SENSITIVITY ANALYSIS OF SNOW PARAMETERS INVERSION PROCEDURE TO THE PASSIVE MICROWAVE MIXED-PIXEL PATTERNS

Tianjie Zhao[1,2], *Yongpan Zhang*[1,2], *Lingmei Jiang*[1,2], *Lixin Zhang*[1,2]

1. State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and Institute of Remote Sensing Applications, CAS, Beijing 100875, China;
2. School of Geography and Remote Sensing Science, Beijing Normal University, Beijing 100875, China;

1. INTRODUCTION

Passive microwave satellite remote sensing can greatly enhance snow measurements because of the ability to penetrate clouds, provide data during darkness and the potential to provide an index of snow depth (SD) or snow water equivalent (SWE). The brightness temperature difference between 19 GHz and 37 GHz horizontal polarization channels (or frequencies not too dissimilar to these) is often used to derive the SWE. But, one of the main problems in the application of satellite microwave radiometry for SWE retrieval is the poor spatial resolution passive remote sensing pixels. Each footprint of a satellite microwave radiometer may include several land and vegetation categories. The measured brightness temperature depends on the characteristics and fraction of each category [1]. If a snow scattering signal is present, it is generally assumed that snow covers the entire area of a coarse spatial resolution passive microwave pixel (or footprint). However, for spatially discontinuous snow packs, snow might be detected in a microwave pixel but it may be inaccurate to assume that snow covers the entire pixel. For a mixed-pixel, the signal only from snow needs to be collected in order to derive the SWE. Some research work has been done about the impact of surface heterogeneity on surface soil moisture retrievals, but little analysis exists about the impact on the snow parameters retrievals. In this paper we analysis the effects of the total brightness temperature and snow fraction error on the snow brightness temperature using a combined model. It is helpful to improve the accuracy of SWE retrieval in the heterogeneous areas.

2. THE COMBINED MODEL

Assuming that one mixed pixel are composed of four parts: bare soil, snow, grassland and forest. The emissions from snow are accounted using the model developed by Jiang et al. [2]. It's a simple, faster computationally parameterized model based on the Dense Media Radiative Transfer Model (DMRT) and AIEM to simulate the dry snow emission with Matrix Doubling approach, considering the multi-scattering in the snow. To calculate the soil emission, the rough bare soil reflectivity model developed at the University of Bern, Switzerland is used [3]. When the vegetation is present over the ground surface, it emits microwave itself and attenuates the radiation from the soil surface. The zero-order ω-τ model was used to calculate the emission of grassland. The value of τ is determined by the b-factor and canopy water content. Since the vegetation in winter is usually sparse and dry, the single scattering albedo can be regarded as 0. And assuming the temperature of vegetation and ground surface is equal. So the brightness temperature of forest was modeled by the formula given in [4]. For each mixed pixel, the brightness temperature is assumed to consist of contributions from the four types, weighted by the fraction of each surface type within the pixel.

3. SENSITIVITY ANALYSIS

The combined model is used to analyze the impacts of observation error and snow fraction error on the retrieved snow brightness temperature. We regard the total brightness temperature derived from the combined model as observation and the snow brightness temperature derived from Jiang's model [2]. Firstly, considering that the satellite observations may have some sensor noise disturbing the measurement of brightness temperature, we add ±5K noise on the "observed value" TB, then the observed snow brightness temperature can be calculated by (1).

$$TB_1^{'} = \frac{TB - f_2 \cdot TB_2 - f_3 \cdot TB_3 - f_4 \cdot TB_4}{f_1} \quad (1)$$

So, we can compare the difference between the snow brightness temperature and the reference value using the index of $(TB_1^{'} - TB_1)/TB_1$. Then, take the "observed value" as real value, if the snow fraction error is from -0.3 to 0.3, with an increment of 0.05, the error of 18 and 37GHz brightness temperature between retrieved and reference value can be calculated. And the variation of brightness temperature difference (18H-37H) with the snow fraction error is investigated. In addition, we investigated the error of retrieved snow brightness temperature with snow depth at different fraction error.

4. CONCLUSIONS

In general, the underestimation of snow fraction could result in the underestimation of snow brightness temperature, but the decrease of 37GHz is higher than that of 18GHz, so the error of brightness temperature difference (18H-37H) is positive. It suggests that the SWE would be overestimated. If we overestimated the snow fraction, the opposite result can be got. In addition, the error increases with the increase of snow depth. Above all, in the process of retrieving SWE using microwave brightness temperature, the accurate snow brightness temperature is needed. For a mixed-pixel, the observation brightness temperature and the snow fraction are important factors to derive snow brightness temperature.

5. REFERENCES

[1] Lauri Kurvonen and Martti Hallikainen, “Influence of Land-Cover Category on Brightness Temperature of Snow,” IEEE Trans. Geosi. Remote Sensing, vol.35, pp. 367-377, 1997.

[2] Lingmei Jiang, Jiancheng Shi, Saibun Tjuatja, Jeff Dozier, Kunshan Chen, Lixin Zhang, “A Parameterized Multiple-Scattering Model for Microwave Emission from Dry Snow,” Remote Sens. Environ, 111, (2-3), pp.357-366, 2007.

[3] Wegmuller, U. and C. Matzler, “Rough Bare Soil Reflectivity Model,” IEEE Trans. Geosci. Remote Sensing, vol.37, pp. 1391-1395, 1999

[4] Jouni T. Pulliainen, Jochen Grandell, Martti T. Hallikainen, “HUT Snow Emission Model and its Applicability to Snow Water Equivalent Retrieval,” IEEE Trans. Geosci. Remote Sensing, vol.37, pp. 1378-1395, 1999.