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Assimilating passive microwave remote sensing data into a land surface model to improve the estimation of snow depth

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Accurate spatiotemporal snow data are crucial for understanding climate systems and managing water resources in cold regions. This paper describes a snow data assimilation system that employs the ensemble Kalman filter to directly assimilate passive microwave brightness temperature data into a snow process model. In the system, the Common Land Model coupled with a snow grain size growth algorithm was adopted to predict layered snow state variables. The forcing data were derived from the Japan Meteorological Administration—Global Spectral Model (JMA-GSM) operational global data assimilation system. The Microwave Emission Model of Layered Snowpacks (MEMLS) was used to convert the snow state variables to brightness temperatures. The snow data assimilation system was one-dimensionally tested at a Siberian cold region reference site of the Coordinated Enhanced Observation Project (CEOP). The validation experiment indicates that the data assimilation system can improve depth estimates during the accumulation period but not the ablation period. The assimilation method proposed herein can be easily applied to an operational weather forecasting system to improve snow depth estimations.

1. Introduction

Snow cover is one of the most critical components in the cryosphere system, and it influences global climate system variability at multiple temporal and spatial levels (Cohen, 1994). Up to 53% of land in the Northern Hemisphere and up to 44% of land globally may be covered with snow during the winter (Foster & Rango, 1982). One-third of the water used for irrigation worldwide is temporarily stored as snow (Steppuhn, 1981). A snow surface can reflect a large fraction of incident solar radiation due to its considerable albedo, and snow cover is an effective insulator between the atmosphere and the soil surface. Therefore, accurate spatiotemporal snow data are crucial for understanding climate systems and managing water resources in cold regions (Ghan & Shippert, 2006; Kazama, Izumi, Sarukkalige, Nasu, & Sawamoto, 2008).

In recent decades, substantial efforts have been made to develop pertinent observations. For large-scale observations of snow, remote sensing is an important and effective method. Visible and near-infrared (VIR) remote sensing can detect the snow cover area (SCA) at a high spatial resolution. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) can detect daily SCA on a global scale (Hall, Riggs, Foster, & Kumar, 2010; Hall, Riggs, Salomonson, DiGirolamo, & Bayr, 2002). Passive microwave (PM) remote sensing has the capability of providing snow depth (SD) and snow water equivalent (SWE) information independent of weather or light conditions. PM remote sensing data, such as data from the scanning multichannel microwave radiometer (SMMR), special sensor microwave/imager (SSM/I), and Advanced Microwave Scanning Radiometer for Earth Observation System (AMSR-E), enable the retrieval of SDs and SWEs on large regional and global scales (Chang, Foster, & Hall, 1987; Che, Dai, Wang, Liu & Zhao, 2012; Dai, Che, Wang, & Zhang, 2012; Foster, Chang, & Hall, 1997; Kelly & Chang, 2003; Tedesco & Narvekar, 2010). Such retrieval algorithms have a common kernel of brightness temperature difference (TBD) at 18 and 37 GHz (or similar frequencies) that is based on the fact that larger amounts of snow crystals can lead to greater volume scattering, which corresponds to a larger TBD. However, recent studies have shown that snow grain size, density, and stratigraphy can significantly influence the accuracy of SD and SWE estimates, which require more quantitative analyses (Che, Li, Jin, Armstrong, & Zhang, 2008; Durand, Kim, & Margulis, 2008; Durand & Liu, 2012; Foster et al., 2005; Parde, Goita, & Royer, 2007).

Another approach for obtaining snow properties is the thermodynamic model of snow process (Andreadis & Lettenmaier, 2012; Bartelt & Lehning, 2002; Loth & Graf, 1993; Lynch-Stieglitz, 1994; Niwano, Aoki, Kuchiki, Hosaka, & Kodama, 2012; Sun, Jin, & Xue, 1999). Snow process models can describe the dynamics of snow state variables based on snow physics. They are capable of obtaining snow density, temperature, wetness, layering, and snow grain size (Langlois et al., 2009), which are the input for snow radiative transfer models or inverse algorithms (Huang, Margulis, Durand, & Musselman, 2012; Kang & Barros, 2012). One advantage of snow process models is that the simulated snow states are spatiotemporally and physically consistent.

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However, obtaining highly accurate predictions for snow variables using snow models is challenging due to the insufficient knowledge of snow processes and their simplifications and parameterizations, as well as the uncertainties in forcing data, initial states and model parameters (Durand et al., 2008; Slater et al., 2001).

According to these analyses, snow observations and snow modeling have specific advantages and disadvantages. Some efforts have attempted to integrate snow observations and snow modeling using the data assimilation method (Andreadis & Lettenmaier, 2006; Clark et al., 2006; De Lannoy et al., 2012; Fletcher, Liston, Hiemstra, & Miller, 2012; Sun, Walker, & Houser, 2004; Takala et al., 2011). In the North American Land Data Assimilation System (NLDAS), in situ snow observations were successfully assimilated into land surface models (Pan et al., 2003; Sheffield et al., 2003); the snow cover fraction (SCF) or SCAs and SWEs derived from remote sensing data were also successfully assimilated (Kumar et al., 2008; Su, Yang, Niu, & Dickinson, 2008). However, Andreadis and Lettenmaier (2006) reported a discouraging result when the SWE products were assimilated into the variable infiltration capacity (VIC) because there are large errors in the AMSR-E SWE products. The assimilation of SCA/SCF into the snow process model by an empirical relationship between SCA and SWE is an indirect method (Andreadis & Lettenmaier, 2006; Clark et al., 2006; Niu & Yang, 2007).

Current methods focus on assimilating snow product data (such as SD and SWE) that were interpolated from ground surface observations or retrieved from PM remote sensing data. However, PM brightness temperature data include not only SD and SWE but also information such as snow grain size, density, and physical temperature as well as stratigraphic conditions (Durand et al., 2008; Foster et al., 2005). In contrast to previous investigations, this study explores the direct assimilation of PM brightness temperature data into a snow process model. The novel assimilation method employs a microwave radiative transfer model of snow to convert the snow state variables into brightness temperatures, which can be observed using satellite PM sensors. Consequently, the assimilation scheme becomes a forward process, and the microwave radiative transfer model input (e.g., SD, grain size, density, and temperature in layered snowpacks) can be simulated using the snow process model. These variables can then be analyzed and updated using the data assimilation algorithm. Therefore, the SD, SWE, and other snowpack variables can potentially be improved through assimilating the PM brightness temperature data.

The purpose of this study is to evaluate the feasibility of the snow satellite data assimilation system, that directly assimilates PM brightness temperature data into a snow process model using a snow microwave radiative transfer model. The snow satellite data assimilation scheme, including the snow process model, snow microwave radiative transfer model, and assimilation algorithm, is introduced in Section 2. Section 3 describes the implementation of snow data assimilation experiments at seven cold region sites of the Coordinated Enhanced Observation Period/Asia–Australia Monsoon Project (CEOP/CAMP), including experimental sites, forcing data, remote sensing data, and their error estimations. The experimental results are interpreted and discussed in Sections 4 and 5, and the conclusion and potential improvements for the current system are described in Section 6.

2. Snow data assimilation scheme

The new snow data assimilation system includes four primary components. First, a model operator forecasts the snow state variables. Second, an observation operator transfers the snow state variables to PM brightness temperatures. The observation operator is a radiative transfer model of snowpack that simulates the brightness temperature using the snow properties as input. Third, an assimilation algorithm fuses the PM brightness temperatures from the system simulation and satellite observation and updates the snow state variables. The last component of the system is the error estimation of the observation and model, which is the foundation of assimilation and involves the above three parts. Fig. 1 depicts the framework of the snow satellite data assimilation system.

2.1. Model operator

The Common Land Model (CoLM) is a recently developed state-of-the-art land surface model (Dai et al., 2003). The original aim of the CoLM was to develop a prototype modular land surface model for weather forecasting and climate studies. In the CoLM model, snow is divided into five layers at most, depending on the SD; the water and energy cycles within the snowpack also absorb three additional outstanding land surface schemes: LSM (Bonan, 1996), BATS (Dickinson, Henderson-Sellers, & Kennedy, 1993), and IAP94 (Dai & Zeng, 1997). For snow compaction, three metamorphisms are considered (destructive, overburden, and melt), whereas the snow layer is combined and subdivided based on the entire SD. The internal models are not described herein but are detailed in other studies (Dai et al., 2003).

In this study, the CoLM was employed as the model operator to predict the snow state variables. Although the current CoLM does not estimate the snow grain size, this is a critical variable for representing the thermal snowpack process. To link the snow process and microwave transfer models, grain size was used to determine the correlation length and microwave scattering properties of snowpacks. Early and recent studies have indicated that snow grain size is a significant snow variable influencing the microwave radiation of a snowpack (Chang, Gloersen, Schmugge, Wilheit, & Zwally, 1976; Durand et al., 2008; Langlois et al., 2012). Therefore, a snow granular growth rate equation, which was proposed by Jordan (1991), was coupled with the current CoLM as follows:

$$\frac{\partial d}{\partial t} = \frac{g_1}{d} D_{e0s}\left(\frac{1000}{P_a}\right)\left(\frac{T}{273.15}\right)^6 C_{kT}\left|\frac{\partial T}{\partial z}\right| \tag{1}$$

where $\frac{\partial d}{\partial t}$ represents the time step variation in the snow optical grain diameter d (m), the adjustable variable g_1 possesses a value on the order of 5.0×10^{-7} (m^4/kg), D_{e0s} is the effective diffusion coefficient for water vapor in snow at 1000 mb and 0 °C (0.92×10^{-4} m^2/s), P_a is the atmospheric pressure (mb) over the snow surface, T is the snow temperature (K), $\left|\frac{\partial T}{\partial z}\right|$ is the temperature gradient in snowpacks (z is the distance to the nodal midpoint from the snow/ground interface (m)), and C_{kT} is the variation in saturation vapor pressure as a function of temperature relative to phase k (N/m^2/K):

$$C_{kT} = \frac{cl_k}{T^2}\left[\frac{L_{vk}}{R_w T} - 1\right]\exp\left(-\frac{L_{vk}}{R_w T}\right) \tag{2}$$

where $k = i$ for a volume fraction of liquid water (θ_l) less than 0.02, and otherwise, $k = l$; L_{vl} is the latent heat for evaporation of water; L_{vi} is the latent heat for sublimation of ice; R_w is the gas constant for water vapor (461.296 J/kg·K); and $c1_l$ and $c1_i$ are constants. When snow is characterized as wet based on the θ_l from the CoLM simulations, a simple relationship can be used to describe the grain size growth as a function of time as follows:

$$\begin{cases} \dfrac{\partial d}{\partial t} = \dfrac{g_2}{d}(\theta_l + 0.05) & (0<\theta_l<0.09) \\ \dfrac{\partial d}{\partial t} = \dfrac{g_2}{d} * 0.14 & (\theta_l \geq 0.09) \end{cases} \tag{3}$$

where the θ_l is the liquid water volume fraction from the CoLM, the time step default is 1 h (3600 s), and g_2 is an approximate fit value (4.0×10^{-12} m^2/s).

Although the grain size of new snow may be related to air temperature, wind and other snowfall conditions, we utilized a constant size for