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Improved snow depth retrieval by integrating microwave brightness temperature and visible/infrared reflectance

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ABSTRACT

The accuracy of snow depth retrieval by remote sensing depends heavily on the characteristics of the snow, and both passive microwave and visible/infrared sensors can contribute to the acquisition of this information. A method integrating these two remotely sensed data sets is presented in this study. Snow depth retrieval is performed using microwave brightness temperature at 19 and 37 GHz from the Special Sensor Microwave/Imager (SSM/I) and the Special Sensor Microwave Image/Sounder (SSMI/S), and visible/infrared surface reflectance from Moderate Resolution Imaging Spectroadiometer (MODIS) products. Microwave brightness temperature provides information about the volume of snow pack, and visible/infrared surface reflectance can indicate snow presence and surface grain size. With these two remote sensing data sets, snow depth is retrieved by a non-linear data mining technique, the modified sequential minimal optimization (SMO) algorithm for support vector machine (SVM) regression. The proposed method is tested by using 16,329 records of dry snow measured at 54 meteorological stations in Xinjiang, China over an area of 1.6 million km^2 from 2000 to 2009. The root mean square error (RMSE), relative RMSE and the correlation coefficient of our method are 6.21 cm, 0.64 and 0.87, respectively. These results are better than those obtained using only brightness temperature data (8.80 cm, 0.90 and 0.73), the traditional spectral polarization difference (SPD) algorithm (15.07 cm, 1.54 and 0.58), a modified Chang algorithm in WESTDC (9.80 cm, 1.00 and 0.62), or the multilayer perceptron classifier of artificial neural networks (ANN) (9.23 cm, 0.94 and 0.72). The daily snow water equivalent (SWE) retrieved by this method has an RMSE of 8.05 mm and a correlation of 0.84, which are better than those of NASA NSIDC (32.87 mm and 0.47) or Globsnow (19.07 mm and 0.59). This study demonstrates that the combination of visible/infrared surface reflectance and microwave brightness temperature via an SVM regression can provide a more accurate retrieval of snow depth.

1. Introduction

Glaciers and snow supply freshwater to approximately one-sixth of the world's population and more than one-fifth of China's population (Barnett, Adam, & Lettenmaier, 2005). Snow cover also directly impacts the Earth's energy balance and climate dynamics. In alpine regions, seasonal snow cover affects soil processes, such as thermal regime, microbiological activities and the elution of solutes (Edwards, Scalenghe, & Freppaz, 2007; Zhang, Wang, Barr, & Black, 2008). To better understand the influence of snow, various hydrological and meteorological models have been developed. These models require frequent snow depth observations on large geographic scales as prior information (Brown, Derksen, & Wang, 2007; Cohen & Entekhabi, 1999; Grippa, Mognard, & Le Toan, 2005). However, the conventional snow depth measurements obtained from sparsely distributed weather stations are not sufficient for this purpose. Therefore, remote sensing has been used to acquire snow depths because it can provide frequent data for large areas.

The retrieval of snow depth based on remote sensing (Table 1) is made possible by a physical property of snowpack: its microwave brightness temperature difference (TBD) at 18 GHz and 36 GHz increases with snow depth. Based on this relation and through empirical studies, linear algorithms have been developed to retrieve snow depth from TBD, such as the Chang algorithm (Chang, Foster, & Hall, 1987; Foster, 1997) and the SPD algorithm (Aschbacher & Rott, 1989). However, further research suggested that this linear dependency might not be valid under some circumstances. For instance, when the snow depth reaches the penetration depth of the microwave at 36 GHz, the TBD will actually decrease as the snow depth increases (Tedesco & Narvekar, 2010). To capture the nonlinear relation between brightness temperature and snow depth, Davis, Chen, Tsang, Hwang, and Chang

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Table 1
Frequently used snow depth retrieval methods.

	Description	References
Linear formula	Multiply empirical factors to brightness temperatures	Chang et al. (1987), Kelly et al. (2003), Tedesco and Narvekar (2010)
Emission model inversion	Calculate or search inverse solutions to radiative transfer models	Pulliainen and Hallikainen (2001), Tedesco et al. (2004)
Radiance assimilation	Assimilate brightness temperature to snow pack evolution models	Dechant and Moradkhani (2011), Durand and Margulis (2007), Takala et al. (2011)

(1993), and Pulliainen and Hallikainen (2001) introduced the inversion of theoretical emission models through numerical computation. Tedesco, Pulliainen, Takala, Hallikainen, and Pampaloni (2004) developed an inversion technique based on artificial neural network (ANN). Their experimental results indicate that data mining algorithms may be effective for the remote sensing-based retrieval of snow depth.

In addition to non-linearities in the TBD–depth relationship, another obstacle is the spatial and temporal heterogeneity of the internal snowpack properties. The linear relation is only valid for large areas, if the snowpack is homogeneous, e.g. of a consistent grain size and density (Durand & Liu, 2012). Generally, larger snow grains tend to scatter microwave radiation much more than smaller ones. When the depth of a snowpack is fixed, the TBD increases with grain size and decreases with snow density (Dai, Che, Wang, & Zhang, 2012; Foster et al., 2005; Tsang, Chen, Chang, Guo, & Ding, 2000). Given that grain size and density vary in time and space, it may be difficult to retrieve snow depth from microwave data across large areas or over long periods. Previous work has attempted to address the heterogeneity of the snowpack properties. For instance, Kelly, Chang, Tsang, and Foster (2003) introduced a model that allows the evolution of grain size and density through time. Josberger and Mognard (2002) proposed the use of a temperature gradient index to represent growth in grain size. Dai et al. (2012) incorporated the properties as a priori information by constructing a look-up table. These methods have addressed the issue of snow pack heterogeneity over large extents by employing extensive fieldwork of measuring snow density, grain size and other parameters inside a snow pack.

Instead of estimates from fieldwork and dynamic models, the grain size can also be retrieved by remote sensing data, which determines the reflectance of the snow surface from visible to near- and shortwave infrared (Domine et al., 2006; Painter, Dozier, Roberts, Davis, & Green, 2003; Xie, Yang, Gao, Kattawar, & Mishchenko, 2006). Typically, the upper layer of snow has lower density and smaller grain diameter than the bottom layers. Previous studies have retrieved snow grain size from visible and infrared sensors such as Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (Painter et al., 2003) or Moderate Resolution Imaging Spectroradiometer (MODIS) (Painter et al., 2009). These studies suggested that the visible/infrared remote sensing data contain sufficient information about surface snowpack properties and information on snow presence to detect snow cover (Liang et al., 2008). Therefore, the visible and near infrared measurements have the potential to improve the accuracy of retrieving snow depth with microwave brightness (Andreadis & Lettenmaier, 2006; Dechant & Moradkhani, 2011; Durand & Margulis, 2007).

According to the discussion above, it appears that the integration of passive microwave, visible/infrared, and nonlinear data mining techniques has the potential to improve the snow depth retrieval without significant fieldwork. In this study, we implement such an approach in Xinjiang, China. The data include the microwave brightness temperatures at 19 and 37 GHz from the SSM/I and SSMIS and the visible/infrared surface reflectance from MODIS (MOD09GA). The data mining method is the improved SMO algorithm for SVM regression, which has proven effective and efficient in various fields (Smola & Schölkopf, 2004). With training samples from various locations and times, the data mining technique may capture the spatial and temporal heterogeneity on snow properties. Two sets of comparisons are made to evaluate the contributions of visible/infrared surface reflectance and nonlinear data mining techniques. First, we compare the accuracy of snow depth retrievals from microwave temperatures and data mining with and without MODIS surface reflectance data. Second, we compare the accuracy using the popular linear formulas, including the SPD (Rott & Aschbacher, 1989) and the Chang algorithm (Chang et al., 1987), to the nonlinear techniques, namely the multilayer perceptron classifier of ANN (Hecht-Nielsen, 1989) and SVM regression (Shevade, Keerthi, Bhattacharyya, & Murthy, 2000). Two existing snow water equivalent (SWE) products (the NASA NSIDC and the Globsnow) are also introduced and compared with the proposed method.

2. Remote sensing data and study area

2.1. The SSM/I and SSMIS brightness temperature

The Special Sensor Microwave/Imager (SSM/I) and the Special Sensor Microwave Imager/Sounder (SSMIS) are aboard the Defense Meteorological Satellite Program (DMSP). These microwave sensors can provide brightness temperature data through clouds and darkness. The radiometric system contains four channels of different frequencies (19.35, 22.2, 37.0 and 85.5 GHz) that are orthogonally polarized. In this study, we used the data from the level-3 Equal-Area Scalable Earth (EASE) grid brightness temperature at 19.35 and 37.0 GHz in vertical and horizontal polarization. The brightness temperatures were obtained daily by the SSM/I (on platform DMSP F13) from 2000 to 2006, and the SSMIS (on F17) from 2007 to 2009, with a resolution of 25 km and 0.1 K. A new microwave sensor, the Advanced Microwave Scanning Radiometer — Earth Observing System (AMSR-E), is also popular in snow depth retrieval, and its SWE product is compared with the proposed method in Section 4.2.

2.2. MODIS surface reflectance

The components of the earth's surface are distinctive in size, which is comparable to different wavelengths of incident light. These components, including grains of snowflakes, air bubbles in ice and others such as soil or sand grains, cause radiance scattering. The measured surface reflectance changes with the grain size. Larger grains have longer path lengths and therefore reflect more radiation. Mounted on NASA's Earth Observing System (EOS) spacecraft, MODIS has provided remotely sensed surface reflectance from the morning-equator-crossing Terra since February 2000, with a wide range of spectral bands (620–670, 841–876, 459–479, 545–565, 1230–1250, 1628–1652, and 2105–2155 nm) and at a relatively high spatial resolution (250 m in 2 bands and 500 m in 5 bands). This study utilized surface reflectance from MOD09GA products (Vermote & Vermeulen, 1999) and calculated the mean value of each channel for the corresponding EASE grid as input. There are approximately 2500 MODIS pixels per EASE grid, so the mean value is assumed to represent the general reflectance of snow.

2.3. Study area and test sites

Located in the northwest of China (from 42 to 50°N and 79 to 92°E), Xinjiang Uygur Autonomous Region (Fig. 1) has a total area of 1.6 million km^2, about one sixth of the country's territory. Xinjiang consists