

An RM-NN algorithm for retrieving land surface temperature and emissivity from EOS/MODIS data

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[1] Three radiative transfer equations are built for MODIS bands 29, 31, and 32, which involve six unknown parameters (average atmospheric temperature, land surface temperature (LST), three band emissivities, and water vapor content). The relationships between geophysical parameters have been analyzed in detail, which indicates that neural network is one of the best methods to resolve these ill-posed problems (LST and emissivity). Retrieval analysis indicates that the combined radiative transfer model (RM) with neural network (NN) algorithm can be used to simultaneously retrieve land surface temperature and emissivity from Moderate-Resolution Imaging Spectroradiometer (MODIS) data. Simulation data analysis indicates that the average error of LST is under 0.4 K and the average error of emissivity is under 0.008, 0.006, and 0.006 for bands 29, 31, and 32, respectively. The comparison analysis between retrieval result by RM-NN and MODIS product algorithm indicates that the generalized split window LST overestimates the emissivity and underestimates land surface temperature. The retrieval results by RM-NN lie between the two products provided by NASA and closer to day/night LST algorithm after statistics analysis. The average error is 0.36 K relative to MODIS LST product (MOD11_L2) retrieved by generalized split window algorithm if we make a regression revision. The comparison of retrieval results with ground measurement data in Xiaotangshan also indicates that the RM-NN can be used to retrieve accurately land surface temperature and emissivity.

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1. Introduction

[2] The extensive requirement of temperature information at a large scale for environmental studies and management

activities of the Earth's sources has made the remote sensing of land surface temperature (LST) and emissivity an important issue in recent decades. Many efforts have been devoted to the establishment of methodology for retrieving LST and emissivity from remote sensing data.

[3] Many split window methods have been developed to retrieve land surface temperature from NOAA/AVHRR and Moderate-Resolution Imaging Spectroradiometer (MODIS) data. The split window method utilizes the differential absorption in adjacent thermal bands to correct the atmospheric effects [Price, 1984; Becker and Li, 1990; Sobrino and Caselles, 1991; Sobrino et al., 1994; Coll et al., 1994; Vidal, 1991; Kerr et al., 1992; Otle and Stoll, 1993; Prata, 1994; Wan and Dozier, 1996; Qin et al., 2001a, 2001b; Sobrino et al., 2004; Mao et al., 2005a, 2005b, 2005c]. The form of these algorithms is the same as the general one, but the calculation of parameters is different. The accuracy of most algorithms is very high, but they still need make some assumptions and some prior knowledge of emissivity and atmosphere (especially water vapor content).

[4] It is very difficult to retrieve simultaneously land surface temperature and emissivity from thermal radiance measurements, because a single multispectral thermal measurement with N bands corresponds to N equations in N + 1 unknowns (N spectral emissivities and LST), which is a typical ill-posed inversion problem. Without any prior information, it is almost impossible for us to accurately

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