 20)\) having an RMSE of 18.5 % with the overall RMSE being 23.7 %. These differences in RMSE between \( \tau_c \) highlight the difficulties in detecting thin clouds correctly.
6.3 Heterogeneous and homogenous cloud conditions with the microwave radiometer

The RRBR method is compared to $\tau_c$ estimates from the microwave radiometer (MWR) using the 12 422 pixels in each USI image with $\vartheta_z < 6^\circ$. Figure 10 shows the comparison of the two methods. Overcast conditions again result in good agreement with RMSE of 6.6 or 48% and $R^2$ of 0.91. Since overcast datapoints were already validated in Sect. 6.3 we now focus on cloud fractions of less than 0.7.

The RMSE is 2.33 for the heterogeneous cases, which is well within the uncertainty of the MWR measurements of ±5.6. The lower correlation of 0.66 between the two methods is probably related (i) the uncertainty of the MWR, (ii) the smaller measurement area (6° angle versus entire hemisphere) combined with temporal and spatial offsets and (iii) the fact that $\tau_c$ retrievals under heterogeneous cloud conditions introduce random errors due to incomplete overlap of the field-of-view of the USI and MWR, (iv) 3-D cloud effects and (v) uncertainty in the MWR $\tau_c$ related to the assumption of $r_e = 8 \mu$. While the SHDOM model calculations also assume constant $r_e$, this only affects the single scattering properties of the cloud, more specifically the phase function. This results in the MWR algorithm being more sensitive to $r_e$ as $r_e$ errors are linearly proportional to MWR errors. A MBE of $-10.5\%$ is observed demonstrating a tendency for the RRBR method to under predict $\tau_c$. This can further be analyzed when MBE is split into $\tau_c$ categories. Thick clouds ($\tau_c > 20$) have the highest MBE of $-34.2\%$ compared to thin clouds ($\tau_c < 5$) that have an MBE of $-5.1$. It is believed that this is caused by 3-D cloud effects. For heterogeneous clouds, the cloud sides are no longer obscured such as those in overcast clouds, this leads to increased cloud illumination relative to overcast clouds. For cloud that are thicker than the radiance peak ($\tau_c = 7.25$) this increased radiance along the sun-facing edge of the cloud results in an under prediction of $\tau_c$. The increase in negative MBE with $\tau_c$ highlights this heterogeneous under prediction error in RRBR. This argument is further substantiated by the MBE increasing with the inclusion of overcast MWR measurements. Just like in overcast conditions...
RMSE is highest for thin clouds ($\tau_c < 5$) at 95.6% and fairly constant at higher $\tau_c$ with medium clouds ($5 < \tau_c < 20$) and thick clouds having an RMSE of 45.7 and 44.8% respectively. The heterogeneous cases are associated with a higher relative RMSE of 82.9% compared to 23.7% reported in Sect. 6.2 for the homogeneous Min method.

### 6.4 DNI measurements

Another option for validation is to calculate $\tau_c$ directly from Beer’s law using the DNI measurement of the MFRSR, which validates $\tau_c$ in the circumsolar region (Fig. 11). Rearranging Beer’s law and solving for $\tau_c$ we obtain,

$$\tau_{\text{MFRSR}} = -\log\left(\frac{\text{DNI}}{\text{DNI}_0}\right) \cdot \cos(\theta_0) \cdot \frac{\tau}{A},$$

where DNI is the measured DNI from the MFRSR, DNI$_0$ is clear sky DNI computed with the Ineichen model (Ineichen et al., 2002). $A = 0.43$ is a constant factor to account for the strong forward peak in the phase function of liquid and ice water clouds. $A$ is obtained by applying a linear least squares best fit between the $\tau_c$ of the RRBR method taken at the nearest time to the MFRSR measurements. The $\tau_c$ of the RRBR method are based on the average measurement for pixels in the solar region ($\theta_s < 5^\circ$).

Several modifications to the validation dataset are required. The maximum detectable $\tau_c$ is limited for the DNI method because for large $\tau_c$ ($\tau_c > 5$) DNI is close to zero and $\tau_c$ retrievals from the DNI measurement become noisy. Because of this all clouds with $\tau_c > 5$ are set to $\tau_c = 5$ for both MFRSR and RRBR. Furthermore, at small $\tau_c$ ($\tau_c < 2$), in the circumsolar region, it becomes very difficult to distinguish thin clouds ($1 > \tau_c > 2$) from clear sky ($\tau_c = 0$) because of the diffraction patterns caused by the custom aperture. The circular aperture causes a circular diffraction pattern (also referred to as Airy disk) that is misidentified as a circular thin cloud. Since the aperture and lens have slight manufacturing tolerances, the diffraction does not result in a perfect disk and is therefore difficult to correct. The Airy disk causes pixels to be assigned
an optical depth of $2.5 < \tau_c < 3.5$ under clear skies. This leads to clear sky conditions yielding an average $1 < \tau_c < 2$ for the pixels in the circumsolar region. The following correction is implemented: For average USI $\tau_c < 2$, $\tau_c$ pixel measurements greater than 2 are removed from the averaging, since they are believed to be caused by the Airy pattern. In clear skies this correction only causes clear pixels to remain with typical average $\tau_c < 0.5$. When thin clouds with $\tau_c < 2$ are observed their pixel to pixel variations are minimal so eliminating any pixels with $\tau_c$ greater than 2 does not affect the average as very few pixels are greater than 2.

Additional errors include stray light being greater for small $\tau_c$ and having a larger impact on the solar region. If $\tau_c$ increases from $\tau_c = 0$, diffuse radiance increases but stray light decreases, leading to two competing factors affecting radiance. For $\tau_c < 1$, the increase in diffuse radiance is much larger than the decrease in stray light but for $1 < \tau_c < 2$ diffuse radiance begins to decrease and stray light continues to decrease resulting in similar radiance to clear sky. Even with the correction the MBE for $\tau_c < 2$ is still high at 169.5 % while the overall MBE is 17.9 % suggesting that clear sky still gets misdetected as thin cloud.

7 Discussion and conclusions

This paper presents an analysis of the atmospheric radiative transfer effects on sky imager cloud detection and retrieval of $\tau_c$ using synthetic images produced by the SHDOM. Synthetic images demonstrate that $\theta_0$, $\tau_c$, $\vartheta_s$, and $\vartheta_z$ all significantly and often non-linearly and non-monotonically affect radiance $I_\lambda$ and RBR of sky image pixels. For thin clouds, $I_\lambda (\vartheta_s)$ increases rapidly as it approaches the sun, as a result of the strong forward peak in the cloud phase function. On the other hand, for thick clouds $I_\lambda (\vartheta_s)$ is found to be near constant with solar pixel angle for $\tau_c > 30$. $\vartheta_z$ has two main effects, horizon brightening for thin clouds, and horizon darkening for thick clouds. Thick clouds fall in the diffusion regime where $I_\lambda$ decreases with $\vartheta_z$, but is independent of other parameters.
At a \( \vartheta_s \) of 45° \( I_\lambda (\tau_c) \) is demonstrated to increase with increasing \( \tau_c \) for thin clouds. It reaches a peak at a \( \tau_c \) between 0–5, depending on \( \vartheta_s \) and \( \vartheta_z \). At \( \tau_c \) greater than 5, \( I_\lambda (\tau_c) \) decreases with increasing \( \tau_c \). Similar characteristics are observed for the RBR although it does not decrease as much after reaching its maximum, making it an effective tool for distinguishing between clear sky and thick clouds. However, neither \( I_\lambda (\tau_c) \) nor \( \text{RBR}(\tau_c) \) are monotonic, leading to the difficulties in cloud detection and \( \tau_c \) characterization with one parameter. The RRBR method combines the RBR and \( I_\lambda \) to overcome the non-monotonic nature of each individual parameters.

Summary statistics of the different validations are presented in Table 2. For overcast skies the RRBR yields \( \tau_c \) that are consistent with the Min method and microwave radiometer measurements. For heterogeneous cloud fields (cloud fraction < 0.7), comparisons with microwave radiometer (MWR) measurements of LWC at zenith demonstrated that the RRBR method provides \( \tau_c \) estimates with typical \( r^2 \) of 0.66 and RMSE of 2.3 which is well within the uncertainty of the MWR instrument (±5.6). A RMSE of 0.95 between the USI and DNI retrieved \( \tau_c \) is observed in the range of 0 < \( \tau_c < 5 \). As demonstrated by the relative RMSE in Table 2, the current method provides relatively accurate \( \tau_c \) estimates over the range of 20 < \( \tau_c < 80 \), while the relative RMSE is larger for \( \tau_c < 5 \). Since \( \tau_c \) is exponentially related to surface irradiance, accurate \( \tau_c \) estimates between 0-10 are the most crucial for solar forecasting and unfortunately are also some of the most difficult to correctly identify.

Characterizing the cloud heterogeneity effects may improve the RRBR method. As the RRBR method is based on interpolants developed from simulations of homogeneous overcast skies, cloud heterogeneity violates the assumptions and is assumed to be the leading source of errors. Errors due to cloud heterogeneity have been analyzed mainly in the context of satellite remote sensing. Varnai et al. (1998) and Chambers et al. (1997) observed that the spatial reflectance variation is smoother than variations in \( \tau_c \). They hypothesized that optically thicker clouds would scatter more light to their thinner neighboring clouds causing the thinner clouds to appear brighter and thicker (looking from space), while the thinner clouds would scatter less light to the thicker
clouds making them appear darker and thinner than expected for a homogeneous cloud scene. A similar but opposite effect is observed in ground based imagery, where thicker clouds shade their neighboring thinner clouds making them appear darker and thicker but this effect is moderated by the location of the sun relative to the clouds. Figure 9 also shows that sun-facing cloud edges scatter more light, increasing \( I_\lambda \), and leading to thinner \( \tau_c \) estimates than the cloud edges on the opposite side. Cloud edges facing away from the sun will be shaded by the rest of the cloud and will be estimated as being thicker. These 3-dimensional effects introduce noise in RRBR estimations of \( \tau_c \).

Although the current method is based on results from homogeneous simulations – outside of the cloud edges – the RRBR method is demonstrated to be reasonably accurate based on qualitative comparisons and validations against other ground measurements. This pixel-by-pixel \( \tau_c \) allows an estimate of the contribution of each individual pixel to the DNI, GHI and diffuse horizontal irradiance at the surface. Solar forecasting will benefit in two ways: (i) Static fields of \( \tau_c \) can be used to spatially modulate surface irradiance fields beyond the standard binary (clear - cloudy) solar irradiance, either in 1D similar to Eq. (9) or using the homogeneous results from SHDOM simulations from a look-up table. (ii) Temporal evolution of \( \tau_c \) can be used to extrapolate future cloud \( \tau_c \) resulting from cloud dynamics. At present, \( \tau_c \) is assumed to be steady as the cloud field is advected. An analysis of \( \tau_c \) evolution especially for individual cumulus or stratocumulus clouds through a timeseries of the \( \tau_c \) could improve solar forecast accuracy and extend forecast horizon. For example, stratocumulus clouds that tend to form overcast layers in coastal southern California thin during the mornings and then break up rapidly over land. The RRBR can detect the cloud thinning rate and forecast break-up time.

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References


**Table 1.** Atmospheric radiative properties for the ARM site used as input to SHDOM. $\tau_a$ and Rayleigh optical depth are averages for the year 2013 from AERONET data.

<table>
<thead>
<tr>
<th></th>
<th>Red (620 nm)</th>
<th>Green (520 nm)</th>
<th>Blue (450 nm)</th>
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<tr>
<td>$\tau_a$ [-]</td>
<td>0.0784</td>
<td>0.1010</td>
<td>0.1212</td>
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<td>Rayleigh optical depth [-]</td>
<td>0.0875</td>
<td>0.1627</td>
<td>0.2296</td>
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<td>Effective Radius ($R_e$) [µm]</td>
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<td>3.9</td>
<td>3.9</td>
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<td>Aerosol $R_e$ distribution</td>
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<td>Lognormal</td>
<td>Lognormal</td>
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<td>Refractive index [-]</td>
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<td>1.41–0.002i</td>
<td>1.40–0.002i</td>
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Table 2. Statistics of RRBR validation against the Min method in overcast skies, microwave radiometer measurements, and DNI measurements from the MFRSR.

<table>
<thead>
<tr>
<th>Method</th>
<th>CF</th>
<th>$\tau_c$</th>
<th>$R^2$</th>
<th>RMSE [-]</th>
<th>RMSE [%]</th>
<th>MAE [%]</th>
<th>MBE [%]</th>
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<tr>
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<td>&gt; 0.7</td>
<td>All</td>
<td>0.93</td>
<td>5.6</td>
<td>23.7</td>
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<td>-5.4</td>
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<td>&lt; 5</td>
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<td>1.5</td>
<td>42.7</td>
<td>33.9</td>
<td>22.8</td>
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<tr>
<td>Min</td>
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<td>&gt; 5</td>
<td>0.70</td>
<td>3.3</td>
<td>29.7</td>
<td>24.1</td>
<td>-15.5</td>
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<tr>
<td></td>
<td></td>
<td>&lt; 20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>&gt; 0.7</td>
<td>&gt; 20</td>
<td>0.85</td>
<td>7.8</td>
<td>18.5</td>
<td>15.5</td>
<td>-3.6</td>
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<tr>
<td>MWR</td>
<td>All</td>
<td>All</td>
<td>0.91</td>
<td>6.6</td>
<td>47.8</td>
<td>28.6</td>
<td>15.4</td>
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<td>&lt; 0.7</td>
<td>All</td>
<td>0.66</td>
<td>2.3</td>
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<td>35.1</td>
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<td></td>
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<td></td>
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<tr>
<td>MWR</td>
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<td>&gt; 20</td>
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<td>44.8</td>
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<td>All</td>
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<td>0.95</td>
<td>44.0</td>
<td>33.1</td>
<td>17.9</td>
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<tr>
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<td>0.28</td>
<td>0.98</td>
<td>213.3</td>
<td>179.9</td>
<td>169.5</td>
</tr>
</tbody>
</table>

Coupling sky images with three-dimensional radiative transfer models

F. A. Mejia et al.
Figure 1. Diagram of the UCSD sky imager (USI) and related solar and sky geometries. $\theta_0$ is the solar zenith angle. The $\vartheta_s$ is the angle subtended by the vector pointing at the sun and the vector pointing at the pixel in question. The $\vartheta_z$ is the angle formed by the vector pointing at the pixel in question and zenith. It is important to note that $\vartheta_s = \theta_0 + \vartheta_z$ only holds in 2-D, but not in 3-D as demonstrated in Fig. 2.
Figure 2. (a) Clear USI image from a clear sky library (CSL) for a solar zenith angle of 60° on 26 March 2013, 15:00 UTC, (b) Solar Pixel Angles, and (c) Pixel Zenith Angles. The red line in Fig. 2b. highlights the pixels with $\vartheta_s = 60^\circ$, while the red line in Fig. 2c highlights the pixels with $\vartheta_z = 60^\circ$, which are often used in the following chapters to illustrate relationships with cloud optical depth and radiance. North is located on the bottom right corner of the image.
Figure 3. (a) Clear sky USI image for 26 March 2013, 15:00 UTC, (b) synthetic image from SHDOM for $\tau_c$ of 0 and $\theta_0$ of 60°, (c) percent error in red channel radiance, (d) USI image for 05 May 2013, 14:08 UTC (e) Synthetic Image for $\theta_0$ of 60° and $\tau_c$ of 30, and (f) percent error in red channel radiance.
Figure 4. (a) SHDOM red channel radiance over various sun pixel angles ($\vartheta_s$) at $\vartheta_z = 60^\circ$, and $\theta_0 = 60^\circ$ (Pixels used for Fig. 4 are highlighted as a red line in Fig. 2c). Results are shown for different cloud optical depths from clear ($\tau_c = 0$) to thick clouds. (b) RBR as a function of $\vartheta_s$ at constant $\vartheta_z = 60^\circ$ and $\theta_0 = 60^\circ$. 
Figure 5. (a) Red and blue channel radiances and (b) RBR over various $\vartheta_z$ at constant $\vartheta_s = 60^\circ$ and $\theta_0 = 60^\circ$. Pixels used for Fig. 5 are highlighted as a red line in Fig. 2b.
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Figure 7. Flowchart of the radiance red blue ratio (RRBR) method for $\tau_c$ estimation. If $I_{620}^{\text{meas}}(\vartheta_s, \vartheta_2)$ is saturated (e.g. in the solar disk), $\tau_c$ is assigned Not-a-Number.
Figure 8. Comparison of RRBR $\tau_c$ retrievals from the sky imager versus the Min method applied to MFRSR measurements for USI cloud fractions greater than 0.7. USI results are averaged over the hemisphere as shown in Eq. (9).
Figure 9. Comparison of USI RRBR versus MWR measurements of cloud optical depth for CF < 0.7 in black and CF > 0.7 in red.
Figure 10. Comparison of RRBR versus DNI method of cloud optical depth retrieval. Since $\tau_c$ becomes unreliable for small DNI $\tau_c > 5$ are identified as $\tau_c = 5$ to illustrate that thick clouds are mostly identified correctly.