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Yaser Jouybari Moghaddam et al./ Elixir Remote Sensing 80 (2015) 31351-31354

Available online at www.elixirpublishers.com (Elixir International Journal)



Elixir Remote Sensing 80 (2015) 31351-31354



# Estimating of Land Surface Emissivity from Landsat-8 Satellite Data Based on NDVI

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## ARTICLE INFO

Article history: Received: 21 October 2014; Received in revised form: 28 February 2015; Accepted: 26 March 2015;

Keywords Landsat,

TIRS sensor, NDVI, OLI, LSE.

# ABSTRACT

As an intrinsic property of natural materials, land surface emissivity (LSE) is an important surface parameter and surface emissivity estimation is a significant factor for the land surface temperature estimation from remotely sensed data. Public domain data are available from the newly operational Landsat-8 Thermal Infrared Sensor (TIRS). Vegetation coverage has a significant influence on the LSE distribution. In this study, emissivity values of bands 10 and 11 have been calculated based on the Normalized Difference Vegetation Index (NDVI) method. The NDVI thresholds values have been determined to separate the bare soil, fully vegetated and mixed areas. Then using a regression relation, the values of emissivity is also used for the fully vegetated area.

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## Introduction

Landsat-8 was successfully launched on 11 February 2013 .It is the eighth satellite in the Landsat program, the seventh to reach orbit successfully. Originally called the Landsat Data Continuity Mission (Landsat-8), it is collaboration between NASA and the United States Geological Survey .Landsat-8 was deployed into orbit with two instruments on-board: i) the Operational Land Imager (OLI) with nine spectral bands in the visual (VIS), near infrared (NIR), and the shortwave infrared (SWIR) spectral regions table 1 shows the spectral bands of Landsat-8; and ii) the Thermal Infrared Sensor (TIRS) with two spectral bands in the LWIR (Irons et al. 2012). TIRS sensor detects radiation in 2 thermal channels; the channels are centered at 10.895 and 12.05 um. The relative spectral response of the TIRS bands is presented in Figure 1. The spatial resolution of TIRS data is 100 m with a revisit time of 16 days, and as a result, applications are different than those of other sensors with coarser spatial resolutions and shorter revisit times. While Landsat-8 images are already freely distributed through the United States Geological Survey, to the best of our knowledge.

LSE is the ratio of energy emitted from a natural material to that from an ideal blackbody at the same temperature. Accurate surface is desired in land surface models for better simulations of surface energy budgets from which skin temperature in the model is calculated (Jin et al. 1997). Generally speaking, the retrieval of LSE from space is not easy. The direct estimation of LSE from passive satellite measurements is impossible due to the combined effects of the land surface temperature (LST) and LSE or the atmospheric contamination (Li, Petitcolin, and Zhang 2000; Jiang, Li, and Nerry 2006). In other words, there are at least two problems to be resolved besides the radiometric calibration and cloud detection (Becker and Li 1995): i) a separation of surface emissivity and temperature from radiance at ground level and. ii) atmospheric corrections. Therefore, land surface emissivity is critical for determining the thermal radiation of the land surface (Caselles et al., 1995). The emissivity of a surface is controlled by some factors such as water content, chemical composition, structure, roughness, and the observation conditions (i.e. wavelength, pixel resolution and observation angle) (Snyder et al., 1998).

The Estimation of LSE from satellite passive sensors data have been already performed using different techniques. Some of the techniques including Day/Night method, the grey body emissivity method, alpha derived relative emissivity method, the reference channel method (Kahle et al., 1980), the emissivity normalization method (Gillespie, 1985), emissivity renormalization (Stoll, 1993), the temperature-independent spectral indices method (Becker and Li, 1990), the spectral ratio method (Watson, 1992b), and the alpha emissivity method (Kealy and Gabell, 1990), the Temperature Emissivity Separation (TES) method, NDVI-based emissivity calculation method and classification-based estimation take numerical approach in absolute emissivity estimation. In this study NDVI based method have been used for retrieve the LSE from Landsat-8.



Figure 1. Landsat-8 TIRS bands' relative spectral response functions

## **Case Study**

A set of images, acquired by the ASTER and Landsat-8 were considered in this study.

The set includes ASTER and Landsat-8 data from the same area and time. This set area is a portion of the Oregon State in USA, located between latitude of  $45^{\circ} 45' 25''$  N and  $45^{\circ} 54' 43''$  N and between longitude of  $121^{\circ} 7' 26''$  W and  $121^{\circ} 18' 24''$  W as shown in Figure 2.This image includes all the important land cover: bare soil, rock, vegetation and mixed area. The ASTER image was used to validate the emissivity retrieve from Landsat-8.

#### Methodology

This section is organized as follows. Section 3.1 introduces the method to retrieve the LST from ASTER data. This LST map assumed as reference data for other section. Section 3.2 introduces the algorithm to retrieve the LST from Landsat-7 data. This LST map used to compare the accuracy of LST derived from Landsat-7 and Landsat-8.



Figure 2. A) ASTER image (R: band 3N, G: band 2, B: band 1) - B) Landsat-8 image (R: band 4, G: band 3, B: band 2) Section 3.3 describes the simulation procedure employed to obtain the emissivity from Landsat-8 using NDVI. Section3.3.1 describes the simulation procedure in the bare soil case. Section 3.3.2 describes the procedure in the vegetation case. 3.3.3 Describes the procedure in the mixed area case.

### TES method for ASTER data

The TES algorithm was developed by Gillespie et.al for the five LWIR bands of the ASTER imaging radiometer. The TES algorithm used three modules:

• The Normalized Emissivity Method (NEM), which removes environmental radiance and gives a first guess of temperature and emissivities assuming a maximum value for emissivities.

• The Ratio module where NEM emissivities are ratioed to their average (equation 1)

• The Minimum Maximum Difference (MMD) (Equation 2) module that allows absolute emissivity retrieval using an empirical relationship to predict  $\varepsilon$  min (equation 3).

$$\beta_{\lambda} = \frac{\varepsilon_{\lambda}}{\frac{1}{k} \sum_{\lambda=1}^{k} \varepsilon_{\lambda}}$$
(1)  

$$MMD = \max(\beta_{\lambda}) - \min(\beta_{\lambda})$$
(2)  

$$\varepsilon_{\min} = r + s \times MMD^{t}$$
(3)

Where r = 0.994, s = 20.687, t = 0.737 for ASTER bands (Gillespie et al. 2012). These coefficients were established for ASTER channels, using spectra of the ASTER spectral library,  $\lambda$  to a wavelength and k is the number of bands. Each emissivity is then estimated with:

$$\varepsilon_{\min} = \beta_{\lambda} \frac{\varepsilon_{\lambda}}{\min(\beta_{\lambda})} \tag{4}$$

NDVI-Based Emissivity (NDVIBE) method on Landsat-8 data

According to some literatures (e.g. Sobrino et.al. 2001), there is a high correlations between NDVI and emissivity values

(Momeni et al. 2007). Because of that in this study, we have used J.H. Salisbury's spectral library (http://speclib.jpl.nasa.gov) to make a regression between the values of emissivity and NDVI. Using these spectral and 11 have been simulated. The simulation starts with the spectral library of the soil and vegetation and Landsat-8 bands response functions and is ended to the regression relations that estimate emissivity of bare soil and mixed area and an estimated emissivity for fully vegetated area. Figure 3 shows the flowchart of these steps.



Figure 3. Flowchart of the simulation

Bare Soil

To estimate the bare soil emissivity: Firstly, by integrating equivalent spectral range of J.H. Salisbury's spectral library (for 41 soil types) with the bands 4,5,10 and11 of Landsat-8, response functions of the different types of soils at the mentioned bands have been simulated. Secondly, simulated reflectance data are used directly to calculate the simulated Landsat-8-NDVI. Simulated reflectance data of bands 10 and 11 are used to calculate corresponding emissivity values as  $\epsilon i=1-Ri$ . Finally, regression relations have been calculated for two pairs of NDVI and  $\epsilon 10$ ; and NDVI and  $\epsilon 11$ . Table 2 represents the correlation coefficients and standard deviations of the calculated regression relations.

## **Fully Vegetated**

Fully vegetated areas are approximate blackbodies. The emissivity spectrum is nearly constant and near unity

(Jiménez-Muñoz et al. 2006). In the case of fully vegetated area, there is a limitation to derive a relation between high NDVI pixels and their emissivity (Momeni et al. 2007). Therefore, emissivity has been calculated for four vegetation types by using the spectral library as described in previous case. Simple average of emissivity simulation has been calculated. This averaged value is used as emissivity in fully vegetated case. Therefore in this case values of 0.982 and 0.985 for  $\varepsilon 10$  and  $\varepsilon 11$  respectively, are derived.

### Mixed area

In this case, a pixel is supposed to be a mixture of bare soil and vegetation. Sobrino et al. (1990) and Kerr et al. (1992) have proposed equation 12 for emissivity estimation of this area:

$$\varepsilon_i = P_v \,\varepsilon_{v,i} + (1 - P_v) \varepsilon_{s,i} + C_i \tag{5}$$

Where  $\varepsilon$ s,i and  $\varepsilon$ v,i are the emissivities of bare soil and vegetation respectively for spectral band i. The term Ci depends on the surface characteristics (i.e. the internal reflections). For evenly distributed very low height vegetation patches in a given soil area, Ci=0 (*Sobrino* et al. 2001). Pv is the vegetation proportion obtained according to equations described in paper of (Carlson et al. 1997):

Bands	Wavelength (um)	Resolution (m)
Band1 – Coastal aerosol	0.43 - 0.45	30
Band2 – Blue	0.45 - 0.51	30
Band3 – Green	0.53 - 0.59	30
Band4 – Red	0.64 - 0.67	30
Band5 – NIR	0.85 - 0.88	30
Band6 – SWIR1	1.57 – 1.65	30
Band7 – SWIR2	2.11 - 2.29	30
Band 8 – Panchromatic	0.50 - 0.68	15
Band 9 –Cirrus	1.36 - 1.38	30
Band 10 – TIRS 1	10.60 - 11.19	100
Band 11 – TIRS 2	11.50 - 12.51	100

 Table 1. Landsat-8 Spectral Bands

 Table 2. Correlation Coefficients and Standard Deviations of Regression Relations for Data Simulated from Spectral Library

	Correlation	<b>Regression relation</b>	Standard deviation
<i>ε</i> 10	0.71	$\varepsilon_{\rm 10}=0.9695+0.0059~\times NDVI$	0.0023
<i>ε</i> 11	0.77	$\varepsilon_{\texttt{11}} = 0.9744 + 0.0073 \times \textit{NDVI}$	0.0020

Table 3. Root mean square errors and biases of ndvibe method obtained from evaluation

Land Cover	Threshold		RMSE	Bias
Bare Soil	NDVI < 0.2	$\varepsilon_{10}$	0.0023	0.0003
		$\varepsilon_{11}$	0.0020	0.0003
Mixed Area	0.2 < NDVI < 0.5	$\varepsilon_{10}$	0.0024	-0.0004
		$\varepsilon_{11}$	0.0022	-0.0004

$$P_v = \left[\frac{NDVI - T_{min}}{T_{max} - T_{min}}\right]^2 \tag{6}$$

Where Tmax = 0.5 and Tmin = 0.2. Taking into account equation 4, the land surface emissivity can be obtained as (if Ci = 0):

$$\varepsilon = mP_V + n \tag{7}$$

Where

$$m = \varepsilon_v - \varepsilon_s \tag{7.1}$$
$$n = \varepsilon_s \tag{7.2}$$

In order to apply this methodology, values of soil and vegetation emissivities are needed. Emissivity of vegetation was calculated in the previous case. To calculate the emissivity of soil, a possible solution is to use the simple mean value for the emissivities of soils which derived in the first case (i.e. bare soil). Thus, surface emissivities for mixed area can be estimated from NDVI for each Landsat-8 thermal band according to the following expressions:

•	
$\varepsilon_{10} = 0.9706 + 0.0112 \times P_v$	(8.1)
$\varepsilon_{11} = 0.9759 + 0.0080 \times P_v$	(8.2)

### **Result and Conclusion**

In some papers, the comparisons are performed between the results of two data sets acquired by two different sensors (Jacob et al. 2004). In this study the comparison has been made between LSE retrieved from Landsat-8 using NDVI based algorithm and LSE map retrieved from ASTER data. We believe that this cross validation (i.e. taking ASTER data of the same time and area as reference LST map) is a suitable way in

comparison with using the ground-based measurement points. Because when we use this method for validation, the LSE map can be validated by the many pixels (over 40000 pixels), while ground-based measurement points are limited. Therefore, the highly reliable emissivities estimated by TES algorithm can be used as reference data in this study.

Table 3 shows the results of comparison between NDVI based implementation and emissivities derived by TES algorithm. In the bare soil case, we have obtained standard deviation of 0.0020 for regression relation on simulated data and 0.0023 Root Mean Square Errors (RMSE) for comparison of implementation of NDVIBE method and TES method on real data. In the Mixed area case, we have obtained standard deviation of 0.0024 for regression relation on simulated data and 0.0028 Root Mean Square Errors (RMSE) for comparison of implementation of NDVIBE method and TES method on real data. At the end we used all the pixel and the result shows the RMSE is equal 0.0025.

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