An Observationally Based Global Band-by-Band Surface Emissivity Dataset for Climate and Weather Simulations

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ABSTRACT

While current atmospheric general circulation models (GCMs) still treat the surface as a blackbody in their longwave radiation scheme, recent studies suggest the need for taking realistic surface spectral emissivity into account. There have been few measurements available for the surface emissivity in the far IR (\(\leq 650 \text{ cm}^{-1}\)). Based on first-principle calculation, the authors compute the spectral emissivity over the entire longwave spectrum for a variety of surface types. MODIS-retrieved mid-IR surface emissivity at 0.05 \(\times\) 0.05 spatial resolution is then regressed against the calculated spectral emissivity to determine the surface type for each grid. The derived spectral emissivity data are then spatially averaged onto 0.5 \(\times\) 0.5 grids and spectrally integrated onto the bandwidths used by the RRTMG_LW—a longwave radiation scheme widely used in current climate and numerical weather models. The band-by-band surface emissivity dataset is then compared with retrieved surface spectral emissivities from Infrared Atmospheric Sounding Interferometer (IASI) measurements. The comparison shows favorable agreement between two datasets in all the bands covered by the IASI measurements. The authors further use the dataset in conjunction with ERA-Interim to evaluate its impact on the top-of-atmosphere radiation budget. Depending on the blackbody surface assumptions used in the original calculation, the globally averaged difference caused by the inclusion of realistic surface emissivity ranges from \(-1.2\) to \(-1.5\) W m\(^{-2}\) for clear-sky OLR and from \(-0.67\) to \(-0.94\) W m\(^{-2}\) for all-sky OLR. Moreover, the difference is not spatially uniform and has a distinct spatial pattern.

1. Introduction

Surface spectral emissivity and surface skin temperature directly determine the amount of upward radiance intensity and radiative flux emitted from the surface. Therefore, surface spectral emissivity is an important radiometric parameter in both infrared remote sensing and the numerical simulation of weather and climate. State-of-the-art infrared retrievals usually take spectral emissivity into full account and surface spectral emissivity is a routinely retrieved product from operational hyperspectral soundings—such as the Atmospheric Infrared Sounder (AIRS; Susskind et al. 2003; Susskind and Blaisdell 2008), the Infrared Atmospheric Sounding Interferometer (IASI; Hilton et al. 2012), and the Cross-track Infrared Sounder (CrIS; Divakarla et al. 2014; Nalli et al. 2013)—and from multispectral imagery radiometer observations, such as the Moderate Resolution Imaging Spectroradiometer (MODIS; Wan and Li 1997). Sophisticated laboratory measurements of high-spectral-resolution emissivity from a variety of surface types are also available for the IR remote sensing of land surface. For example, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Spectral Library has compiled more than 2400 spectral reflectances of natural and manmade materials up to 15.4 \(\mu m\) (i.e., 650 cm\(^{-1}\)) (referred to herein as ASTER Spectral Library, version 2.0; Wilber et al. 1999; Baldridge et al. 2009). No retrievals of surface spectral emissivity are available in the far IR (0–650 cm\(^{-1}\)) because no radiance observations from space have been
made in the far IR except by a pioneer mission of the Infrared Interferometer Spectrometer-D (IRIS-D) on *Nimbus-4* back in 1970/71 that covered 400–600 cm\(^{-1}\) of the far IR (Hanel et al. 1972). Moreover, the far IR is featured with strong water vapor rotational absorption. As a result, in many parts of the globe, surface far-IR emission cannot reach the top of the atmosphere (TOA). Therefore, the observed radiance and flux at the TOA is not very sensitive to surface spectral emissivity. This is the reason why aforementioned laboratory-based measurements in the ASTER Spectral Library, version 2.0, only cover spectral reflectance to 650 cm\(^{-1}\) and not to the far IR. There are spectroscopic measurements of minerals in the far-IR region (e.g., Glotch et al. 2007; Glotch and Rossman 2009), but they are primarily limited to minerals observed or expected on the Martian surface. Numerical weather and climate models so far have not given surface spectral emissivity as much attention as the satellite remote sensing and data assimilation communities do. Mainstream longwave (LW) radiation schemes employed in state-of-the-art numerical weather and climate models still assume the blackbody surface. A recent study by Chen et al. (2014) showed that, for the Antarctic Plateau, discernible difference (~0.8 W m\(^{-2}\)) exists in the monthly mean far-IR all-sky radiation budget at both the TOA and the surface when the blackbody surface emissivity is replaced by more realistic and spectrally dependent emissivity of snow surface and cloud longwave scattering is considered. Another recent study by Feldman et al. (2014) was motivated by the same line of thinking as Chen et al. (2014). Feldman et al. (2014) incorporated snow emissivity derived in Chen et al. (2014) together with spectral emissivity of other three different surface types (sea-water, desert, vegetation) over the entire longwave into the NCAR Community Earth System Model (CESM). The climate simulated by the CESM with such surface spectral emissivity showed noticeable difference from the one by the standard NCAR CESM simulations employing blackbody surface assumptions. These findings suggest the critical need to visit the issue of representation of surface emissivity in the longwave radiation schemes.

Both Chen et al. (2014) and Feldman et al. (2014) focus on the far-IR portion of the LW spectrum. The surface spectral emissivities in Feldman et al. (2014), which were provided by the authors of this study, only had four different surface types and were not thoroughly validated. This fact makes the emissivities in Feldman et al. (2014) only suitable for proof of concept study but not for more feasible and realistic climate simulations. In this study, based on the work that we contributed to Feldman et al. (2014), we further develop a global dataset of surface spectral emissivity. The dataset is anchored on both the first-principle calculation and the retrieved mid-IR surface emissivity from MODIS measurements (Seemann et al. 2008). The dataset will be validated against the mid-IR surface spectral emissivity retrieved from another IR hyperspectral sounding measurements of the IASI (Zhou et al. 2011). We will then use this validated dataset to carry out offline radiative transfer calculation and evaluate the impact of such spectral surface emissivity on the TOA LW radiation budget.

The subsequent sections are arranged as follows. Section 2 describes the techniques used to model the surface spectral emissivity. The comparison with available laboratory measurements is also presented in section 2. Section 3 describes the construction of the global surface spectral emissivity dataset and provides comparisons with IASI retrievals. Section 4 evaluates the impact of the spectral emissivity dataset on the TOA radiation budget. Further discussions and conclusions are given in section 5.

2. Modeling the surface emissivity

Following the simulation strategies described in Chen et al. (2014) and in the appendix of Feldman et al. (2014), angularly dependent spectral emissivities from 10 to 2000 cm\(^{-1}\) are computed for calm water, ice, snow, and desert surfaces.

a. Water and ice surfaces

For calm water and ice surfaces, the spectral emissivities are computed using Fresnel equations (Masuda et al. 1988)—a classical approach in electrodynamics for computing the reflectance \(R\) of an electromagnetic wave when it travels from one medium into another medium with an infinite horizontal interface. According to the Kirchhoff’s law, emissivity is equal to absorptivity, which is \(1 - R\). The spectrally dependent index of refraction is taken from Hale and Querry (1973) for water and Warren and Brandt (2008) for ice, respectively. The calculated spectral emissivities are plotted in Fig. 1 together with the measurements compiled in the ASTER Spectral Library, version 2.0. Though the ASTER Spectral Library does not cover the far-IR region, the compilation by Mironova (1973) of pure water emissivity does cover the entire longwave and shortwave. Our results agree well with the compilation by Mironova (1973) over the entire longwave spectrum (Fig. 2).

There have been studies regarding the influence of the roughness of the ocean surface on surface emissivity (Wu and Smith 1997; Hanafin and Minnett 2005). Using
the approach described in Wu and Smith (1997), we investigated the difference of hemispherical-mean spectral emissivity between wind-roughed ocean surface and a calm water surface, as shown in Fig. 3b. Even for surface wind speeds as large as 15 m s\(^{-1}\), the difference is within 0.02 for the entire LW spectrum. Such a small difference is acceptable for GCM applications. Thus, in this study, we use calculated emissivity of calm water surface for all ocean surfaces. We do note that it is possible to incorporate surface wind speed into the calculation if it is desired to obtain a more accurate estimation of ocean surface emissivity as a function of surface wind speed.

b. Snow surface

Three types of snows with different grain sizes are used in this study. They are fine dendrite snow (median grain size \(D = 70\ \mu m\)), medium granular snow (\(D = 600\ \mu m\)), and coarse grain snow (\(D = 800\ \mu m\)) as described in Table 1 of Hori et al. (2006). The procedures of calculating spectral emissivity of snow surfaces closely follow those described in Chen et al. (2014). To take the densely packed medium into account, single-scattering properties of snow grain computed from the Mie scattering theory are corrected with a “static structure factor correction” method (Mishchenko 1994; Mishchenko and Macke 1997), which are then fed into the Hapke model (Hapke 1993) to get the spectral emissivity. The comparisons of calculated snow surface spectral emissivities with the measurements by Hori et al. (2006) can be found in Fig. 2 in Chen et al. (2014).

c. Deserts

The compositions and morphology of desert surfaces can vary considerably and, thus, their spectral surface emissivities can vary considerably too. This can be seen from the observed surface spectral emissivities from six sites in the Namib Desert and eight sites in the Kalahari Desert (Hulley et al. 2009) shown as light gray curves in Fig. 4. From one site to another, the emissivity in the 1000–1300-cm\(^{-1}\) window can vary from 0.6 to 0.8. Outside this spectral band the spectral emissivity varies...
We use the index of refraction of quartz measured by Spitzer and Kleinman (1961) in our calculation, which is the same index of refraction as archived in the High-Resolution Transmission (HITRAN) 1996 database (Rothman et al. 1998). We model the desert spectral emissivity with a two-step approach. The first step is the same as the one described in section 2b, and we vary the effective radius of sand particles \( r_e \) from 10 to 60 \( \mu \)m. This method is appropriate for modeling silt. The second step is using Fresnel equation to model sand grains that have randomly oriented planar facets (Ronda et al. 2000) with sizes between 60 and 2000 \( \mu \)m, which are larger than the typical IR wavelengths. Then we assume 50% of silt and 50% of sand grains to obtain the desert emissivity. This assumed ratio between silt and sand gives results (color lines in Fig. 4) that agree reasonably well with measurements by Hulley et al. (2009; light gray lines in Fig. 4). Only results with an effective radius outside this range have less agreement with observed desert emissivity (light gray lines in Fig. 4). We will use this group of calculated desert emissivity in our following sections.

d. Vegetation and other considerations

We do not carry out a first-principle calculation of the spectral emissivity for vegetation given the diversity of vegetation and the practical difficulty measuring index of refraction of each type of vegetation. The ASTER Spectral Library provides spectral emissivity of four types of vegetation (grass, dry grass, conifer, and deciduous) measured at a viewing zenith angle of 60°, as shown in Fig. 5. Given the fact that 60° \[ \cos(60°) = 0.5 \] is close to the diffusive angle of 53° \[ \cos(53°) = 0.61 \] used in the Elsasser diffusivity approximation (Elsasser 1942), we directly use the spectral emissivities from the ASTER database for the corresponding vegetation (i.e., assuming isotropic emission of the vegetation canopies in the LW). Since the ASTER database has no far-IR measurements, we simply assume that the far-IR emissivities are constant and equal to the measured emissivities at the longest wavelength—the same assumption used in Feldman et al. (2014). As far as we know, there have been few literatures discussing observed far-IR spectral emissivity of vegetation. Large-scale vegetation coverage are mostly found at places with abundant water vapor, where the far-IR absorption due to water vapor can be strong and, consequently, little knowledge of far-IR surface emissivity of vegetation should only have limited impact on the radiation budget. Quantifying this impact would require new observations of the far-IR emissivity from vegetation.

Plenty of desert regions are covered by grass canopy and sand dunes. As in Hulley et al. (2009), we also define a surface type with 55% vegetation and 45% desert and derive its surface emissivity by averaging the surface emissivities of grassland and desert accordingly. Therefore, in total we have spectral emissivity of 11 different surface types: water, fine snow, medium snow, coarse snow, ice, grass, dry grass, conifer, deciduous, desert (including 16 subtypes with the effective radii of silt varying from 30 to 45 \( \mu \)m), and a combination of...
desert and grassland (55% vegetation and 45% desert averaged over all subtypes). These surface types and associated spectral emissivities are what we will use in the following sections.

3. Development and validation of the 0.5° × 0.5° global surface spectral emissivity dataset

The basic approach adopted for developing this dataset is as follows: We first use a high-spatial-resolution (0.05° × 0.05°) surface emissivity dataset derived from satellite observations and our 11 types of surface spectral emissivity derived in section 2 to decide the surface type of each 0.05° × 0.05° grid. Then we average the emissivities of such grids onto the 0.5° × 0.5° grids and then compare with another surface emissivity dataset derived from another independent satellite observation. In other words, for each month we develop a global surface emissivity dataset for all longwave wavelengths anchored with one satellite observation with spectral emissivities retrieved at discrete hinge points, and then we validate the dataset against another satellite observation with retrievals of spectral emissivity over continuous mid-IR spectrum. As mentioned above, the anchoring and validation are all done in the mid-IR region because of the limitation of observations. The confidence in the far-IR portion relies on the validation of mid-IR emissivity (thus surface type) and the first-principle calculations that we have carried out.

We will describe two satellite datasets that we use in this study first, followed by the comparisons between our results and the observations at 0.5° × 0.5° grid.

a. UW/CIMSS MODIS land surface emissivity and its usage in our study

We use the global land surface IR emissivity database from the University of Wisconsin–Madison (UW)/Cooperative Institute for Meteorological Satellite Studies (CIMSS) to decide the surface type for each 0.05° × 0.05° grid over the entire globe. The UW/CIMSS land surface emissivity was based on MODIS observations on the NASA Terra and Aqua satellites (Seemann et al. 2008). It uses a baseline fit (BF) method relying on the most representative high-spectral emissivity spectra of 123 different land surface materials measured in the laboratory at the University of California, Santa Barbara. The method adjusts a baseline emissivity spectrum based on MODIS level 3 operational land surface emissivity product MYD11 at six spectral bands according to a conceptual model. Emissivity in the UW/CIMSS MODIS land surface emissivity database is presented at 10 frequency hinge points (3.6, 4.3, 5.0, 5.8, 7.6, 8.3, 9.3, 10.8, 12.1, and 14.3 μm). The selection of these 10 hinge points was to best capture emissivity spectral variation between 3.6 and 14.3 μm. The database is available for 0.05° latitude by 0.05° longitude. The BF emissivity generally agrees well with the laboratory-measured emissivity in shape and magnitude; the mean differences between them are smaller than 0.02. More details about the UW/CIMSS MODIS land surface emissivity database can be found in Seemann et al. (2008).

In this study we use the monthly mean CIMSS emissivity from 2008 to 2014 (the same period that the IASI retrievals are available). For each month and each grid, the correlations between UW/CIMSS MODIS retrievals of land surface emissivity at the hinge points between 5.0 and 12.1 μm and the counterparts of the 11 surface types (including subtypes) used in this study are calculated. The surface type with highest correlation is assumed to be the surface type of the entire grid. In other words, each 0.05° × 0.05° grid is assumed to be occupied by only one surface type among all surface types used in this study. Once the surface type of each grid is decided, the calculated emissivity described in section 2 is used and averaged onto 0.5° × 0.5° to form the global spectral surface emissivity dataset for each calendar month.

Since the goal here is to develop surface emissivity dataset usable for global modeling community, we further average the surface spectral emissivity of each grid onto the bandwidths of RRTMG_LW (Iacono et al. 2000)—a radiation scheme adopted by several climate models and numerical weather prediction models. RRTMG_LW has 16 bands in longwave and its bandwidth definitions can be found in Table 1. Our original spectral emissivity dataset can be averaged onto other

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<th>RRTM_LW band</th>
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<td>1</td>
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bandwidths as well because the original calculations are done at spectral resolution much higher than the bandwidths used in radiation schemes.

b. IASI retrievals of land surface emissivity

IASI is a hyperspectral spectrometer aboard MetOp series of satellite launched by the European Space Agency (Hilton et al. 2012). Zhou et al. (2011) retrieved the land surface spectral emissivity from IASI radiance measurements using a multistage linear empirical orthogonal function (EOF) regression approach. This spectrally resolved emissivity product covers all IASI channels from 645 to 2760 cm\(^{-1}\) at a 0.25-cm\(^{-1}\) spectral sampling, which have been monthly integrated into a spatial grid of 0.5° × 0.5° (latitude–longitude) as a climatology dataset. By comparing the retrievals with observed spectral emissivities at the Namib Desert and Kalahari Desert, Zhou et al. (2011) indicated that a standard deviation of retrieval error is less than 0.02. The IASI land surface emissivity retrievals will be used to validate the mid-IR portion of the spectral emissivity dataset that we developed as the retrieved spectral emissivity has continuous spectral coverage in the mid-IR.

MODIS-retrieved surface emissivities are used in this study for helping to determine the surface type, while IASI-retrieved emissivities are used as an independent source for validation. Inevitably, each retrieval algorithm has its own assumptions and uncertainty dependent on its instrumental performance and retrieval processes. Therefore, it is worth examining the systematic differences between the two retrievals first. Figure 6 shows the differences between the MODIS- and IASI-retrieved surface emissivities at 8.3 and 12.1 µm after the
MODIS retrievals are averaged onto 0.5° × 0.5° grids. Both 8.3 and 12.1 μm fall into the mid-IR window. The MODIS minus IASI (MODIS - IASI) difference is largely negative over desert regions for both wavelengths, though some positive differences are seen over the southwestern United States, southern Arabia, and western Australia for the 8.3-μm comparison in January. The differences over the Tibetan Plateau, Andes Mountain, Greenland, and the Antarctic Plateau are positive in 8.3 μm but negligible at 12.1 μm.

These intrinsic differences between two satellite retrieval datasets will affect our following comparisons between the dataset that we developed and the IASI retrievals, since our dataset is anchored on the surface type regression with respect to MODIS retrievals. Nevertheless, the general agreements between MODIS and IASI retrievals are apparent: the global-mean difference is only ~−0.006 for 8.3 μm and ~−0.016 for 12.1 μm and the root-mean-square (RMS) difference is no more than 0.02 for all cases.

c. Comparisons of our global surface spectral emissivity and IASI retrievals

Figures 7 and 8 show the comparisons between surface emissivities as derived in this study and as retrieved by the IASI for four bands used in the RRTMG_LW scheme for January and July, respectively. The top three bands are within the mid-IR window and the last one is in the water vapor ν2 fundamental band. In both figures, the most noticeable difference is seen over the Sahara Desert for the 1080–1180-cm⁻¹ band (i.e., 8.5–9.3 μm). The RMS difference of this band (~0.02–0.026) is also at least twice
as large as the RMS differences of the other three bands. This is consistent with the MODIS – IASI difference shown in Fig. 6, in which the largest difference is also seen in the Sahara region. The differences over the Andes Mountains, Antarctic Plateau, Tibetan Plateau, and Greenland for the 1080–1180-cm$^{-1}$ band also have the same signs as those in Fig. 6. The RMS differences for the other three bands are ~0.01. For all four bands examined here, the global-mean difference is around ±0.005. The statistics for the rest of the RRTMG_LW bands are similar to these shown in Figs. 7 and 8. For RRTMG_LW bands 4–12 shown in Table 1, the mean differences range from −0.006 to 0.018 and the RMS differences are between 0.005 and 0.0273 for all 12 calendar months. Figure 9 shows the histogram of the differences when 12 calendar months are all considered. The global-mean difference is reduced to between −0.001 and −0.002 because of the increase of sampling sizes. The standard deviation is ~0.01 for all four of the bands shown above. The histograms all show a bimodal distribution with one negative peak and one positive peak nearly symmetric to zero difference. Moreover, a fat tail centered on 0.02 can be seen on Fig. 9b. This fat tail is the result of positive differences over high-elevation regions mentioned above.

Besides the comparison of band-averaged surface emissivity over the RRTMG_LW bands, we also directly compare the spectral emissivity derived from our method and the IASI retrievals over the mid-IR (i.e., 650–2000 cm$^{-1}$) spectrum. For illustration, four geographic locations are chosen as shown in Fig. 8 and named as locations A–D. They are located in the Sahara Desert, Simpson Desert in Australia, Siberian Plateau in Russia, and Antarctic Plateau, respectively. The corresponding spectral emissivities and differences are shown in Fig. 10.
For both January and July, the difference is nearly flat over all spectral regions for locations B–D. For location A (Sahara Desert), the largest difference is ±0.05 within the band. This is consistent with the difference between MODIS and IASI retrievals and the complexity associated with desert surface emissivity.

These comparisons show that, in general, the spectral emissivity dataset developed in this study has a good agreement with the retrieved surface spectral emissivities from IASI radiances. The systematic differences over the Sahara Desert and over plateau areas are not a surprise, given the complexity of desert compositions and plateau topography and the simplicity of treating such surfaces in our algorithm. These discrepancies warrant further studies to the retrieval uncertainties of MODIS and IASI retrievals, as well as the future investigations for improving the modeling of surface composition and topography.

4. Offline evaluation of the impact on the LW TOA radiation budget

Using the global surface spectral emissivity dataset developed in previous sections, we evaluate how much it can affect the TOA LW radiation budget when the radiative transfer calculation takes such surface spectral emissivity into account. To do so, we use an entire month of 12-hourly ERA-Interim profiles (Dee et al. 2011) of temperature, humidity, and cloud profiles as input to a radiative transfer model built upon the Principal Component-based Radiative Transfer Model (PCRTM; Liu et al. 2006). The radiative transfer model takes cloud subgrid variability into account and its details can be found in Chen et al. (2013). We use three different configurations for the evaluation:

1) Case 1: All surfaces are assumed to be blackbody and surface radiative skin temperature is assumed to be the surface temperature from ERA-Interim. Thus the upward LW radiation from surface simply observes the Planck’s law and the upward LW flux \( F_{\text{LW}}^{\uparrow} \) can be written as

\[
F_{\text{LW}}^{\uparrow} = \sigma T_{\text{skin}}^4 = \alpha T_s^4,
\]

where \( \sigma \) is the Stefan–Boltzmann constant, \( T_{\text{skin}} \) is the surface radiative skin temperature, and \( T_s \) is the surface temperature.
2) Case 2: All surfaces are assumed to be blackbody. The ocean surface radiative skin temperature is the surface temperature from ERA-Interim, just like case 1. But over land, $T_{\text{skin}}$ is defined as

$$F_{\text{LW}} = F_{\text{LW, surface ERA}} = \sigma T_{\text{skin}}^4,$$  \hspace{1cm} (2)

where $F_{\text{LW, surface ERA}}$ is the total upward LW flux provided by the ERA-Interim. The atmospheric model and data assimilation system used in the ERA-Interim assume surface emissivity outside the 800–1250-cm$^{-1}$ band being 0.99 and the surface emissivity within the band being a function of surface type (ECMWF 2007). Please note $F_{\text{LW, surface ERA}}$ includes both the surface emission and the reflection of downward flux at surface. This treatment is similar to the method used in some GCMs such as the CESM (Neale et al. 2010). For land grids in the CESM, the total upward LW flux is computed in the land module and then passed to the radiation scheme in the atmospheric module, in which the radiative skin temperature is evaluated according to Eq. (2). Note Eq. (2) ensures that total upward LW flux from the land model is the same as that in the atmospheric model even the radiation scheme in the CESM atmospheric module assumes blackbody surface only (thus no reflection of downward LW flux) while the CESM land module assumes broadband graybody surface allowing reflection of downward LW flux.

3) Case 3: For both ocean and land, the surface spectral emissivity is taken from the dataset developed in this study. The surface temperature is taken from ERA-Interim. Thus, the upward LW flux at surface can be expressed as

$$F_{\text{LW}} = \int_{\Delta\nu} \left[ \varepsilon_{\nu}(T_s) \pi \sigma B_{\nu}(T_s) + (1 - \varepsilon_{\nu}) F_{\nu}^c(z = 0) \right] d\nu, \hspace{1cm} (3)$$

where $B_{\nu}(T_s)$ is Planck function, $\varepsilon_{\nu}$ is the surface spectral emissivity, $\Delta\nu$ is the LW spectral range, and subscript $\nu$ denotes spectrally dependent quantities. For each case, the clear-sky OLR and all-sky OLR for January and July 2008 are computed and compared. We refer this comparison as offline evaluation since the only difference is the treatment of surface spectral emissivity in radiative transfer calculation.

**a. Case 3 versus case 1**

The differences between case 3 and case 1 are summarized in Fig. 11 (and in Figs. 13a and 13b). For January and July examined here, the global monthly mean difference is $\sim 1.5$ W m$^{-2}$ for clear-sky OLR and $\sim 0.9$ W m$^{-2}$ for all-sky OLR (Figs. 13a and 13b), indicating a $\sim 0.6$ W m$^{-2}$ cloud masking effect for the global-mean OLR difference.
in both January and July. Since the spectral emissivity in case 3 is no more than 1 for any frequencies and the downward flux at surface is smaller than the blackbody emission of surface (because surface temperature is generally higher than the atmospheric effective emission temperature), the upward LW flux at surface in case 3 (surface emission plus reflected downward flux) is always smaller than its counterpart in case 1 (pure blackbody surface emission). That is why the OLR differences are always negative. The large difference is seen over desert regions in Africa, Asia, and Australia (Fig. 11). This is not a surprise given the fact the spectral emissivity of desert over the band can be as low as 0.6–0.7. The differences in spectral OLR (Figs. 13a and 13b) also confirm that the largest discrepancies are in the band.

As for the oceans, the difference is larger in high latitudes than in low latitudes, which can be seen from Figs. 11. This tendency is due to several facts: 1) the ocean spectral emissivity deviates more from blackbody in the far IR than in the mid-IR, as shown in Fig. 3; 2) according to the Wien’s displacement law, the peak of blackbody emission shifts toward far IR as the surface temperature decreases from the tropics to the polar regions; and 3) the total column water vapor in high latitude is much less than in lower latitudes, which reduces the opacity of atmosphere in the far IR and makes it possible for surface change to affect the radiation budget at TOA (Chen et al. 2014). As a result, the far-IR differences over the ocean region between case 3 and case 1 are larger in high latitudes than in low latitudes.

b. Case 3 versus case 2

Figure 12 shows the differences between case 3 and case 2. The difference between Fig. 12 and Fig. 11 only exists over land areas because both case 2 and case 1 assume blackbody ocean surface and directly use the ERA-Interim surface temperature in the radiative transfer calculation. Similar to Fig. 11, the largest negative difference is seen over desert regions such as Sahara Desert, Gobi Desert, and western Australia. For some arid and semi-arid areas such as the western coast of North America, central Asia, and the southern end of Africa, the differences are positive in Fig. 12 but negative in Fig. 11. For the rest of land areas, the difference in Fig. 12 is not as negative as that in Fig. 11. This indicates that, over such areas, the broadband emissivity approach used in the ERA-Interim agrees much better with the spectral emissivity approach in this study than the blackbody assumption. The globally averaged spectral flux differences between case 3 and case 2 (Figs. 13c and 13d) are similar to those differences between case 3 and case 1 but with smaller amplitudes.
across the entire LW spectrum. The cloud masking effect for the globally averaged OLR difference (all sky vs clear sky) is also similar to the difference between case 3 and case 1.

In addition to the global-mean spectra flux difference, it is also instructive to look the spectral flux difference over different climate zones and over land and ocean separately. Table 2 shows the total OLR difference between case 3 and case 2 for land and ocean in the different climate zones. For all climate zones, the standard deviation of OLR differences among ocean grids is much smaller than that among land grids. The all-sky spectral flux difference is examined in Figs. 13e and 13f. One mid-IR window region \(1000–1400 \text{ cm}^{-1}\) contributes more than other spectral bands for the difference in the tropical land, largely because the low desert surface emissivity in the spectral region. From the tropics to high latitudes, the contribution from the far IR and the lower end of the mid-IR \(<1000 \text{ cm}^{-1}\) becomes more and more important. This is true for both land and ocean.

The above results indicate that using realistic surface emissivity in the radiative transfer calculation will cause discernible differences in the monthly mean TOA radiation budget for both the broadband and spectral OLR differences. The differences are most noticeable over desert regions and high-latitude oceans. It is conceivable that, when the treatment of surface spectral emissivity is coupled with other components in the GCM, such patterns of differences can cause further changes in the atmospheric dynamic field, which in turn can affect the simulated climate in each climate zone.

5. Conclusions and discussion

Motivated by recent studies, we develop a global dataset of surface spectral emissivity for the entire LW spectrum. Using a variety of radiative transfer techniques and available measurements of the index of refraction, we model the spectral emissivities of different surface types. Together with the spectral emissivities of four types of vegetation compiled in the ASTER Spectral Library, we are able to cover the majority of surface types in the real world. Then such spectral emissivities of different surface types are regressed against MODIS retrievals of surface spectral emissivities at every \(0.05^\circ \times 0.05^\circ\) grid and at seven spectral hinge points to decide the surface type of each grid. The dataset derived in this way is then compared with IASI retrievals of surface spectral emissivities at each \(0.5^\circ \times 0.5^\circ\) grid—a resolution comparable to current GCM horizontal grids. For the mid-IR spectrum where IASI retrievals are available, the spectral emissivity dataset developed from the first principle and anchored against MODIS retrievals.
generally has good agreement with IASI retrievals. The largest discrepancies are seen in desert regions and over high-elevation plateaus, where the intrinsic MODIS – IASI discrepancies are large. Such favorable comparisons give us confidence in the dataset, especially for the far-IR regions where no systematic measurements are available for such validation. The ultimate validation of the far-IR portion of our dataset will be comparisons against actual observations. We hope that our study and other relevant studies such as Chen et al. (2014) and Feldman et al. (2014) provide motivation for the observational community to carry out measurements of the far-IR component of surface emissivity in the future, at least for the surface types commonly seen in the polar regions.

When the surface spectral emissivity dataset is used in the atmospheric radiative transfer calculation, its impacts on global-mean clear-sky OLR and all-sky OLR are both nonnegligible. Moreover, the spatial pattern of such impact is not uniform. Comparing to the case of blackbody ocean surface as used in current numerical models, taking spectrally dependent ocean surface emissivity into account will reduce the OLR computed from the radiation scheme. Such reduction of OLR changes with latitude, ranging from $\sim 0.8 \text{ W m}^{-2}$ in the tropics to $\sim 2 \text{ W m}^{-2}$ in the polar regions. Over lands, the

<table>
<thead>
<tr>
<th>Climate Zone</th>
<th>Clear-sky OLR difference (W m(^{-2}))</th>
<th>All-sky OLR difference (W m(^{-2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Land</td>
<td>Ocean</td>
</tr>
<tr>
<td>Global</td>
<td>$-1.21\pm 1.95$</td>
<td>$-1.26\pm 0.72$</td>
</tr>
<tr>
<td>Tropics (30°S–30°N)</td>
<td>$-1.77\pm 3.30$</td>
<td>$-0.81\pm 0.31$</td>
</tr>
<tr>
<td>NH midlatitudes (30°–60°N)</td>
<td>$-0.50\pm 1.57$</td>
<td>$-1.48\pm 0.28$</td>
</tr>
<tr>
<td>SH midlatitudes (30°–60°S)</td>
<td>$-2.07\pm 1.28$</td>
<td>$-1.68\pm 0.25$</td>
</tr>
<tr>
<td>NH high latitudes (60°–90°N)</td>
<td>$-0.80\pm 0.62$</td>
<td>$-2.22\pm 0.35$</td>
</tr>
<tr>
<td>SH high latitudes (60°–90°S)</td>
<td>$-1.13\pm 0.45$</td>
<td>$-2.61\pm 0.34$</td>
</tr>
</tbody>
</table>
largest differences are seen over desert regions. Specifically, changes in OLR due to the inclusion of surface spectral emissivity are most discernible in the mid-IR window as well as the “dirty window” in the far IR, even for the globally averaged differences. The discernible difference in the far-IR dirty window is supporting evidence why the far-IR observations are urgently needed for a complete and accurate understanding of the Earth radiation budget.

To the best of our knowledge, this study is the first attempt to construct a global surface spectral emissivity dataset over the entire LW spectrum. To make the dataset more realistic, certain aspects of the dataset can be further improved. For example, the ocean surface spectral emissivity can be made as a function of surface wind speed at each ocean grid. For another example, the sea ice spectral emissivity is modeled with Fresnel equation. This assumption might not be suitable for all types of sea ices given the complicate morphology of sea ice (Petrich and Eicken 2009). These could be directions for possible improvement of the dataset, especially if high-quality in situ measurements of spectral emissivity of sea ice become available.

The offline evaluation in this study only estimates the impact of surface spectral emissivity on the TOA radiation budget assuming everything else remains unchanged. It does not include any changes of atmosphere, thermodynamically or dynamically, in response to such changes of lower boundary conditions in radiative transfer and, consequently, the changes in radiation budget and in atmospheric-column radiative cooling. A global climate model with the capability of including surface spectral emissivity in its radiation scheme would be needed to assess the impact on simulated climate—that is, the overall dynamical and thermodynamic responses of the climate system to the change of surface spectral emissivity treatment in the radiation scheme, as Feldman et al. (2014) has demonstrated. To evaluate such effect and diagnose the physical causality between the inclusion of surface emissivity and the simulated climate will be the focus of our follow-up study.

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