1. Introduction

Land surface emissivity (LSE) in the thermal infrared (TIR) is an essential parameter in the retrieving land surface temperature (LST) from space. This paper describes the LSE maps in three TIR bands (centered at 10.4, 11.2 and 12.4 μm) used for retrieving the LST from Himawari-8. Himawari-8, a next-generation geostationary satellite has high spatial and temporal resolutions compared to previous geostationary satellites. Because of these improvements, the Himawari-8 LST product is expected to contribute to the observation of small-scale environments in high-frequency. In this study, the LSE is estimated by a semi-empirical method, which is a combination of the classification based method and the normalized difference vegetation index (NDVI) thresholds method. The land cover classification information is taken from the Global Land Cover by National Mapping Organizations version3 (GLCNMO 2013). Material emissivities of soil, vegetation and others are taken from the MODIS UCSB emissivity library and the ASTER spectral library. This method basically follows the semi-empirical methods developed by the previous studies, but advanced considerations are added. These considerations are the phenology of vegetation, flooding of paddy fields, snow/ice coverage, and internal reflections (cavity effect) in urban areas. The average cavity effect on LSE in urban canopies is approximately 0.01, but it reaches 0.02 in built-up areas. The sensitivity analysis shows that the total LSE errors for the three bands are less than 0.02. The LSE estimation is especially stable at the vegetation area, where the error is less than 0.01.

Keywords land surface emissivity; Himawari-8; Advanced Himawari Imager; land surface temperature; thermal infrared; semi-empirical method
Himawari-8 LST product is expected to contribute to the observation of small-scale features in high-frequency compared to the GMS and MTSAT series. The spectral range of 10–12.5 μm in the window TIR is suitable for retrieving LST using a single or multi-channel algorithm (Li et al. 2013a). The AHI has three TIR bands, Bands 13, 14 and 15 (centered at 10.4, 11.2 and 12.4 μm, respectively) in the spectral range of 10–12.5 μm. Therefore, we develop the LSE maps for Bands 13, 14 and 15.

Various LSE estimation methods have been proposed for various sensors, which are generally divided into three types (Li et al. 2013b): semi-empirical methods (Snyder et al. 1998; Peres and DaCamara 2005; Trigo et al. 2008; Sobrino et al. 2008), multi-channel temperature emissivity separation methods (Sobrino et al. 2001; Peres and DaCamara 2004), and physically based methods (Petitcolin and Vemote 2002). Each method has its own advantages and limitations. We employ a semi-empirical method, which is a combination of the classification based method and the normalized difference vegetation index (NDVI) thresholds method. This method basically follows the work of Peres and DaCamara (2005). The classification based method assigns the predetermined LSE value to each pixel on the basis of the use of land cover classification information. The NDVI thresholds method estimates the LSE by considering the surface component as a mixture of bare soil and vegetation. The visible and near-infrared bands of AHI Bands 3, 4 and 5 (centered at 0.64, 0.86 and 1.61 μm, respectively) enable the estimation of the fraction of vegetation, so that it becomes possible to apply the method proposed by Peres and DaCamara (2005). Figure 1 shows the flowchart of our LSE estimation method. Peres and DaCamara (2005) used the NDVI thresholds method considering the internal reflections (cavity effect) due to the vegetation canopy, but we additionally attempt to consider the cavity effect due to the urban canopy. Furthermore, we consider the seasonal variation of vegetation and specific variations in paddy fields using Himawari-8’s visible and near-infrared reflectance. Section 2 describes the NDVI thresholds method and the assignment method to each land cover type. Section 3 describes the predetermined LSE values of soil and vegetation used for the actual observation and the sensitivity analysis for the estimated LSE.

![Flowchart of the procedure for the LSE estimation method](image)

**Fig. 1.** Flowchart of the procedure for the LSE estimation method. Classes 1–11, 13, 14 and 16–18 are the land cover areas applied in the NDVI thresholds method. Class 12 is the paddy field that has specific seasonal variations, such as the flooding and rice transplantation period, the growth period and the fallow period. Classes 15 and 19 are wetland and snow/ice, respectively. The LSEs in these two classes are considered to have unchanged values by the seasonal change of vegetation.
2. Description of the method

2.1 NDVI thresholds method

The NDVI thresholds method has been applied to various sensors (Sobrino and Raissouni 2000; Sobrino et al. 2008; Valor and Caselles 1996; Peres and DaCamara 2005). This method uses the vegetation coverage information in order to estimate the LSE. The LSE is estimated by

\[ LSE = \varepsilon_v FVC + \varepsilon_g (1 - FVC) + d\varepsilon, \]  

where \( \varepsilon_v \) and \( \varepsilon_g \) are vegetation and ground emissivities, respectively. The subscript \( \lambda \) denotes the center wavelength. The method assumes that the surface state of a pixel is composed of soil and vegetation. FVC is the fractional vegetation cover and \( F = 0 \) is considered as the flat surface. The FVC is simply obtained from the NDVI and two different NDVI threshold values as follows (Sobrino and Raissouni 2000; Sobrino et al. 2008):

\[ FVC = \left( \frac{NDVI - NDVI_g}{NDVI_v - NDVI_g} \right)^2, \]  

where \( NDVI_g \) and \( NDVI_v \) are the bare ground and vegetation NDVIs, respectively. The values of \( NDVI_g = 0.2 \) and \( NDVI_v = 0.5 \) obtained by Sobrino et al. (2008) to apply the method in global conditions are used in this study since they have been applied to various sensors, such as the Advanced Very High Resolution Radiometer (AVHRR) aboard the National Oceanic and Atmospheric Administration satellites, Spinning Enhanced Visible and Infrared Imager (SEVIRI) aboard the Meteosat Second Generation, Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua, and Advanced Along Track Scanning Radiometer aboard the Environmental Satellite and Thematic Mapper aboard the LANDSAT-5. In order to estimate FVC in more detail, however, we should recalculate the \( NDVI_g \) and \( NDVI_v \) values corresponding to the observation sites. Of course, FVC is set to zero when \( NDVI \) is less than \( NDVI_g \) and is set to unity when it is greater than \( NDVI_v \). The NDVI is defined as follows:

\[ NDVI = \frac{R_{0.8} - R_{0.6}}{R_{0.8} + R_{0.6}}, \]  

where \( R_{0.8} \) is the reflectance observed in the near-infrared band and \( R_{0.6} \) is the reflectance observed in the visible (red) band. In the Himawari observation area, previous studies used the polar-orbiting satellite data because GMS and MTSAT series did not have the near-infrared band. The AHI/Himawari-8, however, has a near-infrared band as Band 4. Hence, we used Band 3 and Band 4 to estimate the NDVI. The NDVI data is the maximum NDVI in the past 14-day composites. Since NDVI depends on the solar zenith angle, Band 3 and Band 4 data within one hour before and after the time of culmination at each pixel are used. Atmospheric correction is not applied since the NDVI thresholds method does not basically require an accurate atmospheric correction for the estimation of FVC and NDVI (Sobrino et al. 2008; Li et al. 2013b).

The cavity effect term \( d\varepsilon \) in Eq. (1) is estimated as

\[ d\varepsilon = (1 - \varepsilon_v)\varepsilon_g G' (1 - FVC) + [(1 - \varepsilon_v)\varepsilon_g G' + (1 - \varepsilon_v)\varepsilon_g F'']\varepsilon_v. \]  

using a simplified geometrical model assuming the infinitely long Lambertian boxes (Caselles and Sobrino 1989). Here, \( P_v \) is the side proportion observed by the sensor, and \( F', G' \) and \( F'' \) are geometrical factors that the fraction of radiation emitted by a side that reaches the ground, the fraction of radiation emitted by the ground that reaches a side and the fraction of radiation emitted by a side that reaches the adjacent one, respectively (see Fig. 2). These geometrical factors are also given by Caselles and Sobrino (1989) as follows:

\[ F' = (1 + H/S) - \sqrt{1 + (H/S)^2}, \]  

\[ G' = \frac{1}{2}[(1 + S/H) - \sqrt{1 + (S/H)^2}], \]  

\[ F'' = \sqrt{1 + (S/H)^2} - S/H. \]  

Here, \( H \) is the height of the hypothetical vegetation elements and \( S \) is the distance between them (see Fig. 2). \( H \) and \( S \) are determined according to the vegetation type. This model does not take into account the shadow influence and double-scattering process. Sobrino et al. (1990) proposed the derivation of \( P_v \) considering the case of an observation at a low altitude. In this case, the representation of \( P_v \) is quite complicated because \( P_v \) of each element in an instantaneous field of view differs greatly depending on the satellite zenith angle (SZA) of each element. However, in the case of an observation at a high altitude, such as a geostationary satellite, the SZAs of each element in an instantaneous field of view are almost the same. Hence, we consider the fractional amount by a simplified form.
without considering the difference of each SZA. First, the simple geometry shows that the proportion of the top of the cavity element $P_t$ observed by a satellite sensor is constant in SZA $\theta$, whereas the ground proportion $P_g$ linearly decreases as $\theta$ increases until the ground disappears from the view of the sensor. Here, the summation of $P_t$, $P_g$, and $P_s$ is equal to 1. On the contrary, $P_s$ also increases linearly with $\theta$ until the ground disappears from the view of the sensor ($P_g = 0$), but thereafter, $P_s$ keeps constant with increasing $\theta$. Himawari-8 is flying at an altitude of 35786 km and the spatial resolutions of its visible and near-infrared bands are 0.5–1.0 km. Thus, the SZAs at which the ground disappears from the view of the AHI in one pixel, $\theta_d$, are almost the same. Accordingly, $\theta_d$, $P_t$, and $P_s$ can be expressed as

$$\theta_d = \arctan\left(\frac{S}{H}\right),$$  \hspace{1cm} (8)

$$P_t = \frac{F}{F + S},$$  \hspace{1cm} (9)

$$P_s = \begin{cases} \frac{(1-P_t)\theta}{\arctan(S/H)}, & \theta < \theta_d, \\ 1 - P_t, & \theta \geq \theta_d. \end{cases}$$  \hspace{1cm} (10)

where $F$ is the width of a box according to the vegetation type and $\theta$ is the SZA of the AHI (see Fig. 2).

Peres and DaCamara (2005) assumed that the land surface in the urban area is flat and is composed of a mixture of construction concrete and paving asphalt. However, the actual surface is rough because of the buildings (urban canopy). Therefore, we consider the cavity effects of urban structures as well as the vegetation. The surface emissivity in the urban canopy $\varepsilon_u$ is estimated as follows:

$$\varepsilon_u = \varepsilon_t P_t + \varepsilon_s P_s + \varepsilon_g P_g + d\varepsilon_u,$$  \hspace{1cm} (11)

$$d\varepsilon_u = (1-\varepsilon_g)\varepsilon_t F'/P_g' + [(1-\varepsilon_t)G' + (1-\varepsilon_s)F'']P_s,$$  \hspace{1cm} (12)

where $\varepsilon_t$ and $\varepsilon_s$ are top and side emissivities, respectively. That is, we consider a mixture of roofs ($\varepsilon_t$), walls ($\varepsilon_s$) and grounds ($\varepsilon_g$). In case an urban pixel includes vegetation, $\varepsilon_u$ substitutes for $\varepsilon_g$ in the second term on the right side of Eq. (1).

The model assumes that vegetation and urban structures are distributed following infinitely long Lambertian boxes. However, the realistic approximation is the distribution of elements as square finite boxes. Caselles et al. (1997) reported that the systematic error due to the use of two different geometric models is of the order of 0.1 %.

2.2 Assignment to the land cover class

As mentioned above, the NDVI thresholds method basically requires five predetermined values and two pieces of input data. The predetermined values are the vegetation and ground emissivities ($\varepsilon_v$ and $\varepsilon_g$) of each AHI TIR band and the scales of Lambertian boxes ($F$, $H$, and $S$) according to the vegetation type. The input data are the NDVI and SZA. In order to set the predetermined values according to the vegetation type, these values are defined at each pixel on the basis of the land cover class in accordance with Peres and DaCamara (2005). The land cover classification information is taken from the Global Land Cover by National Mapping Organizations (Tateishi et al. 2011; Tateishi et al. 2014; Kobayashi et al. 2017) version3 (GLCNMO 2013). The GLCNMO2013 is based on MODIS data observed in 2013. It employs 20 different land cover classes and its horizontal resolution is around 500 m. Unlike the International Geosphere-Biosphere Program (IGBP) class, it additionally has the paddy field (Class 12), mangrove (Class 14) and an additional two types of bare areas (Classes 16 and 17). The GLCNMO2013 data was resampled to the resolution of AHI/Himawari-8. The terrestrial surface contributes nearly 20 % of all Himawari-8’s main observation area ($85^\circ\text{E}–155^\circ\text{W}$, $60^\circ\text{S}–60^\circ\text{N}$), and the percentage of each land cover class is shown in Table 1. Since rice farming is flourished in this area, the paddy fields (Class 12) account for 3.95 % of all land cover. When a paddy field pixel is judged
as non-vegetated by NDVI criteria, there are two possibilities: one is the dry soil in the fallow period and the other is the flooding water surface in the rice transplanting period. Thus, the paddy field (Class 12) should be considered separately from croplands (Class 11 or 13). In this sense, GLCNMO2013 is suitable for LSE estimation in Asian areas.

The NDVI thresholds method is applied to Classes 1–14 and 16–18. Classes 15 (wetlands) and 19 (snow/ice) are given constant emissivity values regardless of the seasonal changes of vegetation. In terms of the vegetation emissivity, we used the TIR volumetric bidirectional reflectance distribution function (BRDF) model (Snyder and Wan 1998) to calculate the BRDF and integrate it over the hemisphere to obtain the directional hemispherical reflectance and emissivity from the reflectance of each leaf, bark or grass sample measured by laboratories. The TIR volumetric BRDF model form is as follows:

$$f_{vul} = c_1 k_{vul} + c_2 k_{vul}^2 + c_3,$$  \hspace{1cm} (13)

where the kernels are given by

$$k_{vul}^{\rho} = \frac{(\pi - \xi)\cos \xi + \sin \xi}{\cos \theta_i + \cos \theta_r},$$ \hspace{1cm} (14)

and the coefficients are given by

$$c_1 = \frac{2\rho}{3\pi} [1 - \exp(-bF)],$$ \hspace{1cm} (16)

$$c_2 = \frac{2\tau}{3\pi} [1 - \exp(-bF)],$$ \hspace{1cm} (17)

$$c_3 = \frac{\rho}{3\pi} [1 - \exp(-bF)] + \frac{\rho_0}{\pi} \exp(-bF).$$ \hspace{1cm} (18)

Here, $\theta_i$ and $\theta_r$ are the incident zenith angle and reflected zenith angle; $\rho$ is the leaf, bark or grass reflectance; $\rho_0$ is the ground reflectance; $\tau$ is the leaf transmission; $bF$ is the optical depth; $\xi$ is the scattering angle between incidence and reflection. $\xi$ is given by

$$\xi = \arccos (\cos \theta_i \cos \theta_r + \sin \theta_i \sin \theta_r \cos \phi),$$ \hspace{1cm} (19)

where $\phi$ is the relative azimuth angle between the incidence and reflection directions. $\tau$ is taken to be zero for the TIR region and $bF$ is taken to be infinite (Snyder and Wan 1998). Therefore, this model requires not a ground reflectance $\rho_0$ but a leaf, bark or grass reflectance $\rho$ to determine the volumetric BRDFs $f_{vul}$. The leaf, bark and grass emissivities for each TIR band are weighted by the spectral response function of each TIR band. Table 2 shows the leaf, bark and grass samples assigned to land cover types. These samples were selected from the MODIS UCSB emissivity library (http://www.iceess.ucsb.edu/modis/EMIS/html/em.html; Wan et al. 1994) and the ASTER spectral library (http://speclib.jpl.nasa.gov/; Baldridge et al. 2009) and were based on the available spectra as representing the general features of trees, though more kinds of vegetation should be considered. The seasonal change of vegetation is considered as green and senescent states (Snyder et al. 1998). The seasonal states, green or senescent, of each pixel are judged using the maximum NDVI in the past 14-day composites, and the annual mean NDVI value consists of 12 periods of 30-day composites as the thresholds. If the maximum NDVI in the past 14-day composites of a pixel is greater (smaller) than the annual mean NDVI of the same pixel, the seasonal state of the pixel is judged as green (senescent). The combination ratios of Classes 5–10, Class 13 and Classes 15–18 were determined by referring to Peres and DaCamara (2005). The vegetation emissivity ($\varepsilon_{v}$) used for the predetermined value is

| GLCN MO class                  | Percentage (%) |
|-------------------------------|----------------|
| 1. Broadleaf Evergreen Forest | 12.65          |
| 2. Broadleaf Deciduous Forest | 8.86           |
| 3. Needleleaf Evergreen Forest| 3.17           |
| 4. Needleleaf Deciduous Forest| 4.60           |
| 5. Mixed Forest               | 4.75           |
| 6. Tree Open                  | 8.32           |
| 7. Shrub                      | 9.53           |
| 8. Herbaceous                 | 11.41          |
| 9. Herbaceous with Sparse Tree/Shrub | 0.66 |
| 10. Sparse Vegetation         | 8.14           |
| 11. Cropland                  | 10.61          |
| 12. Paddy Field               | 3.95           |
| 13. Cropland/Other Vegetation Mosaic | 6.18 |
| 14. Mangrove                  | 0.15           |
| 15. Wetland                   | 0.56           |
| 16. Bare area, Consolidated (gravel, rock) | 4.39 |
| 17. Bare area, Unconsolidated (sand) | 1.50 |
| 18. Urban                     | 0.44           |
| 19. Snow/Ice                  | 0.13           |
| Total land surface coverage   | 100.00         |
The paddy field (Class 12) has three characteristic periods: the flooding and rice transplantation period, the growth period and the fallow period (Xiao et al. 2002). The state for the paddy field is sub-divided as shown in Table 2. The growth period in the green state means a vegetative growth stage or reproductive stage, whereas the growth or the fallow period in the senescent state means a ripening stage or weeds in the fallow period. In order to judge the flooding and rice transplantation period, the difference between the normalized difference water index (NDWI) and NDVI values (Xiao et al. 2002) consisting of 14-day composites is used. The NDWI is defined as

$$\text{NDWI} = \frac{R_{0.8} - R_{1.6}}{R_{0.8} + R_{1.6}},$$

(20)

where $R_{0.8}$ and $R_{1.6}$ are the near-infrared reflectance observed in Band 4 and Band 5 of the AHI, respectively. If a pixel of the paddy field has smaller NDVI than NDWI, the pixel is judged as a water body and is considered as a wetland (Class 15).

The ground emissivity is also evaluated on the basis of the MODIS UCSB emissivity library and the ASTER spectral library. Each land class is assumed to be covered by materials listed in Table 3. The gross emissivity of each material, for example, “Inceptisol”, is computed by integrating the spectral emissivity in the library with the weight of the sensor response function over the band width. When sub-materials exist, the value is averaged over the sub-materials. It is worth noting that Classes 15 (wetlands) and 19 (snow/ice) are also listed in Table 3 although the NDVI thresholds method is not applied. The ground emissivity of each class ($\varepsilon_{g\lambda}$) is computed as the mean over component materials in Table 3. Table 3 is modified from the corresponding table in the work by Peres and DaCamara (2005) considering the difference in soil components of Asia and Oceania from the region of Europe and Africa. The soil and rock materials of each land cover are decided by referring to the global soil regions map (https://www.nrcs.usda.gov/wps/portal/}

| GLCNMO class                  | Green                                      | Senescent                                      |
|-------------------------------|--------------------------------------------|------------------------------------------------|
| 1. Broadleaf Evergreen Forest | Oak, Bronze Loquat, Evergreen Pear         | Oak, Maple, Bark                               |
| 2. Broadleaf Deciduous Forest | Oak, Bronze Loquat, Evergreen Pear         |                                                |
| 3. Needleleaf Evergreen Forest| Pine (New), Cypress                        |                                                |
| 4. Needleleaf Deciduous Forest| Pine (New), Cypress                        | Pine (Old), Bark                               |
| 5. Mixed Forest               | The mean of classes 1 and 3                | The mean of classes 1, 2, 3 and 4              |
| 6. Tree Open                  | The mean of classes 1 and 3                | The mean of classes 1, 2, 3 and 4              |
| 7. Shrub                      | The mean of classes 1 and 3                | The mean of classes 1, 2, 3 and 4              |
| 8. Herbaceous                 | 20 % of classes 1 and 3 + 80 % of Green grass | 20 % of classes 2 and 4 + 80 % of Dry grass   |
| 9. Herbaceous with Sparse Tree/Shrub | 40 % of classes 1 and 3 + 60 % of Green grass | 40 % of classes 2 and 4 + 60 % of Dry grass   |
| 10. Sparse vegetation         | 20 % of classes 1 and 3 + 80 % of Green grass | 20 % of classes 2 and 4 + 80 % of Dry grass   |
| 11. Cropland                  | Green grass                                | Dry grass                                      |
| 12. Paddy field               | Flooding and rice transplanting: class 15, Growing: Green grass | Flooding and rice transplanting: class 15, Growing or fallow: Dry grass |
| 13. Cropland/Other Vegetation Mosaic | 33 % of class 5 + 66 % of Green grass | 33 % of class 5 + 66 % of Dry grass |
| 14. Mangrove                  | Oak, Bronze Loquat, Evergreen Pear         |                                                |
| 15. Bare area (gravel, rock)  | 20 % of classes 1 and 3 + 80 % of Green grass | 20 % of classes 2 and 4 + 80 % of Dry grass   |
| 17. Bare area (sand)          | 20 % of classes 1 and 3 + 80 % of Green grass | 20 % of classes 2 and 4 + 80 % of Dry grass   |
| 18. Urban                     | 50 % of class 5 + 50 % of Green grass      | 50 % of class 5 + 50 % of Dry grass           |

Table 2. Materials for vegetation of each land cover.

considered as the mean value of the vegetation emissivities of the materials for each class.
nrcs/detail/soils/use/?cid=nrcs142p2_054013). The soil type under broadleaf evergreen forest (Class 1) in the tropical zone is actually “ultisols” but is assumed as in Table 3. This is because the “ultisols” are not included in the ASTER library, but this may not cause much problem since the ground surfaces are usually covered by the crown canopy and the forest floor in these tropical forests. The ground material in the mangrove (Class 14) is set as water, although it has a property of broadleaf evergreen forest. For the snow/ice surfaces, areas other than Class 19 are sometimes also covered by snow or ice. Considering this case, the snow/ice surfaces are detected using the normalized difference snow and ice index (NDSII) in addition to the region in Class 19. The NDSII is defined as (Xiao et al. 2001)

\[ NDSII = \frac{R_{0.6} - R_{1.6}}{R_{0.6} + R_{1.6}}. \]  

(21)

The NDSII data is obtained by past 4-day composites. When NDSII of a pixel is greater than 0.4, the mean emissivity of snow and ice is assigned to the pixel. Although atmospheric correction is required to calculate the NDSII in more detail, it is not considered and is a future task in this study.

Table 3. Materials for ground of each land cover.

| GLCNMO class | Materials |
|--------------|-----------|
| Classes 1 and 2 | Inceptisols, Entisols and Mollisols |
| Classes 3 and 4 | Inceptisols |
| Classes 5 and 6 | The mean of classes 1, 2, 3 and 4 |
| Classes 7, 8, 9, 10 and 17 | Aridisols |
| Classes 11 and 13 | Mollisols |
| Class 12 | Flooding and rice transplanting: class 15, Growing or fallow: Mollisols |
| Class 14 | Water |
| Class 15 | Water and Green grass |
| Class 16 | Aridisols, Igneous and Sedimentary |
| Class 18 | Construction concretes, Road asphalts and Tar |
| Class 19 | Snow and Ice |

Table 4. Values of separation between two adjacent boxes \( S \), height of the boxes \( H \) and width of the boxes \( F \).

| Class | \( S \) (m) | \( H \) (m) | \( F \) (m) |
|-------|-----------|-----------|-----------|
| Classes 1, 2, 3, 4, 5 and 14 | 0.5–1.5 | 2.5–10 | 1–4 |
| Classes 6 and 9 | 3–7 | 2.5–10 | 1–4 |
| Class 7 | 3–7 | 0.5–2.0 | 0.5–2.0 |
| Class 8 | 8–16 | 2.5–10 | 1–4 |
| Classes 10, 16, 17 and 18 | 9–21 | 0.5–2.0 | 0.5–2.0 |
| Classes 11 and 12 | 1–3 | 0.5–2.0 | 0.5–2.0 |
| Class 13 | The mean of 5 and 11 |

Table 4 shows the scales of Lambertian boxes \( (F, H, S) \) of each vegetation type. These values were set on the basis of work done by Sobrino et al. (1990), Valor and Caselles (1996) and Peres and DaCamara (2005). Forest regions are assumed to have short separation and high boxes. Shrub, sparse and unforested regions are assumed to have long separation and low boxes. The length assumed at each face has a reasonable range. We calculate all \( d\varepsilon \) by the combination of three lengths and then consider the mean \( d\varepsilon \) as the representative value of each class.

Since we are to use the retrieved LST in the research on urban environments, special attention is paid to the urban canopy effect. The geometrical model for surface emissivity in urban area also requires the surface emissivities of the top, side and ground of each AHI TIR band and the scales of Lambertian boxes \( (F, H, S) \) according to urban canopy. Table 5 shows the manmade materials and the scales applied to each face of the urban structure. The scales of the urban structure were based on work by Moriwaki et al. (2002), Strommann-Andersen and Satrup (2011) and Ito et al. (2015). The roofing (top) materials are considered to be rubbers and shingles except for the metals. The wall (side) materials are considered to be construction concrete except for bricks, windows glass, paints and wood. The characteristic of urban structure varies depending on a degree of development, such as commercial, industrial and residential area. Although it is possible to set values corresponding to each urban structure by using more detailed land use data (Yang et al. 2015a, b), we made a rough estimate by assuming an average structure.

Table 5. Materials and building shapes of each face of the urban structure.

| Top | Side | Ground |
|------|------|--------|
| Materials | Roofing materials | Construction concretes | Road asphalts and Tar |
| Building shapes | \( F = 10–20 \) m | \( H = 7–15 \) m | \( S = 10–20 \) m |
The mean $d\varepsilon$, of all combinations of three lengths are calculated as the representative cavity effect due to the urban canopy. Note that the internal reflection due to the trees cannot occur over the roof faces since the assumed building height is larger than the assumed tree height in Table 3. Therefore, when we calculate the cavity effect in urban area due to the trees using Eq. (4), the ground emissivities are considered as to consist of construction concrete, road asphalt and tar, not $\varepsilon_u$ (Eq. 11).

3. Results and discussions

3.1 Vegetation and ground emissivity

Tables 6 and 7 show the emissivities of vegetation and ground for each land cover class as derived by the procedure described in the previous section. For the vegetation, both green and senescent states are listed. The deviation (Dev.) is computed by considering the experimental error of each component material comprising a class. The experimental errors of emissivity in the laboratory and the field measurements are assumed as ± 0.005 (Caselles et al. 1997). The “Dev.” is calculated as follows:

$$\text{Dev.} = \sqrt{\frac{1}{3n-1} \left[ \sum_{i=1}^{n} (\varepsilon_i - \bar{\varepsilon})^2 + \sum_{i=1}^{n} (\varepsilon_i + 0.005 - \bar{\varepsilon})^2 \right]}$$

where $n$ is the number of component materials of each class and $\bar{\varepsilon}$ is the mean emissivity of each class. Vegetation basically has higher emissivity and lower deviation than soil or rocks. Senescent vegetation has lower emissivity and higher deviation than green vegetation. Class 16 (bare area, consolidated) has the lowest emissivity and the highest deviation in the ground emissivity. Table 8 shows the emissivity and deviation at each face of the urban structure corresponding to Table 5. The deviations are also calculated considering a ± 0.005 experimental error of component materials. The

| GLCNMNO class | Band 13 | Band 14 | Band 15 |
|---------------|---------|---------|---------|
|               | Green   | Senescent | Green | Senescent | Green | Senescent |
| 1, 14         | 0.9893  | 0.0018   | —     | —        | 0.9895 | 0.0020   |
| 2             | 0.9893  | 0.0018   | 0.9870 | 0.0045   | 0.9895 | 0.0020   |
| 3             | 0.9955  | 0.0019   | —     | —        | 0.9955 | 0.0018   |
| 4             | 0.9955  | 0.0019   | 0.9875 | 0.0067   | 0.9955 | 0.0018   |
| 5, 6, 7       | 0.9924  | 0.0012   | 0.9898 | 0.0020   | 0.9925 | 0.0013   |
| 8, 10, 16, 17 | 0.9937  | 0.0010   | 0.9784 | 0.0012   | 0.9951 | 0.0010   |
| 9             | 0.9934  | 0.0009   | 0.9806 | 0.0017   | 0.9945 | 0.0009   |
| 11, 12        | 0.9940  | 0.0015   | 0.9762 | 0.0015   | 0.9958 | 0.0015   |
| 13            | 0.9935  | 0.0009   | 0.9807 | 0.0010   | 0.9947 | 0.0009   |
| 18            | 0.9932  | 0.0008   | 0.9830 | 0.0012   | 0.9942 | 0.0009   |

| GLCNMNO class | Band 13 | Band 14 | Band 15 |
|---------------|---------|---------|---------|
|               | Green   | Senescent | Green | Senescent | Green | Senescent |
| 1, 2          | 0.9680  | 0.0075   | 0.9720 | 0.0060   | 0.9797 | 0.0058   |
| 3, 4          | 0.9667  | 0.0079   | 0.9699 | 0.0070   | 0.9790 | 0.0051   |
| 5, 6          | 0.9674  | 0.0053   | 0.9709 | 0.0045   | 0.9793 | 0.0038   |
| 7, 8, 9, 10, 17 | 0.9673 | 0.0088   | 0.9698 | 0.0068   | 0.9770 | 0.0056   |
| 11, 12, 13    | 0.9712  | 0.0053   | 0.9731 | 0.0049   | 0.9812 | 0.0046   |
| 16            | 0.9187  | 0.0120   | 0.9432 | 0.0093   | 0.9559 | 0.0074   |
| 14            | 0.9915  | 0.0050   | 0.9919 | 0.0050   | 0.9831 | 0.0050   |
| 15            | 0.9927  | 0.0023   | 0.9938 | 0.0023   | 0.9899 | 0.0023   |
| 19            | 0.9959  | 0.0007   | 0.9817 | 0.0023   | 0.9608 | 0.0051   |
deviation is high especially at the top. This is because the roofing materials have a large variety in emissivity. The values for Bands 13, 14 and 15 range from 0.8598 to 0.9661, from 0.9177 to 0.9725 and from 0.9288 to 0.9808, respectively. If the metal roofing materials and windows glass are considered, there is a possibility of higher deviation because these emissivities are quite low, less than 0.8.

### 3.2 Magnitude of the cavity effect

The cavity effect of vegetation, $d_e$, is shown in Fig. 3 as a function of SZA and FVC for the green state. The left-hand column of Fig. 3 shows the SZA dependences of $d_e$ for the three TIR bands. They were calculated assuming $VFC = 0.5$. The right-hand column shows the FVC dependences for the three TIR bands. They were calculated assuming $SZA = 20^\circ$. The values of $d_e$ greatly vary with the vegetation type, and $d_e$ of Classes 1, 2, 3, 4 and 5 are especially high. Conversely, $d_e$ of the regions assumed low-height trees ($H$ in Fig. 2) and long-separation between them ($S$ in Fig. 2), such as Classes 10, 16, 17 and 18, are less than 0.01. Thus, we may not consider the cavity effects in those regions. $d_e$ slightly increases with increasing SZA, whereas it obviously decreases with increasing FVC. In reality, the FVC (the side proportion) is not constant, but it increases with increasing SZA. Therefore, as mentioned by Valor and Caselles (1996), it is considered that $d_e$ decreases with increasing SZA.

The cavity effect due to the urban structure, $d_{eu}$, for SZA ranging from $0^\circ$ to $60^\circ$ is shown in Table 9. $d_{eu}$ of Bands 13 and 14 are greater than 0.01 for all the SZAs and $d_{eu}$ of Band 15 is approximately 0.01. Atitar and Sobrino, (2009) reported that an emissivity error greater than 0.01 causes a LST retrieval error of approximately 1.0 K. Hence, it is necessary to consider the cavity effect in urban areas to be the same as the vegetation. Yang et al. (2015a) estimated the LSE in the TIR band of the Landsat 8 in an urban area using the building GIS data. They reported that the differences reach 0.02 between the material emissivity and the effective emissivity considering the cavity effect especially over built-up areas. Table 10 shows the urban surface emissivity $\varepsilon_u$ and $d_{eu}$ of two geometrical shapes: one has a large $d_{eu}$ (type A: $F = 10\ m$, $H = 15\ m$, $S = 20\ m$) and the other has a small $d_{eu}$ (type B: $F = 20\ m$, $H = 7\ m$, $S = 10\ m$) for the three TIR bands in the SZA ranging from $0^\circ$ to $60^\circ$ at intervals of $20^\circ$. The $\varepsilon_u$ and $d_{eu}$ differences between types A and B are shown at the bottom of Table 10. Both types A and B are assumed for the estimation of $d_{eu}$ in this study as shown in Table 5. $d_{eu}$, of type A for Band 13 certainly reaches 0.02. The $\varepsilon_u$ and $d_{eu}$ differences between types A and B for Bands 13 and 14 are greater than 0.01. Therefore, if we observe the urban areas in more detail, it should require land use data having a higher spatial resolution, such as the building GIS data. A similar sophisticated method may be possible for other vegetation and/or bare soil areas, if the detailed in-situ database is available. Then, it will be possible to acquire more detailed $\varepsilon_u$, $d_{eu}$ ($\varepsilon_D$), and $F$, $H$ and $S$ information.

### 3.3 Seasonal and dynamic changes of LSE

Figure 4 shows the time changes of LSEs for three AHI TIR bands, NDVI and NDSII over a cropland in Japan ($42.74^\circ$N, $143.14^\circ$E) from August 2015 to December 2015. The NDVI decreases gradually through the observed term. On the other hand, the LSEs suddenly decreased in late October when NDVI become smaller than a threshold for the judgment of seasonal state of the pixel. After the decrease, the LSEs kept constant or increased a little. In this period, the cavity effect of vegetation increased with decreasing FVC in November. In December, sudden changes of the NDSII and LSEs due to snow/ice coverage were observed.

When a land surface is covered by snow/ice, the observed value of NDVI becomes low. Thus, a LSE estimation error due to the misjudgment of snow/ice coverage is almost the same as the difference between ground emissivity of each class and snow/ice emissivity of Class 19 (see Table 7).

Figure 5 shows the time changes of LSEs for three AHI TIR bands, NDVI and NDWI over a paddy field in Japan ($37.58^\circ$N, $138.85^\circ$E) from April 2016 to June 2016. The NDVI is generally larger than the NDWI. However, the NDWI became larger than the NDVI from May to early June. This was due to the flooding and rice transplantation. The LSEs changed according to this inversion of the relation between NDVI and NDWI. If the NDWI is not considered, the LSE for the flooding and rice transplantation period is assigned as near the value of ground emissivity. Thus, the LSE...
Fig. 3. The SZA and FVC dependence of the cavity effect ($d\varepsilon$) for each land cover. The left figures show the SZA dependence for Bands 13, 14 and 15. The right figures show the FVC dependence for Bands 13, 14 and 15.

Table 9. The cavity effect ($d\varepsilon$) in the urban area for the three TIR bands.

| Band | SZA (°) | 0    | 10   | 20   | 30   | 40   | 50   | 60   |
|------|---------|------|------|------|------|------|------|------|
| 13   |         | 0.0104| 0.0115| 0.0125| 0.0136| 0.0147| 0.0155| 0.0161|
| 14   |         | 0.0104| 0.0109| 0.0114| 0.0119| 0.0124| 0.0128| 0.0131|
| 15   |         | 0.0089| 0.0092| 0.0096| 0.0099| 0.0102| 0.0106| 0.0108|
estimation error due to the misjudgment of flooding is near the difference between the ground emissivity of Class 12 and the emissivity of Class 15 (see Table 7). The misjudgments of seasonal and dynamic states, such as senescent vegetation, snow/ice coverage and flooding in the paddy field, may cause large LSE errors. Although these are the inherent disadvantages of the classification based method and the NDVI thresholds method, our considerations using NDSII and NDWI reduce the errors.

3.4 Sensitivity analysis

The in-situ evaluation of LSE is practically impossible, so we assess the possible total LSE error for each class instead. We perform a sensitivity analysis with regard to input data. On the basis of Eqs. (1)–(10), the total LSE error is defined as (Caselles et al. 1997)
\[ \delta \varepsilon = \left| \frac{\partial \varepsilon}{\partial F} \right| \delta F + \left| \frac{\partial \varepsilon}{\partial H} \right| \delta H + \left| \frac{\partial \varepsilon}{\partial S} \right| \delta S. \]  

The emissivity errors of each class (\(\delta \varepsilon_{\lambda, v}\), and \(\delta \varepsilon_{\lambda, g}\)) are computed by considering \(\pm 0.005\) experimental errors for all materials and bands (i.e., these errors are equal to Dev. of each class as shown in Tables 6 and 7). \(F, H\) and \(S\) errors are assumed as 10 % of their value (i.e., \(\delta F, \delta S\) and \(\delta H\) are the deviations corresponding to the errors of \(\pm 0.1 F, \pm 0.1 S\) and \(\pm 0.1 H\), respectively). For example, when we calculate \(\delta F\) for \(F = 1.0\) m of Class 1, \(\delta F\) is calculated as \(\sqrt{(1.1-1.0)^2 + (0.9-1.0)^2}\). These emissivity and shape errors are based on work done by Caselles et al. (1997). For the proportions of \(F, H\) and \(S\), Caselles et al. (1997) considered a mixed pixel of \(FVC = 0.5\) and an SZA of \(P_s = 0.2\) and \(P_v = 0.3\). Instead, we consider a situation where \(FVC = 0.5\) and \(SZA = 20^\circ\). On this basis, the FVC estimation error is assumed to vary between 5 % and 25 %, which is an appropriate estimation error range based on vegetation indices (Caselles et al. 1997; Peres and DaCamara 2005). Urban canopy is additionally considered in this study. Therefore, instead of \(\delta \varepsilon_{\lambda, g}\), for an urban area, \(\varepsilon_{\lambda, gu}\), is calculated by

\[ \delta \varepsilon_{\lambda, gu} = \left| \frac{\partial \varepsilon_{\lambda}}{\partial \varepsilon_{\lambda}} \right| \delta \varepsilon_{\lambda} + \left| \frac{\partial \varepsilon_{\lambda}}{\partial \varepsilon_{\lambda}} \right| \delta \varepsilon_{\lambda} + \left| \frac{\partial \varepsilon_{\lambda}}{\partial \varepsilon_{\lambda}} \right| \delta \varepsilon_{\lambda} + \left| \frac{\partial \varepsilon_{\lambda}}{\partial \varepsilon_{\lambda}} \right| \delta \varepsilon_{\lambda} \]

\[ + \left| \frac{\partial \varepsilon_{\lambda}}{\partial F} \right| \delta F + \left| \frac{\partial \varepsilon_{\lambda}}{\partial H} \right| \delta H + \left| \frac{\partial \varepsilon_{\lambda}}{\partial S} \right| \delta S. \]  

The above results except for urban areas (Class 18), have an estimation accuracy comparable to previous studies with the semi-empirical method (Snyder et al. 1998; Peres and DaCamara 2005). For the urban area, it is obvious that a large LSE error occurred in the spatial resolution of the global map (approximately 0.01°) by making a rough estimate of the urban surface structure.

### 3.5 Possible misclassification in GLCNMO2013

The LSE error due to misclassification of land cover map should also be considered. Kobayashi et al. (2017) reported the misclassification ratio of GLCNMO2013, in that classification accuracies in some forest types (Classes 2–11 and 13) are low. The “user’s accuracies” of these classes range from 47 % to 79 % and “the producer’s accuracies” range from 48 % to 74 %. Evergreen forests (Class 1) and mangroves (Class 14) have more than 84 % user’s accuracy and more than 90 % producer’s accuracy. Paddy fields (Class 12) have 84 % user’s accuracy and 77 % producer’s accuracy. It is generally difficult to distinguish different forest types, so a similar tendency of misclassification is found in other global land cover maps, such as the International Geosphere-Biosphere Program Data and Information System (IGBP-DIS) and the MODIS MOD12Q1 land cover product (Peres and DaCamara 2005). For other classes, wetlands (Class 15) have 87 % user’s accuracy and 65 % producer’s accuracy. Bare areas (consolidated) (Class 16) have 78 % user’s accuracy and 76 % producer’s accuracy. Bare areas (unconsolidated) (Class 17) have 89 % user’s and producer’s accuracies. Urban areas (Class 18) have 100 % user’s accuracy and 98 % producer’s accuracy. Snow/ice (Class 19) has 98 % user’s and producer’s accuracies.

Misclassification is most likely to occur within different vegetation classes. Both vegetation and ground emissivity differences between vegetation classes for
Fig. 6. The LSE error for each GLCNMO class and TIR band. The left figures show the LSE error in the green state, and the right figures show the LSE error in the senescent state.
the green state are less than 0.01 for the three bands (see Tables 6, 7). For the senescent state, however, the vegetation emissivity difference may reach to around 0.015 (e.g., the difference between Classes 7 and 8 in Band 14). Another source of misclassification resides in bare areas (Classes 16 and 17), which may cause larger LSE errors (about 0.02–0.05). As described in Section 2.2, different emissivity assignment methods are applied to paddy fields, urban areas, wetlands and snow/ice. Misclassification in these classes leads to misapplication between the methods, which may cause large LSE errors. Fortunately, paddy fields, urban areas, wetlands and snow/ice have high classification accuracies. Therefore, it is thought that the misapplication of emissivity assignment is expected to be small.

3.6 Influence on LST estimation

Yamamoto et al. (2018) evaluated the sensitivities of their newly developed LST algorithm, the nonlinear three-band algorithm, to the uncertainties of LSEs for three bands (± 0.02) and compared with other existing algorithms: the nonlinear split-window algorithm by Sobrino and Romaguera (2004) and the three-band algorithm by Sun and Pinker (2003). The nonlinear three-band algorithm has a LST calculation formula which is improved by adding quadratic terms of the difference between two brightness temperatures to the three-band algorithm by Sun and Pinker (2003). The algorithm makes maximum use of AHI window TIR bands, Bands 13, 14 and 15. It is reported that the LST estimation error caused by the ± 0.02 LSE uncertainties for the nonlinear split-window, three-band and nonlinear three-band algorithms is 2.90 K, 3.00 K and 1.84 K (at nadir), respectively. The sensitivity analysis for LSE estimation (Fig. 6) ensures a smaller LST estimation error than the LST errors calculated by Yamamoto et al. (2018). The misjudgments of seasonal and dynamic states may cause ± 0.02 LSE errors at maximum, which in turn yield the LST error evaluated by Yamamoto et al. (2018). Therefore, the LSE error influence on the final LST retrieval accuracy is concluded within the allowable range. Only the misclassification in bare areas (Classes 16 and 17), however, may cause larger LST errors since the ground emissivity difference between them is large.

4. Conclusions

The LSE maps for the AHI’s three TIR bands were developed using a semi-empirical method based on work done by Peres and DaCamara (2005). These are to be used in the LST retrieval from Himawari-8. Peres and DaCamara (2005) assigned the emissivity value of the mixture of vegetation and soil to each pixel on the basis of the IGBP land cover class. The fractional vegetation cover of each pixel is estimated from the NDVI observation. Because the AHI also has visible and near-infrared bands, which is needed to calculate the NDVI, it becomes possible to apply their method. In this study, the land cover classification information is taken from the GLCNMO2013, and material emissivities of soil, vegetation and others are taken from the MODIS UCSB emissivity library and the ASTER spectral library.

We newly added three considerations over Peres and DaCamara (2005). In order to consider phenology, two seasonal states, green and senescent, are considered using the NDVI value on the basis of the annual mean NDVI consisting of 12 periods of 30-day composites. Accordingly, a slightly lower emissivity is assigned to the senescent state and a higher emissivity value is assigned to the green state. Second, the flooding and rice transplantation period in the paddy fields and snow/ice coverage are detected using the NDWI, NDVI and NDSII. When a pixel is covered by snow/ice, the emissivity value of snow/ice is assigned independently to the pixel class. For paddy fields, when a pixel is judged as the flooding and rice transplantation period, a high emissivity value that has both grass and water properties is assigned. Third, the cavity effect due to the urban canopy is considered by extending the geometrical model for the vegetation canopy proposed by Caselles and Sobrino, (1989). Several typical urban structures and the gross emissivity of each face of urban structure are assumed. Peres and DaCamara (2005) assumed that the land surfaces in the urban area are flat, and reported that the estimation error was low. However, our result shows that the average value of the cavity effect on LSE is as large as 0.01 and it varies greatly depending on the urban structure. It reaches 0.02 especially over built-up areas. The total LSE error is also estimated, which was especially high in urban areas. Thus, it is obvious that the cavity effect of urban structures cannot be ignored even on a global (approximately 1.0 km) scale.

The sensitivity analysis shows that the total LSE errors for the three bands are less than 0.02. The error is especially stable at the vegetation area, where it is less than 0.01. However, we have to pay attention to the misclassification in bare areas and the misjudgments of seasonal and dynamic states, which may cause large LSE error. Because this accuracy of the LSE is comparable to that in previous studies (Snyder et al. 1998; Peres and DaCamara 2005), the LSE
maps are sufficiently applicable to multi-channel LST algorithms, such as the split-window algorithm and the three-band algorithm. Our LSE product may also provide initial-guess estimates for the two-temperature method that retrieves the LST and LSE simultaneously (Peres and DaCamara 2004).

Acknowledgments

Himawari 8/9 gridded data and the Global Map–Global Land Cover (GLCNMO) version 3 are distributed by Center for Environmental Remote Sensing (CEReS), Chiba University, Japan.

References

Atitar, M., and J. A. Sobrino, 2009: A split-window algorithm for estimating LST from meteosat 9 data: Test and comparison with in situ data and MODIS LSTs. *IEEE Geosci. Remote Sens. Lett.*, 6, 122–126.

Baldrige, A. M., S. J. Hook, C. I. Grove, and G. Rivera, 2009: The ASTER spectral library version 2.0. *Remote Sens. Environ.*, 113, 711–715.

Caselles, V., and J. A. Sobrino, 1989: Determination of frosts in orange groves from NOAA-9 AVHRR data. *Remote Sens. Environ.*, 29, 135–146.

Caselles, V., E. Valor, C. Coll, and E. Rubio, 1997: Thermal band selection for the PRISM instrument: 1. Analysis of emissivity-temperature separation algorithms. *J. Geophys. Res.*, 102, 11145–11164.

Ito, R., T. Satomura, and T. Takemi, 2015: Idealized experiments on the development of urban warming under various geographical conditions using a meso-scale meteorological model. *Proceeding of ICUC9 - 9th International Conference on Urban Climate jointly with 12th Symposium on the Urban Environment*, Toulouse, France, 6 pp.

Kobayashi, T., R. Tateishi, B. Alsaaidhe, R. C. Sharma, T. Wakaizumi, D. Miyamoto, X. Bai, B. D. Long, G. Gegentana, A. Maitiniyazi, D. Cahayana, A. Haireti, Y. Moriﬁji, G. Abake, R. Pratama, N. Zhang, Z. Alifu, T. Shiraht, L. Mi, K. Iizuka, A. Yusupujiang, F. R. Rinawan, R. Bhattarai, and D. X. Phong, 2017: Production of global land cover data – GLCNMO2013.

Li, Z.-L., B.-H. Tang, H. Wu, H. Ren, G. Yan, Z. Wan, I. F. Trigo, and J. A. Sobrino, 2013a: Satellite-derived land surface temperature: Current status and perspectives. *Remote Sens. Environ.*, 131, 14–37.

Li, Z.-L., H. Wu, N. Wang, S. Qiu, J. A. Sobrino, Z. Wan, B.-H. Tang, and G. Yan, 2013b: Land surface emissivity retrieval from satellite data. *Int. J. Remote Sens.*, 34, 3084–3127.

Moriwaki, R., M. Kanda, T. Watanabe, and K. Matsunaga, 2002: Estimation of land-surface parameters in urban boundary layer. *Proc. Hydraul. Eng.*, 46, 91–96 (in Japanese).

Peres, L. F., and C. C. DaCamara, 2004: Land surface temperature and emissivity estimation based on the two-temperature method: Sensitivity analysis using simulated MSG/SEVIRI data. *Remote Sens. Environ.*, 91, 377–389.

Peres, L. F., and C. C. DaCamara, 2005: Emissivity maps to retrieve land-surface temperature from MSG/SEVIRI. *IEEE Trans. Geosci. Remote Sens.*, 43, 1834–1844.

Petitcolin, F., and E. Vermote, 2002: Land surface reflectance, emissivity and temperature from MODIS middle and thermal infrared data. *Remote Sens. Environ.*, 83, 112–134.

Snyder, W. C., and Z. Wan, 1998: BRDF models to predict spectral reflectance and emissivity in the thermal infrared. *IEEE Trans. Geosci. Remote Sens.*, 36, 214–225.

Snyder, W. C., Z. Wan, Y. Zhang, and Y.-Z. Feng, 1998: Classification-based emissivity for land surface temperature measurement from space. *Int. J. Remote Sens.*, 19, 2753–2774.

Sobrino, J. A., and N. Raissouni, 2000: Toward remote sensing methods for land cover dynamic monitoring: Application to Morocco. *Int. J. Remote Sens.*, 21, 353–366.

Sobrino, J. A., and M. Romaguera, 2004: Land surface temperature retrieval from MSG1-SEVIRI data. *Remote Sens. Environ.*, 92, 247–254.

Sobrino, J. A., V. Caselles, and F. Becker, 1990: Significance of the remotely sensed thermal infrared measurements obtained over a citrus orchard. *ISPRS J. Photogramm. Remote Sens.*, 44, 343–354.

Sobrino, J. A., N. Raissouni, and Z.-L. Li, 2001: A comparative study of land surface emissivity retrieval from NOAA data. *Remote Sens. Environ.*, 75, 256–266.

Sobrino, J. A., J. C. Jiménez-Muñoz, G. Sória, M. Romaguera, L. Guanter, J. Moreno, A. Plaza, and P. Martínez, 2008: Land surface emissivity retrieval from different VNIR and TIR sensors. *IEEE Trans. Geosci. Remote Sens.*, 46, 316–327.

Stromann-Anderson, J., and P. A. Sattrup, 2011: The urban canyon and building energy use: Urban density versus daylight and passive solar gains. *Energy Build.*, 43, 2011–2020.

Sun, D., and R. T. Pinker, 2003: Estimation of land surface temperature from a Geostationary Operational Environmental Satellite (GOES-8). *J. Geophys. Res.*, 108, 4326, doi:10.1029/2002JD002422.

Tateishi, R., B. Uryangqai, H. Al-Bilbisi, M. A. Ghar, J. Tsend-Ayush, T. Kobayashi, A. Kasimu, N. T. Hoan, A. Shalaby, B. Alsaaidhe, T. Enkhzaya, Gegentana, and H. P. Sato, 2011: Production of global land cover data – GLCNMO. *Int. J. Digital Earth*, 4, 22–49.

Tateishi, R., N. T. Hoan, T. Kobayashi, B. Alsaaidhe, G. Tana, and D. X. Phong, 2014: Production of global land cover data – GLCNMO2008. *J. Geogr. Geol.*, 6, 99–122.
Trigo, I. F., L. F. Peres, C. C. DaCamara, and S. C. Freitas, 2008: Thermal land surface emissivity retrieved from SEVIRI/Meteosat. *IEEE Trans. Geosci. Remote Sens.*, **46**, 307–315.

Valor, E., and V. Caselles, 1996: Mapping land surface emissivity from NDVI: Application to European, African, and South American areas. *Remote Sens. Environ.*, **57**, 167–184.

Weng, Q., 2009: Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. *ISPRS J. Photogramm. Remote Sens.*, **64**, 335–344.

Xiao, X., Z. Shen, and X. Qin, 2001: Assessing the potential of VEGETATION sensor data for mapping snow and ice cover: A normalized difference snow and ice index. *Int. J. Remote Sens.*, **22**, 2479–2487.

Xiao, X., S. Boles, S. Frolking, W. Salas, B. Moore III, C. Li, L. He, and R. Zhao, 2002: Observation of flooding and rice transplanting of paddy rice fields at the site to landscape scales in China using VEGETATION sensor data. *Int. J. Remote Sens.*, **23**, 3009–3022.

Yamamoto, Y., H. Ishikawa, Y. Oku, and Z. Hu, 2018: An algorithm for land surface temperature retrieval using three thermal infrared bands of Himawari-8. *J. Meteor. Soc. Japan*, **96B**, 59–76.

Yang, J., M. S. Wong, M. Menenti, and J. Nichol, 2015a: Modeling the effective emissivity of the urban canopy using sky view factor. *ISPRS J. Photogramm. Remote Sens.*, **105**, 211–219.

Yang, J., M. S. Wong, M. Menenti, and J. Nichol, 2015b: Study of the geometry effect on land surface temperature retrieval in urban environment. *ISPRS J. Photogramm. Remote Sens.*, **109**, 77–87.

Wan, Z., D. Ng, and J. Dozier, 1994: Spectral emissivity measurements of land-surface materials and related radiative transfer simulations. *Adv. Space Res.*, **14**, 91–94.