

The study of estimation method of broadband emissivity from EOS/MODIS data^①

Mao Kebiao (毛克彪)^② * * * * *, Ma Ying * * * * *, Shen Xinyi * * * * *, Sun Zhiwen * * * * *,
He Tianjue * * * * *, Xia Lang * * * * *, Xu Tongren * * * * *

(* National Hulunber Grassland Ecosystem Observation and Research Station, Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, P. R. China)

(** Guangzhou Institute of Geography, Guangzhou 510070, P. R. China)

(*** Department of Geography, University of Toronto, Toronto M5S3G3, Canada)

(**** Hydrometeorology and Remote Sensing Laboratory, The University of Oklahoma, Norman 73072, USA)

(***** Institute No. 503 of China Academy of Space Technology, Beijing 100081, P. R. China)

(***** State Key Laboratory of Remote Sensing Science, School of Geography, Beijing Normal University, Beijing 100875, P. R. China)

Abstract

The broadband emissivity is an important parameter for estimating the energy balance of the Earth. This study focuses on estimating the window (8 – 12 μm) emissivity from the MODIS (moderate-resolution imaging spectroradiometer) data, and two methods are built. The regression method obtains the broadband emissivity from MOD11B1_5KM product, whose coefficient is developed by using 128 spectra, and the standard deviation of error is about 0.0118 and the mean error is about 0.0084. Although the estimation accuracy is very high while the broadband emissivity is estimated from the emissivity of bands 29, 31 and 32 obtained from MOD11B1_5KM product, the standard deviations of errors of single emissivity in bands 29, 31, 32 are about 0.009 for MOD11B1_5KM product, so the total error is about 0.02 and resolution is about 5km \times 5km. A combined radiative transfer model with dynamic learning neural network method is used to estimate the broadband emissivity from MODIS 1B data. The standard deviation of error is about 0.016, the mean error is about 0.01, and the resolution is about 1km \times 1km. The validation and application analysis indicates that the regression is simpler and more practical, and estimation accuracy of the dynamic learning neural network method is higher. Considering the needs for accuracy and practicalities in application, one of them can be chosen to estimate the broadband emissivity from MODIS data.

Key words: moderate-resolution imaging spectroradiometer (MODIS), broadband emissivity, land surface temperature

0 Introduction

The extensive requirement of broadband emissivity information at a large scale estimation of energy balance of the earth's radiation has made the remote sensing of broadband emissivity an important issue in recent decades. Especially, the knowledge of the surface emissivity at surface window wavelengths is critical in radiation budget studies of the earth-atmosphere system. A constant and uniform emissivity is commonly used in many land surface energy balance and numerical weather prediction models. In order to retrieve broadband emissivity from remote sensing data, many people

are devoted to establish estimating methods for broadband emissivity. We often obtained the global emissivity map by making classification for remote sensing data, and gave the emissivity for each type of surface with corresponding spectral libraries^[1,2]. Although it is relatively easy to obtain a map of emissivity at a global scale, this method does not consider the change of surface type over time. Thus an error is likely to result when we use the emissivity obtained via this method as the input parameter of model. The multiple regression method was used to relate window emissivity to the five ASTER emissivities^[3]. Even though the accuracy of the regression method is very high, the accuracy of broadband emissivity depends on the estimated error of

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② To whom correspondence should be addressed. E-mail: maokebiao@126.com

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a single band emissivity. Mao, et al.^[4] proved that the neural network can improve the retrieval accuracy of broadband emissivity from ASTER data. MODIS is a 36 bands EOS (earth observing system) instrument, which is particularly useful to environmental research because of its global range, radiometric resolution and dynamic ranges, and accurate calibration in multiple thermal infrared bands designed for retrievals of SST, LST and atmospheric properties^[5].

In this study, we develop a regression method using spectral libraries to estimate the broadband emissivity from MOD11B1_5KM product in Section 2.1, and neural network method is used to estimate the broadband emissivity from MODIS 1B data in Section 2.2. Application and validation analysis is provided in Section 3.

1 Regression and RM-NN Methods

1.1 Regression method

The calculation formula of broadband emissivity between 8 – 12 μm is defined as Eq. (1)^[3].

$$\varepsilon_{8-12} = \frac{\int_{\lambda=8}^{\lambda=12} \varepsilon(\lambda) B(\lambda, T) d\lambda}{\int_{\lambda=8}^{\lambda=12} B(\lambda, T) d\lambda} \quad (1)$$

where ε_{8-12} is the broadband emissivity, $B(\lambda, T)$ is the Planck function, $\varepsilon(\lambda)$ is the spectral emissivity at the wavelength λ , and T is the surface temperature. For MODIS sensor, the broadband emissivity can be expressed as a linear combination of MODIS band 29, 31, 32 emissivities (ε_i):

$$\varepsilon_{8-12} = \sum_{i=29, 31, 32}^{32} A_i \varepsilon_i + B \quad (2)$$

where A_i and B are coefficients obtained from linear regression by using spectral libraries. A total of 188 spectra are collected from ASTER spectral library^[6,7], and 45 spectra are selected from Ref. [8]. We assume that $T = 300\text{K}$ is assumed in this analysis, and Eq. (1) is used to compute the broadband emissivity between 8 and 12 μm . Of the original spectra collected, 128 spectra are used to build the regression method, and the equation is like Eq. (3). 95 spectra are used to make validation (see Fig. 1). The standard deviation of error is about 0.0118 and the mean error is about 0.0084.

$$\varepsilon_{8-12} = 0.07508 + 0.45842\varepsilon_{29} + 0.42551\varepsilon_{31} + 0.03455\varepsilon_{32} \quad (3)$$

Two algorithms proposed by Wan et al.^[9,10] are used as global product algorithm for NASA to retrieve

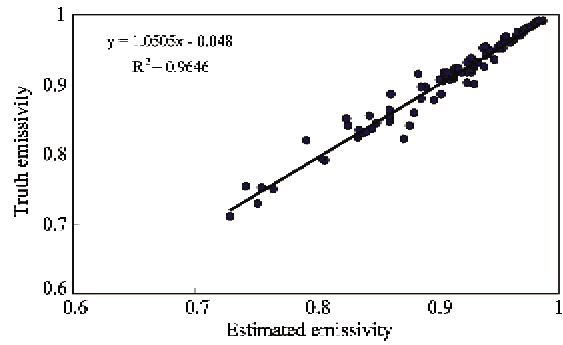


Fig. 1 The comparison between truth emissivity and emissivity estimated by regression method

land surface temperature and emissivity from MODIS data. MOD11_L2 LST_1KM product provides the emissivities in band 31 and band 32 which are derived from land cover classification and spectral database^[9]. The classification data is not simultaneously changed with the other data, and the emissivity of band 29 is missing. Therefore the MOD11_L2 LST_1KM product is not a good choice. MODIS_Grid_Daily_5km_LST (MOD11B1) with 5km \times 5km spatial resolution is retrieved by the day/night LST algorithm^[10], which provides emissivities in band 20, 22, 23, 29, 31, and 32. The standard deviations of errors in retrieved emissivities in bands 31 and 32 are about 0.009 for MOD11B1_5KM product for 80 spectra. The standard deviation of error of emissivity in band 29 is greater than 0.01 because the range of emissivity of different land surface types in band 29 changes greatly. Considering the standard deviation of error of single band emissivity, the total standard deviation of errors of broadband emissivity is over 0.02 for the regression method. The advantage of regression method is that the coefficients of equation are fixed, thus it is simpler and more practical in application.

1.2 Neural network Method

Mao, et al.^[11] proposed radiative transfer model with the neural network algorithm to estimate LST and emissivity from MODIS 1B data. This algorithm uses the brightness temperatures in bands 29, 31, 32, and the water vapor content as the input nodes of neural network. The land surface temperature and emissivities in bands 29, 31, 32 are made as the output nodes of neural network. Analysis indicates that the neural network method can be used to accurately retrieve land surface temperature and emissivity^[11].

In this study, an analysis for atmospheric profile of mid-latitude summer is made and the MODTRAN4^[12] is used to simulate the process of radiance transfer. The simulation datasets are considered as ref-

erence data from a known ground truth. The input parameters for MODTRAN4 include: every band emissivity in bands 29, 31, 32, the range of LST from 270 to 320K with step size 10K, the near surface air temperature (at 2m height) arbitrarily assumed from 273 to 310K with step sizes of 3 and 8K, and the range of atmospheric water vapor content from 0.2 to $4\text{g} \cdot \text{cm}^{-2}$ with a step size of $0.5\text{g} \cdot \text{cm}^{-2}$. The simulation data are randomly divided into two groups. A total of 9131 sets are used as training data, and the other 3890 sets are testing data. The radiances in bands 29, 31, 32 and water vapor content are the four input nodes, and the broadband emissivity is considered as output node. The dynamic learning neural network^[13] is selected to estimate broadband emissivity, which uses the Kalman filtering algorithm to increase the convergence rate in the learning stage and enhance separately the ability for the highly nonlinear boundary problem^[13]. More introductions can be referred to Ref. [11]. Part of the test results is shown in Table 1. The mean error of broadband emissivity is under 0.01 when two hidden layers are with 400 nodes each, and the validation is shown in Fig. 2.

Table 1 The fitting error by using neural network

Hidden nodes	Emissivity		
	Correlation coefficient	Standard deviation of error	Mean error
10-10	0.697	0.029	0.031
20-20	0.89	0.023	0.019
40-40	0.917	0.022	0.016
60-60	0.934	0.02	0.014
80-80	0.934	0.019	0.014
100-100	0.944	0.018	0.013
200-200	0.951	0.018	0.012
300-300	0.955	0.017	0.011
400-400	0.964	0.016	0.01
500-500	0.945	0.019	0.011
600-600	0.935	0.022	0.012
700-700	0.893	0.027	0.012

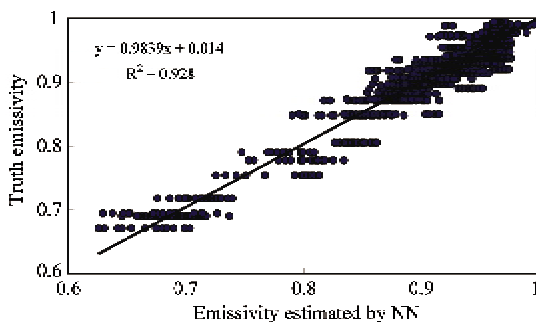


Fig. 2 The comparison between truth emissivity and emissivity estimated by NN

2 Validation and application analysis

The validation has been partly made by simulation data in Section 2 which can be shown in Fig. 1 and Fig. 2. It is very difficult to obtain the in-situ ground truth measurement of broadband emissivity matching the pixel scale ($5\text{km} \times 5\text{km}$ and $1\text{km} \times 1\text{km}$ at nadir) of MODIS data at the satellite pass for the validation of algorithm. Generally speaking, broadband emissivity varies from point to point on the ground, and ground measurements are generally point measurement. It is a problem to obtain the measured broadband emissivity matching the pixel of MODIS data. Therefore, an indirectly validation is made further through application analysis.

The MODIS/TERRA image of Shandong peninsula, China, 09/09/2005 is selected as the research region. Fig. 3 (a) is a high resolution image obtained from Google Earth, which shows high details of the ground, and Fig. 3 (b) is the unsupervised classification result by using the MODIS bands 1-5. Fig. 4 (a) is the broadband emissivity retrieved from the DL neural network which has been trained above and the resolution is about $1\text{km} \times 1\text{km}$. The inputs of neural network are radiances in bands 29, 31, 32, and water vapor content retrieved from MODIS bands 2/5/17/18/19. The output is the broadband emissivity. Fig. 4 (b) is the broadband emissivity estimated from MOD11B1_5KM product using the regression method and the resolution is about $5\text{km} \times 5\text{km}$. By comparing with Fig. 3 and Fig. 4, the broadband emissivity (Fig. 4 (a)) can reflect different ground types after considering different resolutions, and the resulting estimation can be accepted. Fig. 4 (a) is more consistent with Fig. 3 than with Fig. 4 (b). The advantage of neural network is that the estimation accuracy is higher, and its disadvantage is that the neural network must be trained and tested every time.

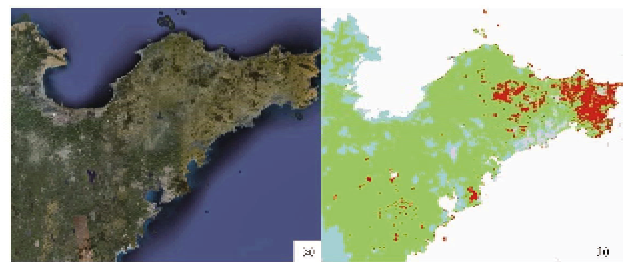


Fig. 3 (a) high resolution image ($30\text{m} \times 30\text{m}$), (b) unsupervised classification map (band 1-5) ($500\text{m} \times 500\text{m}$)

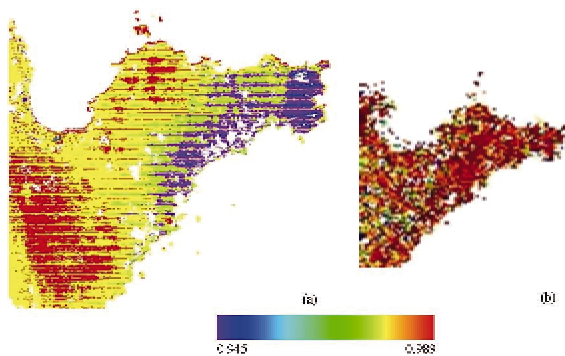


Fig. 4 (a) broadband emissivity estimated by neural network ($1\text{km} \times 1\text{km}$), (b) broadband emissivity estimated from MOD11B1_5KM product ($5\text{km} \times 5\text{km}$)

3 Conclusion

Two methods are proposed to estimate the broadband emissivity ($8 - 12\mu\text{m}$) from EOS/MODIS data. The regression method estimates the broadband emissivity from single emissivity of MOD11B1_5KM product. Although the total standard deviation of error is about 0.02, the regression method is simpler and more practical in application. The combined radiative transfer model with dynamic learning neural network algorithm is used to estimate the broadband emissivity from the radiance at sensor. The standard deviation of error is about 0.016 and the mean error is about 0.01, and the resolution is about $1\text{km} \times 1\text{km}$ which is higher than MOD11B1_5KM product ($5\text{km} \times 5\text{km}$), thus the accuracy of neural network is higher. Both methods have advantages and disadvantages, and we can choose one of them according to the specific practical requirements. On the other hand, 128 spectra are used in this study, and some values of them are under 0.8. In fact, most emissivities of land types are between 0.95-0.09, the retrieval accuracy can be improved further if we just consider the main types.

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Mao Kebiao, born in 1977. He received his Ph.D degrees in Chinese Academy of Sciences in 2007. He also received the M. S. degree from Nanjing University in 2004, and the B. S. degree from Northeast Normal University in 2001. He has published more than 70 papers in international and Chinese scientific journals and applied for three patents for inventions. His research interests include global climate change, agricultural disaster, geophysical parameters retrieval (like land surface temperature and emissivity, soil moisture, water vapor content).