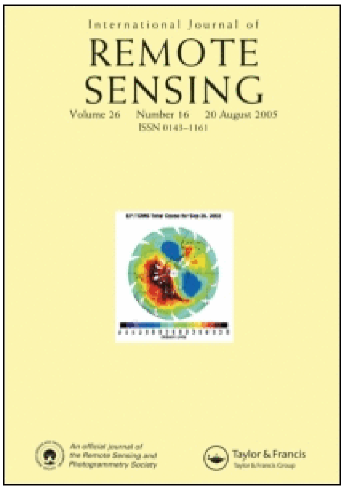

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Letter

Near-surface air temperature estimation from ASTER data based on neural network algorithm

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An algorithm based on the radiance transfer model (MODTRAN4) and a dynamic learning neural network for estimation of near-surface air temperature from ASTER data are developed in this paper. MODTRAN4 is used to simulate radiance transfer from the ground with different combinations of land surface temperature, near surface air temperature, emissivity and water vapour content. The dynamic learning neural network is used to estimate near surface air temperature. The analysis indicates that near surface air temperature cannot be directly and accurately estimated from thermal remote sensing data. If the land surface temperature and emissivity were made as prior knowledge, the mean and the standard deviation of estimation error are both about 1.0 K. The mean and the standard deviation of estimation error are about 2.0 K and 2.3 K, considering the estimation error of land surface temperature and emissivity. Finally, the comparison of estimation results with ground measurement data at meteorological stations indicates that the RM-NN can be used to estimate near surface air temperature from ASTER data.

1. Introduction

Near surface air temperature (NSAT) is an increasingly important climate parameter which governs the moisture and energy exchanges between land surface and atmosphere (Sun *et al.* 2005). Due to the complex spatial and temporal patterns of NSAT, no single method has been developed well for its efficient measurement. There are two methods to obtain NSAT: a physical method based on the energy budget approach, which requires parameters such as aerodynamic resistance for characterizing the status of soil and vegetation for physically based energy budget approaches (however such data is rather difficult to obtain; see Sun *et al.* 2005); and an empirical method based on relationships of the related variables (Boyer 1984,

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Ishida and Kawashima 1993). The empirical method is a general approach to obtain NSAT through taking advantage of geographic information systems (GIS) to interpolate meteorological parameters observed by station. Well-distributed NSAT information for the empirical method cannot be obtained if there are insufficient meteorological stations, and if the distribution is not random, especially for mountainous regions (Burrough and Donnell 1998).

ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) is an imaging instrument aboard the Terra satellite, which was launched in December 1999 as part of NASA's Earth Observing System (EOS). http://science.hq.nasa.gov/earth-sun/index.htmlASTER has 15 bands which cover the visible, near-infrared, short-wave infrared and thermal infrared regions, and the spatial resolution is from 15 to 90 m. Five thermal infrared bands provide a chance to obtain detailed maps of land surface temperature and emissivity (Gillespie *et al.* 1998, Mao *et al.* 2008). The radiance measured by the sensor is very sensitive for land surface temperature and is not very sensitive for NSAT; but NSAT is influenced by land surface temperature, and these parameters together determine the variation of atmospheric temperature profile. This paper presents an analysis of a neural network (NN) estimating NSAT from remote sensing data (§2), MODTRAN4 simulation and estimation analysis (§3) and an evaluation of NSAT estimation (§4).

2. Analysis of neural network for estimating near-surface air temperature from ASTER data

The derivation of general algorithms for estimating land surface temperature and emissivity is based on the thermal radiance of the ground and its transfer from the ground through the atmosphere to the remote sensor. Equation (1) can be used to depict the process after some simplification (Mao *et al.* 2005).

$$\begin{aligned} B_i(T_i) = \varepsilon_i(\theta)\tau_i(\theta)B_i(T_s) + [1-\tau_i(\theta')][1-\varepsilon_i(\theta)]\tau_i(\theta) \\ B_i(T_{ia}) + [1-\tau_i(\theta)]B_i(T_{ia}), \end{aligned} \tag{1}$$

where T_s is land surface temperature (LST), T_i is the brightness temperature in band i at the sensor, $\tau_i(\theta)$ is the atmospheric transmittance in band i at viewing direction θ (zenith angle from nadir), θ' is the downwelling direction of atmospheric radiance, $\varepsilon_i(\theta)$ is the ground emissivity in band i at viewing direction θ, $B_i(T_i)$ is the radiance measured by the sensor, $B_i(T_s)$ is the ground radiance, and T_{ia} is the effective average atmospheric temperature in band i, which varies with the wavelength-dependence of the water vapour absorption. The effective average atmosphere temperature in different band is mainly determined by the water vapour content and NSAT at a height of 2 m above the ground (Mao *et al.* 2007).

$$T_{ia} = A_i + B_i T_0, \tag{2}$$

where T_0 is NSAT at 2 m above the ground, A_i is constant, and B_i is coefficient in band i. On the other hand, NSAT is influenced a lot by land surface temperature. There is a linear relationship (like equation (2)) between NSAT and land surface temperature, but the relationship changes with time in different locations. In equation (1), there are three unknowns (one band emissivity, land surface temperature and NSAT) in one equation, so the equations cannot be resolved and other conditions must be found; this is a typical ill-posed inverse problem. The individual thermal band transmittance ($\tau(\theta)$) is also an unknown which is a function of the water vapour content and other absorption gas. The thermal band is mainly sensitive for water vapour content.

$$\tau_i(\theta) = f(WVC, O), \tag{3}$$

where WVC is water vapour content, and O is other gas, such as carbon dioxide, nitrogen oxide, ozone oxide, methane or carbon monoxide, which can be assumed as constant. Mao *et al.* (2007, 2008) proposed a method to overcome the ill-posed problem by building the local linear relationship between neighbour band emissivities because the emissivity is almost constant for a thermal band. For every type (soil, vegetation, water, etc), the equation can be depicted as:

$$\varepsilon_i(\theta) = C_i + D_i\varepsilon_j(\theta), \tag{4}$$

$\varepsilon_i(\theta)$ and $\varepsilon_j(\theta)$ (i is 10, 11, 12, 13, 14) is different band emissivity at angle θ, C_i is constant, D_i is the coefficient in band i. For every land type, five emissivity unknowns can be made as one. This potential information is not made full use of by us because it is very difficult to depict it with a few functions (Mao *et al.* 2007, 2008). This analysis indicates that one or two empirical equations cannot accurately depict the relationship well for most land surface types, and the simplification of nonlinear functions (such as the Planck function) may produce some error.

The conventional algorithm needs to spend a lot of time developing the rules (Li and Becker 1993, Wan and Li 1997). In contrast to conventional methods, neural networks do not require that the relationship between input parameters and output parameters is known, and this directly determines the relationship between the inputs to the network and the outputs from the networks from the training data (Mao *et al.* 2007, 2008).

3. MODTRAN4 simulation and neural network estimation analysis

To train and test the neural network, the radiance transfer model MODTRAN (Berk *et al.* 1987) is applied to generate the training data and testing datasets, which must accord to the characteristic of spectral emissivity (ASTER spectral library, 2002:http://speclib.jpl.nasa.gov). The atmospheric profile is different in different regions (altitude, latitude and longitude), so the key point of the NN algorithm is how to build a reliable training database. In order to increase the accuracy of the algorithm, different training and testing databases need to be built for different regions. The advantage of this method is that it can overcome measurement error and accurately maintain relationships between geophysical parameters. These simulation datasets can be viewed as reference data from a known ground truth. When necessary, additional datasets may be obtained from the reliable measured data observed by meteorological stations.

The land surface emissivities of water, soil and vegetation (about 50 kinds of land surface type) in ASTER bands 11–14 are used as input parameters of MODTRAN4. The range of land surface temperatures is 280–320 K and the correspondent NSAT (at 2 m height) is arbitrarily assumed also to be 280–320 K. The range of atmospheric water vapour content is from 0.2 g cm^{-2} to 4 g cm^{-2} for the simulation. The profiles of water vapour content and atmosphere temperature under 17 km are set as the rule of standard atmosphere. The transmittance of thermal radiance is mainly influenced by water vapour content, so the other parameter is set as default in standard atmosphere of mid-latitude.

Table 1. Summary of the estimation error.

Hidden nodes	T_0		Hidden nodes	T_0'		Hidden nodes	T_0''	
	r	SD		r	SD		r	SD
10–10	0.933	3.6	5–5	0.982	1.3	10–10	0.955	3.1
20–20	0.932	3.6	10–10	0.982	1.3	20–20	0.949	3.3
30–30	0.933	3.6	15–15	0.982	1.3	30–30	0.979	2.3
40–40	0.917	3.9	20–20	0.986	1.1	40–40	0.978	2.4
50–50	0.933	3.6	25–25	0.987	1.1	50–50	0.977	2.4
60–60	0.934	3.6	30–30	0.99	1	60–60	0.975	2.5
70–70	0.934	3.6	35–35	0.982	1.3	70–70	0.97	2.7
80–80	0.937	3.5	40–40	0.982	1.3	80–80	0.976	2.5

r: correlation coefficient
SD: standard deviation of the fit
T_0, T_0' and T_0'' are near surface air temperatures

In this study, the dynamic learning neural network (DL) (Tzeng *et al.* 1994) is used to estimate NSAT. DL uses the Kalman filtering algorithm to increase the convergence rate in the learning stage and to enhance the separate ability for problems of highly nonlinear boundaries. The initial neural network weights are set to be small random numbers (−1, 1). The Kalman filtering process is a recursive mean square estimation procedure. Each updated estimation of neural network weight is computed from the previous estimation and the new input data. The weights connected to each output node can be updated independently. DL quickly achieves the required rms error in just a couple of iterations, and the result obtained by NN is very stable. So the root error threshold is often set to be $10e^{-3}$ and the epochs of iteration is two. For more details see Tzeng *et al.* (1994). The detailed scheme is as follows.

1. The simulation data is divided randomly into two parts. The training data is 2345 sets and the testing data is 945 sets.
2. The neural network is trained and tested.

The input nodes of the NN are brightness temperature in bands 11–14 (T_i, i=11, 12, 13, 14), and the output node is NSAT. After trial and error, the accuracy is the highest when the size of two hidden layers is 30 nodes each, and the mean and the standard deviation of estimation error are about 3.0 K and 3.5 K. The detailed test dataset information can be referred to T_0 in table 1.

As shown in table 1, the estimation accuracy of NSAT is not very high because the brightness temperature at the satellite is not very sensitive for NSAT. In order to advance the estimation accuracy, the land surface temperature (AST08) and emissivity (AST05) estimated from ASTER1B (AST1B) data are used as prior knowledge. The detailed scheme is shown in figure 1.

1. The values of land surface temperature and emissivity are read from AST08 and AST05 products, which are made as input parameters of MODTRAN4 for every pixel. For example, the value of land surface temperature is 300 K, and the values of emissivity in bands 11–14 are 0.97, 0.97, 0.98, 0.97 in one pixel, which are made as prior knowledge of MODTRAN4. The range of atmospheric water vapour content is from $0.2\,\mathrm{g\,cm^{-2}}$ to $4\,\mathrm{g\,cm^{-2}}$ for simulation, and the range of NSAT is from 300 K to 315 K, and the atmospheric profile of mid-latitude summer is used.

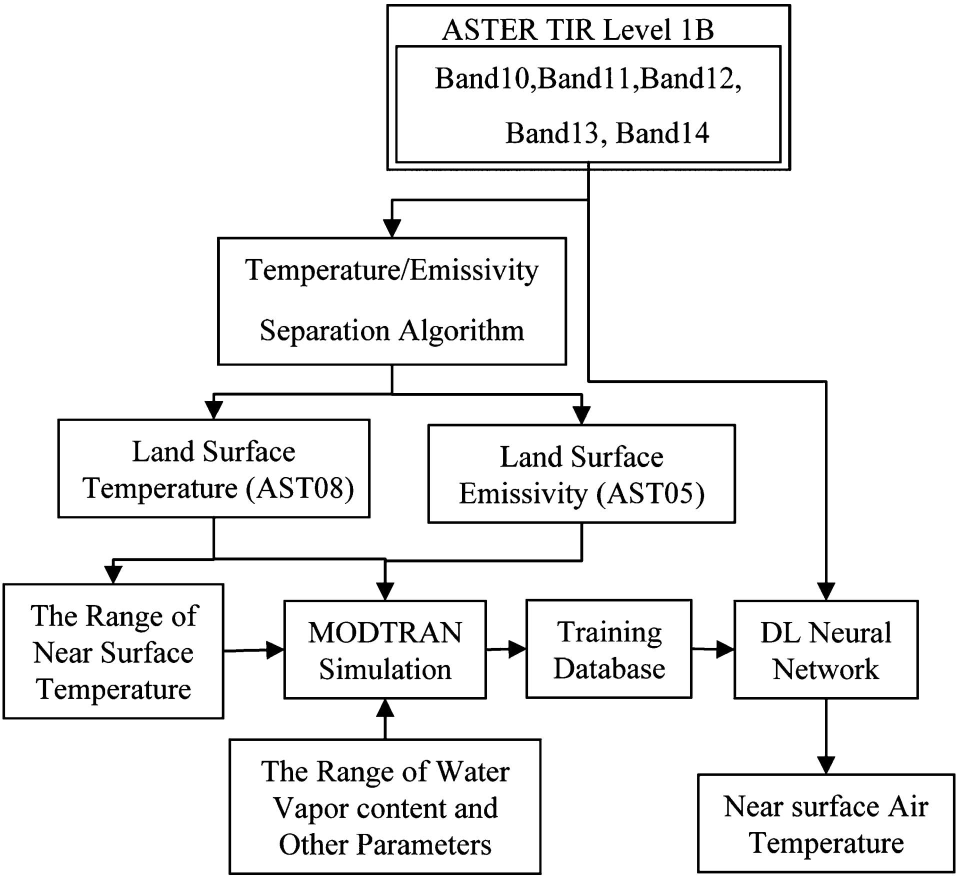

Figure 1. The frame of near surface air temperature estimation.

2. The simulation data are divided into two parts. The training data consist of 95 sets and the testing data consist of 46 sets. After training and testing, the estimation result is T_0' in table 1. As shown in table 1, the mean and the standard deviation of estimation error are both about 1.0 K when the size of two hidden layers is 30 nodes each. The accuracy is very high because the land surface temperature and emissivity are made as prior knowledge.
3. The estimation accuracies of land surface temperature and emissivity are within about ± 1.5 K and ± 0.015 from ASTER data (Gillespie *et al.* 1998). In order to make the method more practical, the estimation error within about ± 3 K for land surface temperature and ± 0.05 for emissivity are considered. LST-3 K $\leqslant$ LST $\leqslant$ LST + 3 K, and $\varepsilon_i - 0.05 \leqslant \varepsilon_i \leqslant \varepsilon_i + 0.05$ are made as prior knowledge of input parameters in MODTRAN4 for every pixel. For example, the value of land surface temperature is 300 K, and the values of emissivity in bands 11–14 are 0.97, 0.97, 0.98 and 0.97 in one pixel. The land surface temperature at 297–303 K, and the values of emissivity (0.94–1, 0.94–1, 0.95–1, 0.94–1) in bands 11–14 are made as prior knowledge of MODTRAN4. The range of atmospheric water vapour content is from 0.2 g cm^{-2} to 4 g cm^{-2} for simulation, and the range of NSAT is from 300 K to 315 K, and atmospheric profile of mid-latitude summer is used. The simulation data are divided into

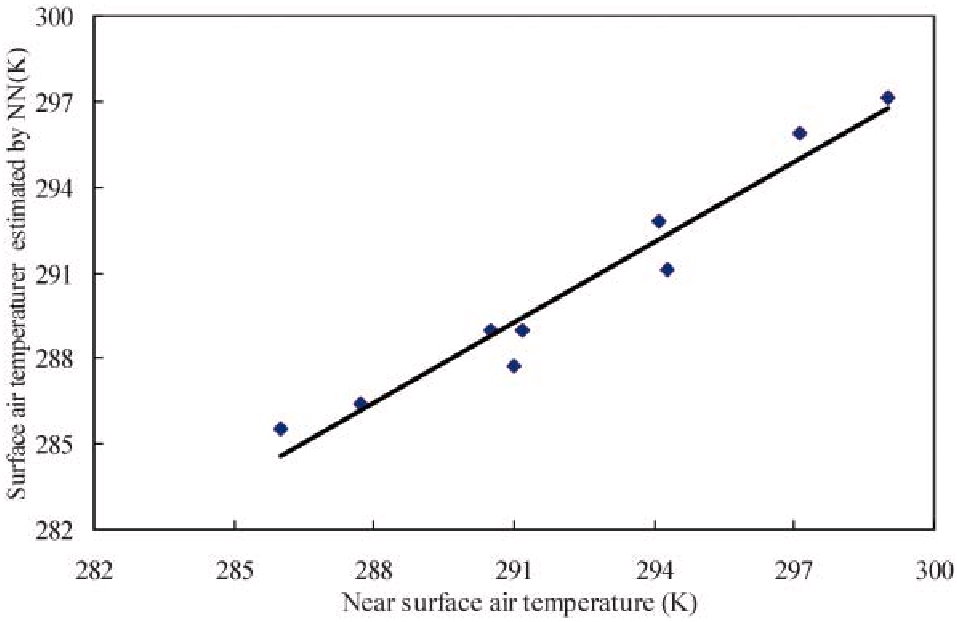

Figure 2. Validation results.

two parts. The training data consist of 736 sets and the testing data consist of 378 sets. After training and testing, the estimation result is T_0'' in table 1. As shown in table 1, the mean and the standard deviation of estimation error are about 2.0 K and 2.3 K.

4. Evaluation

For validation of the algorithm, it is very difficult to obtain the ground truth measurement of NSAT matching the pixel of ASTER data at the satellite pass. Generally speaking, NSAT varies from point to point on the ground, and ground measurement is generally point measurement. On the other hand, ASTER observes the ground at different angles, and precisely locating the pixel of the measured ground in ASTER data is also a problem. Since there are so many difficulties in obtaining ground truth data, validation by using ground truth data is quite difficult. Nine data were obtained from meteorological branches in Harbin city, Suihua, Zhaodong and Anda city. Project 973 of China made ground measurements in Xiaotangshan and provided a dataset of two sites (116.448E and 40.182N; 116.447E and 40.177N) from May 2004 to July 2004 (Mao *et al.* 2007). Two pixels are extracted from the ASTER data through the longitude/latitude. The comparison between estimation result by NN and *in situ* NSAT is shown in figure 2, and the mean error (equation (5)) is about 1.8 K.

$$\frac{\sum_{i=1}^{n} |T_{0r} - T_0|}{n} \tag{5}$$

As we know, the influence factor for ground temperature measurement is too high, especially for mixed pixels. On the other hand, another advantage of the NN is that the estimation accuracy can be enhanced by compensating with some training data. This paper shows that this method is available, and more comparison analysis and application will be reported in the future.

5. Conclusion

Through this study, a new method is being explored in an attempt to synergize the radiance transfer model (MODTRAN4) and a neural network to estimate NSAT from remote sensing data. The analysis indicates that the thermal remote sensing data is not suitable for directly estimating NSAT. The estimation mean error of NSAT is about 1.0 K when the land surface temperature and emissivity are made as prior knowledge for building a training database for every pixel. The estimation mean error of NSAT is about 2.0 K when the estimation errors of land surface temperature and emissivity within about ± 3 K and ± 0.05 are considered. Finally, the analysis and evaluation indicate that the mean error of NSAT estimated from ASTER1B data is about 2.0 K if land surface temperature and emissivity are made as prior knowledge. In order to further enhance the estimation accuracy, a suggestion is that the training database should be compensated for by using observed data of meteorological stations.

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