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Support vector regression snow-depth retrieval algorithm using passive microwave remote sensing data

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ABSTRACT

Snow cover is an informative indicator of climate change because it can affect local and regional surface energy and water balance, hydrological processes and climate, and ecosystem function. Passive microwave (PM) remote sensing data have long been used to retrieve snow depth and snow water equivalent with large uncertainties. The objective of this study is to develop snow-depth retrieval algorithm based on support vector regression (SVR) technique using PM remote sensing data and other auxiliary data. Ground-based daily snow depth data from 1223 stations across Eurasian continent were used to construct and validate the snow-depth retrieval algorithm. This SVR snow-depth retrieval algorithm partitioned three snow cover stages, and four land cover types then generated twelve snow-depth models for each phases. A non-linear regression method based on support vector regression (SVR) was used to retrieve snow depth with PM brightness temperatures, location (latitude and longitude), and terrain parameters (elevation) as input data and land cover as auxiliary data. In addition, we compared the performance of the SVR snow-depth retrieval algorithm with four alternative algorithms: the Chang algorithm, the Spectral Polarization Difference (SPD) algorithm, the Artificial/Neural Networks (ANN) and, an algorithm based on linear regression. Comparing results obtained from these five snow-depth retrieval algorithms against the ground-based daily snow depth data, the SVR snow-depth retrieval algorithm performs much superior with reduced uncertainties. We report the results aimed at evaluating the impact of the variation of snow cover stages and land cover types. The preliminary results suggest that the SVR snow-depth algorithm could detect deep snow with high accuracy and decrease the impact of saturation effects. These results suggest that the SVR snow-depth retrieval algorithm integrating PM remote sensing data and other auxiliary data (land cover types, location, terrain, snow cover stage with indirectly considering grain size variation) can be a more efficient and effective algorithm for retrieving snow depth and snow water equivalent over various scales.

1. Introduction

Snowmelt is an important water source for rivers and lakes. Seasonal snow and glaciers store large amounts of freshwater and are critical for water cycles, hydrology, climatology and water management (Armstrong and Brodzik, 2002; Immerzeel et al., 2010; Robinson and Frei, 2000; Tedesco et al., 2014; Tedesco and Narvekar, 2010; Wang et al., 2015). Snow cover has important implications for energy exchange processes between the land and atmosphere because of its high surface albedo and consequent thermodynamic processes in winter (Cohen and Entekhabi, 2001; G.Barry and Gan, 2011; Gong et al., 2007; Hall et al., 2014). In addition, snow cover has a significant influence on soil thermal regime (Goodrich, 1982; Zhang, 2005; Zhang et al., 1996), winter soil CO_2 efflux, soil carbon and soil nitrogen mineralization, tundra vegetation composition and canopy structure (Schimel et al., 2004; Sturm et al., 2005; Tape et al., 2006; Welker et al., 2000). Both in situ and satellite observational records show that the Northern Hemisphere snow cover extent has significantly reduced in the past 90 years (IPCC AR5, 2013).

Due to the heterogeneity of snow properties in spatiotemporal distribution, conventional snow measurements lack the ability to capture the spatial and temporal variability snow characteristic. Satellite observations provide an effective approach to monitor snow cover with continuous observations and global coverage. Passive Microwave (PM) remote sensing has become an efficient method to estimate snow depth and snow water equivalent, as it provides more information of spatiotemporal snowpack variation. Snow physical properties, including snow depth, snow water equivalent, liquid-water content, grain size, density

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and stratification among others, exhibit substantial temporal and spatial variability (Hall, 1987; Rosenfeld and Grody, 2000). Microwave remote sensing observation is based on the thesis that snow-emitted microwave radiation has a strong dependence on snow physical properties, besides snow depth, mainly on snow density, grain size, and stratification (Rosenfeld and Grody, 2000). PM brightness temperature data reflects snowpack scattering information in terms of the combined effect of snow density, liquid water content, snow metamorphism, and grain size, which also affect the dielectric properties of snowpack. Changes in snow property directly affect microwave brightness temperature. Snow depth is positively related to volumetric scattering of microwave radiation and negatively related to measured brightness temperature from satellite microwave sensors (Gan et al., 2013). Moreover, Zhong et al. (2014) found that snow density is positively related to latitude and negatively related to elevation based on ground-based daily snow depth data. Studies also demonstrated that topographic factors play a critical role in snow distribution and snow physical properties (Bi et al., 2015; Gharaei-Manesh et al., 2016; Li et al., 2015; Savoie et al., 2009; Smith and Bookhagen, 2016). Snow cover products obtained from PM remote sensing data have been widely applied to investigate regional and global climate change, and validate hydrological and climate models (Brown and Robinson, 2011; Brown and Mote, 2009; MacKay et al., 2003). In contrast with visible and thermal infrared bands, PM radiation can probe through clouds and interact with snowpack providing dual polarization data at different frequencies (Chang et al., 1987; Che et al., 2008; Liang et al., 2015; Tait, 1998; Tedesco et al., 2004).

To quantify and model the snowpack, it is necessary to account for spatial differences in snow cover over different land cover types. Because vegetation overlaying snow attenuates its microwave scatter signal, underlying land cover adds to the complications of estimating snow depth and snow water equivalent from PM data (Che et al., 2016; Foster et al., 1999; Yu et al., 2012). Vander Jagt et al. (2013) pointed out that microwave signal sensitivity to snow depth was reduced by 23–63% due to the presence of vegetation in some places. To reduce the effect of forest cover, the forest fraction was included to derive snow depth and snow water equivalent (Che et al., 2008; Foster et al., 1997). Additionally, attenuation of passive radiation between snow depth or snow water equivalent and different land cover types are both pronounced and different. Goïta et al. (2003) developed different algorithm according to different land cover types. Romanov and Tarpley (2007) improved the snow depth retrieval algorithm and accounted for tree cover fraction and the tree types (deciduous or coniferous).

There have been several algorithms developed to estimate snow depth and snow water equivalent using PM brightness temperature data (Aschbacher, 1989; Chang et al., 1987; Che, 2006; Che et al., 2008; Grippa et al., 2004; Kelly, 2009; Kelly et al., 2003; Rott and Aschbacher, 1989; Takala et al., 2011; Tedesco et al., 2004). Typically, most snow-depth retrieval algorithms were developed using the difference between horizontal polarized brightness temperatures of 19 (or 18) GHz and 37 GHz. However, recent studies have shown that snow-depth retrieval algorithms using brightness temperatures from other channels, such as ~10 GHz (Derksen, 2008) and 85 GHz (Kelly, 2009), may better resolve shallow snow cover and be less sensitive to saturation of microwave signal at 19 GHz (Kelly, 2009; Smith and Bookhagen, 2016; Tedesco and Narvekar, 2010). PM brightness temperatures are available on Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), the Advanced Microwave Scanning Radiometer 2 on the Global Change Observation Mission – Water (GCOM-W AMSR2), the Special Sensor Microwave Imager (SSM/I) and the Special Sensor Microwave Imager Sounder (SSMIS). Most snow-depth retrieval algorithms were employed based on the notion that PM brightness temperature differences between 18 and 37 GHz may reflect snow depth and snow water equivalent (Chang et al., 1987). These retrieval algorithms tend to underestimate snow depth and snow water equivalent (Basak et al., 2007; Gan et al., 2013). Meanwhile, new modeling approaches (e.g. artificial neural networks, support vector regression, decision tree) are emerging (Gharaei-Manesh et al., 2016). These new approaches are intended to replace traditional linear methods and to explore, using data-mining, non-linear functional relationships between input (brightness temperatures) and output (snow depth) variables. Knowledge of snowpack physical processes is not necessary for these modeling approaches. Tedesco et al. (2004) applied ANN to estimate snow water equivalent and snow depth. Liang et al. (2015) in their study used a Support Vector Machine (SVM) integrating PM brightness temperature and visible reflectance to retrieve snow depth and snow water equivalent. However, there are still limitations for those methods due to the complexity of topography, heterogeneous land cover types which attenuate microwave scatter signal.

The primary goal of this study is to develop a support vector regression (SVR) snow-depth retrieval algorithm using PM remote sensing data and related auxiliary datasets. The developed SVR snow-depth retrieval algorithm accounts for three snow cover stages and four land cover types (forest, shrub, prairie and bare-land). In Section 2, we introduce data for the SVR snow-depth retrieval algorithm over the Eurasian continent. In Section 3, we describe the process of snow depth retrieval and methods used at each step. Following this approach, we use the SVR snow-depth retrieval algorithm to estimate snow depth across Eurasian continent and evaluate the algorithm performance against the in situ measured daily snow depth data. We also run five other existing snow-depth retrieval algorithms against the same in situ measured daily snow depth data for algorithm comparison.

2. Data

Snow accumulation (snow depth) is heterogeneous and some secondary forces (such as wind, avalanche, land cover etc.) may redistribute snow and change snow condition. Previous studies have shown that snow depth has a close relationship with PM brightness temperature in different channels, and brightness temperature difference increases with snow depth (Aschbacher, 1989; Chang et al., 1987; Che, 2006; Che et al., 2008). Moreover, previous studies have demonstrated that many factors or parameters influence snow physical properties and the distribution of snow cover including, but not limited to, vegetation (Che et al., 2016; Derksen et al., 2005; Foster et al., 1997), near-surface soil temperature and air temperature (Grippa et al., 2004; Josberger and Mognard, 2002; Singh and Gan, 2000), snow grain size and snow density (Dai et al., 2012), elevation (Savoie et al., 2009), geographic location and time of day (Sturm et al., 2010), wind speed and topographic relief (Smith and Bookhagen, 2016). In this study, we propose the following formulas (Eqs. (1) and (2)) to describe snow depth and snow water equivalent retrieval processes:

$$[\mathrm{DS}] = \mathrm{F}(\mathrm{A}, \mathrm{T}, \mathrm{G}, \mathrm{L}, \mathrm{S}, \mathrm{D}\ldots) + \varepsilon \quad (1)$$

in which, F ( ) denotes the transformation function. DS is the digital signal from remote sensing sensor (PM, active microwave, visible spectral remote sensing etc.). A is the atmosphere (wind speed, air temperature, humidity, precipitation etc.). T is the topography (elevation, terrain slope, aspect etc.). G is the ground (ground surface temperature, vegetation type etc.). L is the location (latitude, longitude). S is the snow properties (snow grain size, density, reflectance, snow depth, snow water equivalent etc.). D is the day of year. ε is residual error or uncertainty (uncertainty between sensor signal and measured snow properties).

Using the parameters (A, T, G, L, S, D …) to yield DS, is called the snow forward process (Eq. (1)). For example, Forman and Reichle (2015) used snow property parameters (S), which includes snow water equivalent, density and snow temperature, near-surface air temperature (A), soil and vegetation temperature (G) as input parameters of SVM approach (F(·)) to estimate PM brightness temperatures. Contrarily, when DS and other parameters (A, T, G, L, D …) are used to generate estimated value of snow parameters (e.g. snow depth), this process is