Directional variation in surface emissivity inferred from the MYD21 product and its influence on estimated surface upwelling longwave radiation

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Abstract

The land surface emissivity (LSE) in the MYD21 product contains the effects of viewing zenith angle. The influence of the angular variation of LSE on the surface upwelling longwave radiation (SULR) estimation is still unexplored at the satellite scale. We performed statistical analyses of MYD21 emissivity retrievals over different land surface types for three longwave bands centred around 8.55 μm (Band 29), 11 μm (Band 31) and 12 μm (Band 32), respectively. A look-up table was generated to describe the angular variations for both single-band and broadband emissivities. The results showed that the angular variation of directional emissivity in Band 29 could

reach up to 0.03, but was <0.01 for Bands 31 and 32. The angular variation in broadband emissivity was intermediate to that for individual bands. In all cases, the directional emissivity was greatest and symmetric around nadir. By integrating the directional broadband emissivity, the influence of angular variation of the LSE on estimated SULR was quantified using simulation and measurements at seven stations from the US surface radiation budget network (SURFRAD). The difference between the directional and integrated hemispheric broadband emissivity was within 0.01. As a result, the influence of angular variation of LSE on the SULR estimation was modest. For the SURFRAD stations, the differences of root-mean-square error (RMSE) before and after considering the angular variation of LSE were generally $<1 \text{ W m}^{-2}$. We conclude that the angular variation of broadband emissivity is not pronounced because of the small linear weight for Band 29 in the calculation of broadband emissivity. Ignoring the anisotropy of emissivity does not introduce large errors in SULR estimation generally.

Key Words: MYD21, LSE, angular variation, SULR

1. Introduction

Land surface emissivity (LSE) is defined as the ratio of the surface emitted radiance to the radiance emitted from a black body at the same thermodynamic temperature (Li et al. 2013; Norman and Becker 1995). It is an important parameter related to land surface composition and land cover change, and LSE plays a significant role in surface-atmosphere interaction processes such as evapotranspiration (Hulley et al. 2014; Wang et al. 2015). In climate, weather, and some hydrological models, LSE is an indispensable input parameter (Jie et al. 2012). Moreover, LSE is increasingly being recognized as one of the most important Earth System Data Records by NASA

and other international organizations (García-Santos et al. 2015; Hulley et al. 2014; King 1999).

Several methods of estimating LSE have been published. Snyder et al. (1998) proposed a classification-based method to estimate LSE using land cover classification and seasonal factors. The method was adopted to retrieve land surface temperature (LST) from observations by the Moderate Resolution Imaging Spectroradiometer (MODIS) using a generalized split-window algorithm (Wan and Dozier 1996). Wan and Li (1997) developed the day/night physical approach that used pairs of daytime and night-time observations to simultaneously estimate LST and LSE. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Temperature/Emissivity Working Group (TEWG) proposed the Temperature and Emissivity Separation (TES) algorithm to estimate LSE and LST simultaneously, using a calibrated curve between minimum emissivity and emissivity spectral contrast (Gillespie et al. 1998). The TES algorithm was subsequently modified for simultaneous LST and LSE retrieval from MODIS data (Hulley and Hook 2011). Recently, Masiello et al. (2013) implemented a Kalman filter approach to retrieve LST and LSE concurrently using geostationary measurements from the Spinning Enhanced Visible and Infrared Imager (SEVIRI). They reported an accuracy of ± 0.005 when compared to other emissivity products (Masiello et al. 2015; Blasi et al. 2016). Another retrieval scheme was developed using a principal component analysis transform to retrieve LSE, LST, and atmospheric parameters simultaneously from high spectral resolution infrared observations. The scheme was applied to Infrared Atmospheric Sounder Interferometer (IASI) measurements and the LSE retrievals showed very good agreement with in-situ emissivity measurements (Masiello et al. 2018).

An intrinsic property of LSE is its dependency on viewing zenith angle (VZA), which can be attributed to factors such as land surface composition (García-Santos et al. 2012; Lagouarde et al. 1995), roughness and structure (Snyder et al. 1998), and spatial heterogeneity (Hu et al. 2015; Ren et al. 2014). Even for flat and homogeneous surfaces such as open water, the emissivity is VZA-dependent (Masuda et al. 1988). The variation in LSE can influence the subsequent retrieval of LST and surface upwelling longwave radiation (SULR) (Cheng and Liang 2014; García-Santos et al. 2015; García-Santos et al. 2012; Lagouarde et al. 1995; Ren et al. 2011). The angular variation of LSE has been studied from three perspectives: field and laboratory measurement; modelling; and satellite-scale analysis.

Using the measured emissivity spectra, Cheng and Liang (2014) analysed the difference between integrated hemispheric broadband emissivity and directional broadband emissivity for different materials (e.g. ice, sand and clay). Surface longwave net radiation estimation errors from using directional emissivity instead of hemispheric integrated emissivity were simulated. Results showed the error was over 10 W m^{-2} for water and bare ice and below 6 W m^{-2} for other materials. García-Santos et al. (2012) measured the angular variation in thermal infrared emissivity for inorganic soils and analysed the impact of ignoring angular effects on estimated outgoing longwave radiation. The resulting error was 2 - 8% depending on soil properties. Other researchers concluded that the emissivities of sparsely vegetated surface, bare soil, sand, clay and water decrease with the VZA; whereas for dense vegetated canopies, angular variation can be ignored (Cuenca and Sobrino 2004; García-Santos et al. 2012; García-Santos et al. 2014; Labed and Stoll 1991; Lagouarde et al. 1995; Ren et al. 2011; Sobrino and Cuenca 1999; Sobrino et al. 2005).

Sobrino et al. (2005) classified canopy directional emissivity models into geometrical models and radiative transfer models. In geometrical models, such as MGP (Pinheiro et al. 2004) and the model for row crops of Sobrino and Caselles (1990), vegetation is conceptualised as an opaque medium and the thermal infrared (TIR) radiance is estimated by weighted combination of the radiance from several components based on their fraction cover. In radiative transfer models such as FRA97 (Francois et al. 1997) and 4SAIL (Verhoef et al. 2007), the TIR radiation propagation and interactions within the canopy are simulated. The canopy is represented as a set of planar elements statistically distributed into horizontally homogeneous layers and the radiance is estimated as a function of viewing angle, temperature distribution and leaf angle distribution within the canopy (Sobrino et al. 2005). In addition to these two categories, hybrid models exist that consider the gap frequency within the canopy based on the geometric models (Du et al. 2007; Ren et al. 2013). Computer simulation models such as DART (Guillevic et al. 2003) and TRGM (Liu et al. 2007) account for the architecture of the canopy by introducing three-dimensional scenes.

With respect to satellite observations, Petitcolin et al. (2002) used the Temperature Independent Spectral Indices of Emissivity concept (Becker and Li 1990) to show that estimates of emissivity from Advanced Very High Resolution Radiometer exhibited little spectral and angular variations for vegetated surfaces, with values larger than 0.96. Over bare or sparsely vegetated surfaces, with emissivity <0.95 , they did find significant directional effects, with emissivity decreasing by 3% between VZAs ranging from nadir to 60° . Ren et al. (2011) generated a look-up table (LUT) of directional emissivity from the ~ 5 -km resolution MOD11B1 product retrieved with the day/night algorithm and applied it to the generalized split-window algorithm to refine the MODIS LST. They found that the angular variation of LSE generated differences

of -1 to 3 K in the estimated LST. García-Santos et al. (2015) analysed the angular variation of MODIS longwave emissivities estimated using the TES algorithm over arid regions and found that the LSE in Band 29 decreased as much as 0.038 for VZAs between nadir and 60°, while LSEs in Bands 31 and 32 did not show significant variation. However, their analysis focused on sandy deserts only. Masiello et al. (2018) investigated the angular dependence of emissivity retrieved from IASI hyperspectral soundings using a PCA-based scheme over homogenous and flat gravel plains. They showed that emissivity retrieved for Field of View (FOV) < 15° were greater than for FOV > 25°.

SULR is a component of the surface radiation budget and plays an important role in the energy exchange between the land surface and atmosphere (Hu et al. 2016; Jiao et al. 2015; Wang et al. 2009). LSE is a significant parameter in the estimation of SULR, whose angular variation can affect the quality of the produced SULR products (Wang et al. 2009; Wu et al. 2012). As such, the uncertainties in estimated SULR caused by LSE anisotropy need to be analysed (Hu et al. 2017; 2016). The modified TES algorithm that was applied to the MODIS data has attracted much attention due to its simultaneous retrieval of LST and LSE (Coll et al. 2016; García-Santos et al. 2015; Hulley and Hook 2011). In the TES algorithm, the temperature and emissivity are estimated simultaneously and the effect of observation angles is kept in the products, which is of interest here. The estimated emissivity is considered to contain the angular effect. In this case, a LUT of directional emissivity can be generated using the emissivity in the MYD21 product based on the criteria of day/night difference, seasonal variation and the land cover types in the International Geosphere Biosphere Program (IGBP) scheme at 1-km spatial resolution. And the influence of the angular variation of LSE on SULR estimation can be explored quantitatively based on the built LUT.

Our objectives are to analyse the angular variation of TIR emissivity and assess the impact on the estimation of SULR. We aim to do this by characterizing the angular variation in the single-band emissivity in MODIS Bands 29 (8.55 μm), 31 (11 μm) and 32 (12 μm) as well as the broadband emissivity using the MYD21 product, and by quantifying the influence of angular variation of LSE on the estimated SULR through simulation analysis and comparison with ground-based measurements from the US surface radiation budget network (SURFRAD).

2. Data and method

The original MYD11 LST and LSE products were generated using two different algorithms: a generalized split-window algorithm (MYD11_L2) (Wan and Dozier 1996) and a day/night algorithm (MYD11B1) (Wan and Li 1997). In the MYD21 product, LST and LSE are estimated simultaneously from the MODIS Aqua observations using the TES algorithm (Hulley et al. 2014; Hulley and Hook 2011). TES retrievals use radiances in MODIS Bands 29, 31 and 32. The retrieved LSE are assumed to be VZA-dependent and include angular information.

Our approach to analysing the MYD21 data is illustrated in Fig. 1. We constructed a LUT of directional emissivity for different land surface types. Subsequently, the broadband emissivity was calculated as a linear weighted combination of single-band emissivities. The angular variations of both single-band and broadband emissivities were analysed. Next, the hemispheric broadband emissivity was calculated by integrating the directional broadband emissivity over the upper hemisphere. Finally, the influence of angular effects of emissivity on SULR estimation was analysed by comparing SULRs calculated using the directional and hemispheric broadband emissivities, respectively.

Fig. 1 Flowchart of the analysis.

2.1. Data

2.1.1 MODIS products

Two key steps in the MYD21 retrieval are the atmospheric correction and the TES algorithm. Uncertainties in atmospheric correction affect the accuracy of the TES retrievals (Gillespie et al. 1998; Hulley et al. 2016; Hulley et al. 2009). In order to reduce the errors in the atmospheric correction, a Water Vapour Scaling (WVS) method was used in the MYD21 retrieval algorithm to improve the accuracy of the atmospheric correction (Hulley et al. 2016; Tonooka 2005).

The latest version atmospheric radiative transfer model RTTOV v11 was used for the MYD21 products (Hulley et al. 2016). The RTTOV model is a very fast radiative transfer model for nadir-viewing passive visible, infrared and microwave satellite radiometers, spectrometers and interferometers (Saunders et al. 2015). Atmospheric parameters to drive the model were derived from NASA's Modern Era Retrospective-Analysis for Research and Applications-2 (MERRA-2) reanalysis data with a temporal

resolution of 6 hrs and a spatial resolution of $0.5^{\circ} \times 0.625^{\circ}$ (Gelaro et al. 2017). The MERRA-2 profiles were first interpolated temporally to the MODIS observations using the two nearest reanalysis times before input into RTTOV. The $0.5^{\circ} \times 0.625^{\circ}$ output atmospheric parameters were interpolated to 1-km resolution using bi-cubic interpolation. This could cause considerable uncertainty, especially in humid regions where atmospheric water vapour could vary greatly in space. The WVS approach was implemented to mitigate these errors and refine the estimated atmospheric parameters on pixel-wise and band-wise method using a scaling factor that was first computed for each graybody pixel. For non-graybody pixels, the scaling factor was calculated after horizontally interpolating and smoothing the scaling factor from all the graybody surfaces adjacent to the non-gray pixels within an effective radius of 50 km using the inverse distance weighting method (García-Santos et al. 2015; Hulley et al. 2016; Malakar and Hulley 2016).

The TES algorithm has three component modules. These are the Normalized Emissivity Method (NEM), the RATIO, and the Maximum-Minimum Difference (MMD) modules. In the NEM module, emissivity estimates for the three TIR bands are calculated by iteratively calculating the emitted radiance from the surface with the initial emissivity set to 0.99 for all wavelengths. The iteration is repeated until convergence when the change in the emitted radiance between iterations is less than a threshold that is set as the sensor noise-equivalent temperature (0.05 K). The RATIO module takes the NEM emissivity values and divides by their average emissivity value to calculate a so-called beta spectrum. Next, the MMD is calculated from the beta spectrum by subtracting the minimum beta value from the maximum beta value. The computed MMD value is used to calculate the minimum emissivity using a power-law relationship:

$$\varepsilon_{min} = \alpha_1 - \alpha_2 MMD^{\alpha_3} \quad (1)$$

where $\alpha_1 = 0.985$, $\alpha_2 = 0.7503$ and $\alpha_3 = 0.8321$. The TES emissivities are finally calculated by rescaling the beta spectrum as follows:

$$\varepsilon_i = \beta_i \frac{\varepsilon_{min}}{\min(\beta_i)} \quad (2)$$

where ε_i is the final TES emissivity at band i , β_i is the beta spectrum. The LST is calculated using the maximum value of TES emissivities and the radiance at the band with the maximum emissivity (García-Santos et al. 2015).

The MYD21A1 products in 2010 and 2011 were selected to build the LUT because crosstalk in Band 29 of the sensor onboard Terra could influence the accuracy of MOD21A1 products. The data pre-processing flowchart is illustrated in Fig. 2. Two limitations were imposed to reduce the uncertainty in the LSE retrieval. First, a threshold of 1.5 cm for the precipitable water (PW) content was used to limit the study to relatively dry scenes to control uncertainties in LSE retrieval (Hulley et al. 2012; Hulley 2017). Second, only pixels with quality assurance showing excellent performance for emissivity accuracy (uncertainty <0.01) were retained.

The MYD05_L2 data were used to provide the PW. Since the MYD05_L2 data are swath products, a swath-to-grid transformation was conducted on the products to match the MYD21 grid data with a sinusoidal projection. In the transformation, the MYD05_L2 products were first reprojected based on the geolocation information from MYD_03 products and then reconstructed into sinusoidal tiled grids.

The annual land-cover product MCD12Q1 with a spatial resolution of 500 m was used as the data source for land cover type in the LUT. To match the MYD21A1 products spatially, the MCD12Q1 data were aggregated to 1 km resolution. In the aggregation, only when all the four 500 m pixels in the $1 \text{ km} \times 1 \text{ km}$ window had the

same land cover types would the aggregated pixel be accepted as valid. The corresponding value would be assigned to the aggregated pixel.

Fig. 2 Flowchart of data preprocessing.

2.1.2 SURFRAD measurements

The SURFRAD network was established in 1993 with the support of NOAA's Office of Global Programs. At each station, SULR and surface downwelling longwave radiation (SDLR) are measured using the precision infrared radiometer (model PIR, Eppley Laboratories, Newport, Rhode Island, US) in the spectral range of 3-50 μm (Cheng and Liang 2016; Wang et al. 2009). The overall accuracy of measurements from the sensor is approximately $\pm 9 \text{ W m}^{-2}$ (Augustine et al. 2000). SURFRAD measurements are organized into daily files of 3-min average values. The instruments are positioned about 8 m above the surface and the maximum signal is received around the VZA of 45° , with a footprint on the ground of about 200 m^2 . Wang et al. (2009) analysed the spatial representativeness of SURFRAD measurements for 1 km^2 footprint of MODIS using the brightness temperature from ASTER and concluded that SURFRAD ground data can be used to evaluate the SULR estimation of MODIS. Here,

measurements at seven SURFRAD stations in 2010 and 2011 were used as ‘real values’ of SULR (Table 1 and Fig. 4).

Table 1 SURFRAD stations and corresponding IGBP land cover classes.

Station Code	Name	Latitude	Longitude	Land Cover
BON	Bondville	40.05192° N	88.37309° W	Cropland
BOU	Boulder	40.12498° N	105.23680° W	Grassland
DRA	Desert Rock	36.62373° N	116.01947° W	Open Shrubland
FPE	Fort Peck	48.30783° N	105.10170° W	Grassland
GCR	Goodwin Creek	34.2547° N	89.8729° W	Woody Savannas
PSU	Penn. State Univ.	40.72012° N	77.93085° W	Deciduous Broadleaf Forest
SXF	Sioux Falls	43.73403° N	96.62328° W	Cropland

2.2. Method

2.2.1. LUT of directional single-band and broadband emissivity

The LUT of directional emissivity was built using the LSE from MYD21 data and the MCD12Q1 land cover data, which included the MODIS thermal single-band emissivities (Bands 29, 31 and 32). The angular range of directional emissivities was between $\pm 60^\circ$. The structure of the LUT is detailed in Fig. 3. Land surface type is the basic criterion for the LUT. Considering the difference of LSE between the daytime and night-time (Li et al. 2012; Masiello et al. 2014; García-Santos et al. 2015), their values were calculated separately. Since the emissivities of vegetated surfaces were assumed to relate to the vegetation fraction (Ren et al. 2011; Masiello et al. 2015), seasonal values were also calculated separately for vegetated surfaces. Directional emissivity curves were created for data stratified by the seasonality, land cover type, and day/night. To make the acquired LUT representative of angular LSE variation, two requirements were applied: 1) the average sample number among all the VZAs in one curve should be $>10^4$; and 2) VZAs with sample numbers $>10^4$ should account for $>90\%$ of all the VZAs.

Fig. 3 The structure of LUT for directional emissivity.

Broadband emissivity is indispensable in the calculation of SULR, which can be calculated as a linear combination from the MODIS single-band emissivity values. Two different methods have been proposed by Wang et al. (2005) and Cheng et al. (2013), respectively:

$$\varepsilon_{bb1} = 0.2493\varepsilon_{29} + 0.4447\varepsilon_{31} + 0.3088\varepsilon_{32} \quad (3)$$

$$\varepsilon_{bb2} = 0.095 + 0.329\varepsilon_{29} + 0.572\varepsilon_{31} \quad (4)$$

where ε_{29} , ε_{31} and ε_{32} refer to emissivities in Bands 29, 31 and 32, respectively. Both the calculation formulas were evaluated here.

2.2.2. Analysis of influence of LSE anisotropy on SULR estimation

SULR in the range 4 - 100 μm is defined as the sum of the radiation emitted from the surface and the first-order reflected component of the SDLR (Cheng and Liang 2014; Jiao et al. 2015). The traditional temperature-emissivity algorithm to estimate SULR is used in most land surface models (Bonan 2002; Cheng et al. 2013):

$$SULR = \sigma\varepsilon T_s^4 + (1 - \varepsilon)L_a \quad (5)$$

where σ is the Stefan-Boltzmann constant ($5.670367 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$), ε is the broadband emissivity, T_s is the surface temperature, L_a is the SDLR. Generally, the directional broadband emissivity is used (Wang et al. 2009; Wu et al. 2012). Here, we took into account the angular variation of LSE by substituting the directional broadband

emissivity with the integrated hemispheric broadband emissivity in the estimation of SULR. The resulting influence of the angular variation of LSE on SULR can be determined as

$$\Delta SULR = \Delta \varepsilon (\sigma T_s^4 - L_a) \quad (6)$$

where $\Delta \varepsilon$ is the difference between the directional broadband and integrated hemispheric emissivities.

The hemispheric emissivity can be calculated as follows (Cheng and Liang 2014):

$$\varepsilon_{hemis} = 2 \int_0^{\frac{\pi}{2}} \varepsilon(\theta) \cos\theta \sin\theta d\theta \quad (7)$$

where $\varepsilon(\theta)$ is the directional emissivity, ε_{hemis} is the hemispheric emissivity. However, the VZA range of the directional emissivity in the LUT is only between $\pm 60^\circ$. Under the assumption that the hemispheric emissivity can be calculated using the directional emissivity between $\pm 60^\circ$, Eq. 7 can be modified to

$$\varepsilon_{hemis} = \frac{8}{3} \int_0^{\frac{\pi}{3}} \varepsilon(\theta) \cos\theta \sin\theta d\theta. \quad (8)$$

To test the assumption, the integrated hemispheric broadband emissivities calculated using directional emissivities between $\pm 60^\circ$ and $\pm 90^\circ$ were compared. Before using Eq. 7, the relationship between the directional broadband emissivity and the cosine of VZA was regressed using a quadratic polynomial first. The directional emissivity was extrapolated to the range between $\pm 90^\circ$ based on the fitted relationship. Next, the hemispheric emissivity was calculated by using two different directional emissivities: the directional emissivity from 0° to 60° was extracted from the MYD21 emissivity product, the directional emissivity from 60° to 90° was calculated from the regression polynomial.

3. Study area

Our analysis focused on the contiguous USA and seven SURFRAD network stations located within it. Eight sinusoidal MYD21 tiles covering most of the region were analysed to create the LUT of directional emissivities (Fig. 4). All 17 land surface types recognised in the IGBP scheme occur in the region, but the main types are evergreen needleleaf forest, open shrubland, grassland, cropland, deciduous broadleaf forest, and mixed forest.

Fig. 4 The study area showing the spatial locations of SURFRAD stations (in black). The background are land cover types from MCD12Q1. The MODIS sinusoidal tiles are displayed in red.

4. Results and analysis

In total, 80 directional emissivity curves for 10 different land cover types in the four seasons and for daytime and night-time were collected. Among these curves, the average sample exceeded 10^5 over evergreen needleleaf forest, mixed forest, open shrubland, grassland, and cropland, consistent with their large spatial coverage. The only main land cover type with average sample size $<10^5$ was deciduous broadleaf

forest, due to the typically higher atmospheric water vapor over these areas. The average sample number for deciduous broadleaf forest was still $>5 \times 10^4$. Note that the curves of barren/sparsely vegetated surface in the IGBP scheme were not included in the LUT due to the large intra-class variation, even though they met the selection criteria (discussed in Section 5.2).

4.1. Angular variation of LSE

4.1.1. Angular variation of single-band emissivity

Comparison over different land surface types

The analysis of LSE angular variation was conducted over six land cover types here, including evergreen needleleaf forest, deciduous broadleaf forest, open shrubland, woody savannas, grassland and cropland. These land surface types cover most of the contiguous US and encompass the SURFRAD sites. The analysis for the other land cover types is not included here due to the limited space.

For all land surface types, angular variation in LSE is the most pronounced for Band 29 (Fig. 5). Directional emissivity decreases between nadir and 60° . The relationship is largely symmetrical around nadir. Maximum directional emissivity occurs at nadir but variation is minor until 30° . For Band 29, the differences of directional emissivities between nadir and large angles can reach up to 0.03. For Bands 31 and 32, the angular variations of directional emissivities are much less than in Band 29. Especially in Band 31, the angular variation is not pronounced over all the land surface types. The angular variations in Band 32 are greater than Band 31, but still <0.01 . The characteristics of low spectral contrast and high emissivities for graybodies over dense vegetated surfaces, including deciduous broadleaf forest, woody savannas, and evergreen needleleaf forest, were shown clearly between $\pm 30^\circ$. Outside the range

of $\pm 30^\circ$, the graybodies also show large spectral contrast due to the different angular variations among the bands. For open shrubland, likely to include gravel and sparse foliage, the emissivity shows the expected high spectral contrast and low emissivities, especially in Band 29 due to the reststrahlen doublet of quartz at $8.6\ \mu\text{m}$ (Masiello et al. 2013).

Comparison between daytime and night-time emissivity

The directional emissivity patterns during daytime and night-time are very similar (Fig. 5). Angular variations at night are more regular and smoother generally. Emissivities for daytime are greater than for night-time over different land surface types, except over open shrubland, where the situation is the opposite: emissivities for night-time are greater than for daytime, especially in Band 29. This was attributed to the fact that the emissivity of water is larger than that of quartz, especially in Band 29 due to the reststrahlen doublet effect. Consequently, water vapor absorption by the soil from the atmosphere can increase emissivity at night and the diurnal variation is more pronounced in Band 29 (Li et al. 2012; Masiello et al. 2014; García-Santos et al. 2015). With respect to other vegetated surfaces, the similar pattern of emissivity diurnal change was also found by Masiello et al. (2013). The reason needs to be explored further in the future. Compared with the clear diurnal variation of LSE in Band 29 (~ 0.01), LSEs in Bands 31 and 32 show no significant diurnal variation, consistent with other research previously (Li et al. 2012; Masiello et al. 2014; García-Santos et al. 2015).

Fig. 5 Spring time angular variation of LSE at MODIS Bands 29 ($8.55 \mu\text{m}$), 31 ($11 \mu\text{m}$) and 32 ($12 \mu\text{m}$) in the day (circle) and at night (triangle).

Seasonal variation in emissivity

Directional emissivity patterns also vary with the seasons, shown for the dominant land cover type grassland in Fig. 6. The directional emissivity patterns are similar for the four seasons. LSE in summer has the most pronounced angular variation among the four seasons as expected (Ren et al. 2011), with a range of approximately 0.02 in Band 29. In general, LSE in Band 32 is slightly larger than in Band 31 for all seasons, consistent with the analysis by Snyder et al. (1998). The seasonal changes of LSE in Bands 31 and 32 are minor (<0.005). In contrast, the emissivity for Band 29 in winter is significantly greater (0.01) than in summer due to vegetation senescence in winter. This increase of emissivity for dry vegetation compared with green vegetation in Band 29 was also found by Masiello et al. (2015).

Fig. 6 Seasonal change of night-time single-band LSE over grassland.

4.1.2. Angular variation of broadband emissivity

Comparison between directional and hemispheric broadband emissivities

Because broadband emissivity is calculated as a linear combination of the three single-band emissivities, the angular variations of the broad-band emissivities are intermediate to single-band emissivities, decreasing with VZA and symmetrical around nadir (Fig. 7). Compared with the angular variation of LSE in Band 29, the magnitude of the angular variation for broadband emissivity is much smaller (within 0.01). This is because in calculating broadband emissivity with Eqs. 3 or 4, the weight for the emissivity in Band 29 is only approximately 0.3. As a consequence, the influence of LSE in Band 29 on broadband emissivity is modest. By contrast, LSE in the other bands, without strong angular variation, influence the broadband emissivity more. Emissivities calculated using Eq. 3 are consistently larger than those calculated using Eq. 4 by approximately 0.005. Fig. 8 shows the difference between the hemispheric broadband emissivity and directional broadband emissivity. The absolute difference can approach 0.01 at night, but the maximum difference is less during the day. Differences between the hemispheric and directional broadband emissivities calculated using Eqs. 3 and 4 are almost negligible. A minor fluctuation occurred over open shrubland, which is due to the aforementioned intra-class variation of emissivity for barren soil underneath after the senescence of foliage in the autumn.

A VZA between 40° and 60° can be found, for which the directional broadband emissivity equals hemispheric broadband emissivity, confirming Cheng and Liang (2014). However, the VZA value varies between seasons and a general rule cannot be extracted. At large VZAs, directional broadband emissivity is commonly smaller than hemispheric broadband emissivity, and vice versa for small VZAs.

Fig. 7 Angular variation of broadband emissivity in the autumn. BBE1 and BBE2 represent the broadband emissivities calculated from Eqs.3 and 4, respectively. Horizontal lines show hemispheric broadband emissivity calculated from directional values.

Fig. 8 Difference between hemispheric and directional broadband emissivities in the autumn. Diff1 and Diff2 represent the broadband emissivities calculated using Eqs. 3 and 4, respectively.

Comparison of hemispheric emissivity calculated using different angular ranges

A fitted quadratic polynomial function of the cosine of VZA explains much of the directional variation in broadband emissivity (Fig. 9). The coefficient of determination (R^2) exceeds 0.97 for all surface types. A VZA within the angular range of MODIS

observations (between 0° and 60°) can be found for which the directional emissivity equals the hemispheric emissivity.

Fig. 9 Regression between the directional broadband emissivity and the cosine of VZA in the autumn for the night-time. BBE1 and BBE2 are the broadband emissivities calculated using Eqs.3 and 4, respectively. The horizontal lines are the calculated hemispheric broadband emissivity using Eq. 8.

Fig. 10 compares the hemispheric broadband emissivities for the night-time with and without the extrapolation of directional emissivity using the fitted functions for different land surface types. BBE was calculated using Eq. 3 considering the negligible difference between Eq. 3 and Eq. 4. There are minor differences between hemispheric emissivities estimated with and without extrapolation, but they are <0.005 for all seasons. For most land surface types, the difference of the broadband emissivities with and without the extrapolation can be assumed negligible for practical purposes. This is because hemispheric emissivity is effectively a weighted sum of directional emissivities with weights given by $\cos\theta\sin\theta$. The maximum weight is at $\theta=45^\circ$. The directional emissivities within 0° to 60° extracted from the MYD21 LSE product have much larger

weights than the extrapolated directional emissivity within 60° to 90° . Although the extended directional emissivities within 0° to 90° were used for the analysis to assure theoretical completeness in this paper, the directional emissivities within 0° to 60° that can be extracted directly from the MYD21 product are recommended to use for practical purposes.

Fig. 10 Comparison of hemispheric broadband emissivities for the night-time with and without extrapolating directional emissivity from the angular range between $\pm 60^\circ$ to $\pm 90^\circ$. BBE is the broadband emissivity calculated using Eq. 3. BBE_p and BBE represent the hemispheric emissivity with and without the extrapolation, respectively. DBF, OS, WS, GD and CD represent evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), open shrubland (OS), woody savannas (WS), grassland (GD) and cropland (CD), respectively.

4.1.3. Statistics of the LUT

Table 2 lists the statistical information of the directional emissivities at the three TIR bands and the broadband emissivity over 9 natural surface types in the study area. The emissivities in summer for the night-time were selected considering the angular

variation was stronger in such conditions. Among all the 9 natural surface types, angular variation in Band 29 is strongest over grassland, with the greatest standard deviation (s.d. = 0.0064) and range (0.0270). For the other land surface types, s.d. and range in Band 29 are around 0.005 and 0.02, respectively. Based on the range of emissivity in Bands 31 and 32, the next greatest variations are over evergreen needleleaf forest (0.0262) and cropland (0.0256). Angular variation of the broadband emissivity is about half that in Band 29 due to the linear averaging.

Table 2 Statistics of angular variation of directional emissivities over different land cover types in summer for the night-time. Mean is the average directional emissivities between $\pm 60^\circ$. s.d. is the standard deviation of the directional emissivity. Range is the difference of the maximum and the minimum directional emissivities. The broadband emissivity was calculated using Eq. 3.

Land cover type	Statistics	Band 29	Band 31	Band 32	Broadband
Water	mean	0.9636	0.9784	0.9714	0.9753
	s.d.	0.0044	0.0011	0.0036	0.0026
	range	0.0194	0.0042	0.0157	0.0115
Evergreen Needleleaf Forest	mean	0.9693	0.9784	0.9795	0.9792
	s.d.	0.0064	0.0016	0.0018	0.0028
	range	0.0262	0.0064	0.0066	0.0114
Deciduous Broadleaf Forest	mean	0.9701	0.9789	0.9793	0.9796
	s.d.	0.0054	0.0015	0.0017	0.0025
	range	0.0246	0.0065	0.0081	0.0115
Mixed Forest	mean	0.9705	0.9785	0.979	0.9794
	s.d.	0.0046	0.0012	0.0014	0.0021
	range	0.0202	0.0056	0.0054	0.0092
Open Shrubland	mean	0.9407	0.9672	0.9746	0.9656
	s.d.	0.0045	0.0006	0.0008	0.0016
	range	0.0216	0.0037	0.0034	0.0081
Woody Savannas	mean	0.9685	0.9775	0.9796	0.9786
	s.d.	0.0046	0.0011	0.0013	0.002
	range	0.0222	0.0060	0.0058	0.010
	mean	0.9622	0.9738	0.9783	0.975

Grassland	s.d.	0.0064	0.0012	0.0015	0.0026
	range	0.0270	0.0049	0.0063	0.0105
Cropland	mean	0.9628	0.9750	0.9782	0.9757
	s.d.	0.0055	0.0015	0.0014	0.0024
	range	0.0256	0.0063	0.0062	0.011
Cropland and Natural Vegetation Mosaic	mean	0.9670	0.9773	0.9788	0.9779
	s.d.	0.0049	0.0013	0.0015	0.0023
	range	0.0216	0.0059	0.0070	0.0099

4.2. Influence of LSE angular variation on SULR estimation

4.2.1. Simulation analysis of influence of LSE angular variation on SULR

Cheng and Liang (2014) analysed the quantity of the non-emissivity term ($\sigma T_s^4 - L_a$) in Eq. 6 using the Thermodynamic Initial Guess Retrieval (TIGR) atmospheric profiles and the MODTRAN 4.0 atmospheric radiative transfer model. The mean of this term was 21.69 W m^{-2} , and the absolute value ranged from 0 to 342.75 W m^{-2} . Using the former number, Table 3 provides estimates of the influence of ignoring the anisotropy of broadband emissivity on the SULR estimation using Eq. 6 for different land surface types. Considering the angular variation was strongest for summer night-time, emissivities for this period were selected. Among the six land surface types among the stations, the influence is largest for the evergreen needleleaf forest and cropland (up to 2.98 W m^{-2}) and least for the open shrubland site ($<1.92 \text{ W m}^{-2}$).

Table 3 Simulation analysis of the difference in the estimated SULRs using directional and hemispheric broadband emissivities. The emissivities in summer at night were selected when the angular variation was the most pronounced.

Land Surface Type	$\Delta\epsilon$		ΔSULR (W/m^2)
	Minimum	Maximum	
Evergreen Needleleaf Forest	-0.0087	0.0036	0 - 2.98
Deciduous Broadleaf Forest	-0.0079	0.0039	0 - 2.71
Open Shrubland	-0.0056	0.0036	0 - 1.92
Woody Savannas	-0.0078	0.0030	0 - 2.67

Grassland	-0.0078	0.0034	0 - 2.67
Cropland	-0.0087	0.0033	0 - 2.98

4.2.2. Analysis based on SURFRAD measurements

The SULR was calculated with broadband emissivity and LST from the MYD21 product using Eq. 5. The SDLR data were obtained from the SURFRAD measurements. The ancillary QC data in the MYD21 products were also used to remove bad-quality pixels. The MYD05 products were used to select relatively dry pixels to ensure the quality of LST and LSE. Directional and hemispheric broadband emissivities were used in the estimation of SULR. The SULR estimates were evaluated using the SURFRAD measurements. For daytime, the root-mean-square error (RMSE) of SULR estimated using the hemispheric broadband emissivities is generally smaller than if estimated using directional emissivities, but differences are generally $<1 \text{ W m}^{-2}$ (Fig. 11). At night, the influence of LSE on estimated SULR is smaller than for daytime, and the RMSE of the SULR estimates is much smaller than for daytime. The overall moderate influence of the angular variation of LSE on SULR estimation can be attributed to two causes: 1) the angular variation of broadband emissivity is not very pronounced; 2) the upwelling radiation from the surface and downwelling atmospheric radiation have opposite signs, mitigating the influence of LSE. RMSE at all stations is $<10 \text{ W m}^{-2}$ during night-time. The values of broadband emissivity calculated using Eqs. 3 and 4 are close, and this is reflected in a similar RMSE for corresponding SULR estimates.

Fig. 11 Comparison of RMSE in the estimated SULR. Di_BBE1 and Di_BBE2 represent the estimated SULRs using the directional broadband emissivity based on Eqs. 3 and 4, respectively. He_BBE1 and He_BBE2 represent the estimated SULRs using the hemispheric broadband emissivity based on Eqs. 3 and 4, respectively.

Figs. 12 and 13 show the scatterplots of SULR estimated using the modified temperature-emissivity method. For daytime, the RMSE is between 10 and 20 W m^{-2} for most stations. At night, the RMSE at all stations is $<10 \text{ W m}^{-2}$. Comparing mean bias for daytime and night-time, the absolute value of bias is also generally smaller during night-time than during daytime. Although the broadband emissivity was calculated using Eq. 4 only in Figs 12 and 13, we expect that Eq. 3 would have produced the same results, given the negligible differences.

499 **Fig. 12** Scatterplot of the estimated SULR for the daytime using the temperature-emissivity method
500 considering the anisotropy of emissivity. Broad-band emissivity is calculated using Eq. 4.

Fig. 13 Scatterplot of the estimated SULR at night using the temperature-emissivity method considering the anisotropy of emissivity. Broadband emissivity is calculated using Eq. 4.

The accuracy of SULR estimates for night-time is much better than for daytime. We speculate that this is because at night, the non-isothermal conditions are less pronounced than during the day, which is closely related to thermal directionality.

5. Discussion

5.1. Comparison with previous research on LSE angular variation

Our results showed that the angular variation of directional emissivity in Band 29 is quite pronounced; but very minor in Bands 31 and 32. This was found for all land surface types considered. Our finding is consistent with the previous research for bare soil by García-Santos et al. (2015; 2012), but goes further to demonstrate that the phenomenon also exists for other land cover types.

Ren et al. (2011) analysed the angular variation of LSE over much of East Asia using the MOD11B1 product derived with the day/night algorithm. The pattern of

directional emissivity at the thermal bands was similar to those found here. In terms of seasonal differences, the angular variation in summer was similarly observed to be the most pronounced in their study. There are two major differences between their and our analyses. The first is the empirical relationship between directional emissivity and the cosine of VZA. Ren et al. (2011) used an exponential formula to describe the relationship, whereas we used a quadratic polynomial, producing a higher R^2 . Second, we found different magnitudes of angular variations in the three thermal bands, whereas Ren et al. (2011) did not. These contrasts can probably be attributed to different approaches in the retrieval of LSE. The angular effect of LSE on LST estimation was reported to be between -1 and 3 K by Ren et al. (2011). For comparison, we applied the directional emissivity LUT extracted here to the generalized split-window to estimate LST by considering angular variation of LSE. Fig. 14 shows histograms of the difference between the new LST retrievals and MYD11_L2 products on two selected days. The new LST retrievals are generally higher than the MYD11_L2 products due to the decreasing emissivity at large VZAs, with peaks between 0.5 and 1 K. Most of the differences are between -0.5 and 1.5 K. Further research would be required to comprehensively analyze the influence of LSE angular variation on LST retrieval, but is out of the scope of the present paper.

Fig. 14 Histogram of temperature difference between the new LST retrievals and MYD11_L2 LST products on two selected days (a) the 182nd day, and (b) the 274th day in 2010 over the contiguous

U.S. The new LST was retrieved by applying the built directional emissivity LUT to the generalized split-window algorithm.

5.2. Large intra-class variation of LSE over barren /sparsely vegetated surface

We considered the directional emissivity curve for barren/sparsely vegetated surface to be invalid due to the large intra-class variation of LSE within this IGBP class, which caused an artefact in the emissivity curve (Fig. 15c). To illustrate this, two desert sites in the U.S. were selected: the White Sands (WS) National Monument (32.8038°N, 106.2742°W) and the Great Sands (GS) National Park (37.7589°N, 105.5514°W). WS is composed of 99% gypsum and 1% quartz, and GS of 98% sand, 1.5% silt and 0.5% clay (García-Santos et al. 2015). The directional emissivity of dry pixels (PW <1.5 cm) with good quality assurance from 2010 to 2014 were collected over WS and GS (Fig. 12). A large difference exists in Band 29 between the two sites due to the surface composition. It also occurs in the other two bands, but with a much smaller magnitude. When combining the LSE retrievals at the two sites to produce a directional emissivity curve (Fig. 15c), pronounced fluctuations occur due to the large emissivity difference between the two desert sites and incomplete angular coverage of any single site. The same situation occurs across the contiguous US given the relatively small barren area and the large intra-class variation. Thus, the emissivity retrievals over barren soils were not pooled to produce a single directional emissivity curve. However, the angular variation and diurnal change of emissivity are still clear at both sites, where the angular variation exceeds 0.05 at GS (Fig. 15b). The emissivity for night-time is greater than for daytime due to the water vapor absorption of soil at night (Li et al. 2012; Masiello et al. 2014; García-Santos et al. 2015).

Fig. 15 Angular variation of LSE at MODIS Bands 29 ($8.55 \mu m$), 31 ($11 \mu m$) and 32 ($12 \mu m$) at desert sites (a) WS, (b) GS and (c) WS+GS. WS+GS represents the directional emissivities combining emissivity retrievals at both WS and GS.

5.3. Uncertainties in the analysis

There are uncertainties that may have affected our analysis. The TES algorithm and error in the respective inputs introduce uncertainties into the LSE retrieval. Hulley et al. (2012) developed an LST and LSE uncertainty simulator by considering contributions from TES algorithm, atmospheric and measurement noise. The uncertainty was parameterized according to VZA and total column water vapor. In comparison with lab measurements, the uncertainties in MxD21 LSE retrievals for graybodies (i.e. water, snow, ice, and vegetation) were shown to be small (around 0.001) for all bands when PW was <2 cm and generally decreased with longer wavelengths (Hulley et al. 2012). For bare surfaces, the uncertainties were reported to be generally below 0.01 in Bands 31 and 32, and up to 0.03 in Band 29 (García-Santos et al. 2015; Hulley et al. 2012). As such, the analysis in this study was only conducted using the LSE retrievals under a relatively dry atmosphere from Aqua (PW <1.5 cm) and with good quality assurance (uncertainty <0.01). The LSE angular variation in this study (up to 0.03 and 0.05 over vegetated and barren surfaces, respectively) is clearly larger than the uncertainties of LSE retrievals reported in previous researches (García-Santos et al. 2015; Hulley et al. 2012). This suggests that the angular change is not from the retrieval

uncertainty but intrinsic anisotropy. García-Santos et al. (2015) compared directional emissivity curves of bare soil in Band 29 depicted using emissivities retrieved from the MODTES (MODIS TES) algorithm and model simulations/in-situ measurements, respectively. The respective curves were very consistent, which supports the existence of LSE angular variation in retrievals from the MODTES algorithm. The regularity of the variation pattern in directional emissivity further suggests that the variation can not be attributed to random retrieval uncertainties.

With respect to the influence of LSE retrieval uncertainty on diurnal and seasonal variations of LSE, Band 29 has clear variations (~ 0.01) between day and night, and between winter and summer, which are greater than the retrieval uncertainty. However, the minor diurnal and seasonal variations in Band 31 and 32 may be obscured by the retrieval uncertainty.

In the calculation of BBE, two linear regression functions were used (Eqs. 3 and 4), which may induce uncertainties to the calculated BBE. For Eq. 3, Wang et al. (2005) reported that the residual and maximum error of regression are 0 and 0.0023, respectively. For Eq. 4, Cheng et al. (2013) reported a correlation coefficient and bias of 0.932 and 0, respectively. Moreover, the negligible differences between the BBEs calculated using Eq. 3 and Eq. 4 that acted as a cross-validation further support the accuracy of the equations. Overall, we expect that the uncertainties introduced by the regression functions should not have affected the conclusions of the angular variation in BBE.

In the MMD module of TES algorithm, an empirical relationship was regressed between the minimum emissivity and spectral contrast of emissivity. However, angular variation of emissivity was not accounted for in the fitting process, which may introduce uncertainties in the directional emissivities. To investigate this influence, we

compiled a simulation data set consisting of the directional emissivities of vegetation canopy, minerals, ice/snow and water. For the simulation of vegetation canopy, the new directional canopy emissivity model CE-P developed by Cao et al. (2018) was used. Ten soil samples and ten vegetation samples were selected from the UCSB emissivity library as the component emissivities. LAI varied between 0.5 and 5.0 in 0.5 intervals. For the simulation of the other materials, the Hapke model and Fresnel equation were used following Cheng and Liang (2014). In total, 1016 emissivity spectra were calculated at each VZA between nadir and 65°. Table 4 shows the regression relationships for different VZAs. The values of α_1 are quite similar for different VZAs; but the values of α_2 and α_3 change. The regression coefficients are slightly different from those used in the MODTES algorithm due to the different emissivity libraries used in the regression. The biases between nadir and the other VZAs increase with VZA, but are still <0.005 at all VZAs <65°. Note that the MMD values of vegetated surfaces are usually much smaller than 0.03 in practice (Hulley et al. 2012), thereby causing smaller biases. Therefore, we conclude that the uncertainties of the LSE retrievals caused by the empirical relationship can be ignored, when compared with the LSE angular variation.

Table 4 Regression relationships between minimum emissivity and emissivity spectral contrast at different VZAs. $\alpha_{1..3}$ are the regression coefficients in Eq. 1. Bias is calculated by subtracting the calculated minimum emissivity using the regression relationship at nadir from those using the relationships at other VZAs given that MMD is set to 0.03.

VZA	α_1	α_2	α_3	RMSE	Bias
0°	0.9944	0.7481	0.8500	0.0040	-
5°	0.9944	0.7497	0.8507	0.0040	<0.0010
10°	0.9443	0.7537	0.8522	0.0040	<0.0010
15°	0.9942	0.7609	0.8549	0.0040	<0.0010
20°	0.9941	0.7709	0.8587	0.0040	<0.0010
25°	0.9940	0.7851	0.8639	0.0040	<0.0010
30°	0.9938	0.8028	0.8702	0.0041	<0.0010
35°	0.9936	0.8241	0.8775	0.0041	<0.0010

40°	0.9933	0.8495	0.8857	0.0042	<0.0010
45°	0.9930	0.8789	0.8947	0.0042	0.0012
50°	0.9927	0.9111	0.9038	0.0043	0.0015
55°	0.9923	0.9430	0.9116	0.0044	0.0020
60°	0.9920	0.9717	0.9168	0.0045	0.0026
65°	0.9916	0.9922	0.9171	0.0046	0.0035

Interpolated PW from MERRA-2 reanalysis data were used for the atmospheric correction in producing MYD21; whereas the PW information from MYD05_L2 was used to select relatively dry scenes in this study for the convenience of data processing. A comparison was conducted between these two PW retrievals. Results showed that the difference between these two products was small. Fig. 16 shows a comparison over the western part of U.S. The valid PW values from MYD05_L2 are close to those from the MERRA-2. The histogram (Fig. 16(c)) shows that over 80% of the PW differences are within ± 0.3 cm. Thus, we expect that MYD05_L2 can provide information on PW that is consistent with the interpolated MERRA-2 reanalysis data.

Fig. 16 Comparison between the PW retrievals from the MYD05_L2 product and interpolated MERRA-2 reanalysis data on 1st May, 2018 over the western part of U.S. The pixels in white in (a) represent invalid values.

In this study, the contiguous US was used as our study area because of the availability of high-quality, long-term and high-frequency SULR measurements from the SURFRAD network. Networks of comparable quality appear to be lacking elsewhere, which limits our analysis for other areas. The analysis was conducted using the data from the two years 2010 and 2011. However, given the widely varying vegetation and weather conditions contained within the observations, we do not expect

observations for a longer period would alter our results. This paper focused on the analysis of LSE angular variation for the major land surface types over the contiguous US. A similar analysis could be performed for other land surface types following the same method.

6. Conclusion

Angular variation is an intrinsic property of LSE that can affect its subsequent applications. We analysed the angular variation of LSE using the MYD21 product that were produced using the modified TES algorithm adapted to the MODIS data. Furthermore, the influence of angular variation in LSE on SULR estimation was assessed by simulation analysis and evaluation against SURFRAD measurements.

The analysis showed that angular variation in Band 29 is up to 0.03 and much more pronounced than in Bands 31 and 32. The angular variation of broadband emissivity is not pronounced and is intermediate to that for individual bands, owing to the linear weights for different bands in the calculation of broadband emissivity. The difference between directional and hemispheric broad-band emissivity is within 0.01.

Based on the simulation analysis, substituting the hemispheric broadband emissivity with the directional broadband emissivity can introduce an error less than 4 W m^{-2} to SULR estimation generally. And the influence varies with the land surface types and the condition of surface-atmospheric system.

Validation results against the SURFRAD measurements showed that the influence of angular variation in LSE on SULR estimation is generally $<1 \text{ W m}^{-2}$. This could be attributed to the moderate angular variation of broadband emissivity and the opposite signs of the upwelling surface emissions and downward atmospheric radiation.

In summary, angular variations in broadband emissivity are small, and the influence of LSE angular variation on the estimation of SULR is generally not pronounced. Future research will focus on the influence of LSE angular variation on LST retrieval.

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