ASSIMILATION OF MODIS SNOW COVER FRACTION FOR IMPROVING SNOW VARIABLES ESTIMATION IN WEST CHINA

Chunlin Huang
Cold and Arid Regions Environmental and Engineering Research Institute, CAS,
Lanzhou, 730000, China

ABSTRACT

Accurate estimation of snow properties is important for effective water resources management especially in mountainous areas. In this work, we develop a snow data assimilation scheme based on ensemble Kalman filter (EnKF), which can assimilate remotely sensed snow observations into the Common Land Model (CoLM) to produce spatially continuous and temporally consistent snow variables. The snow cover fraction (SCF) product (MOD10C1) from the moderate resolution imaging spectroradiometer (MODIS) aboard the NASA Terra satellite was used to update CoLM snow properties. The assimilation experiment is conducted during 2003-2004, in Xingjiang province, west China. The preliminary results are very promising and show that distributions of snow variables (such as SCF, snow depth, and SWE) are more reasonable and reliable after assimilating MODIS SCF data. The results also indicate that EnKF is an effective and operationally feasible solution for improve snow properties prediction.

Keywords: MODIS SCA, Data Assimilation, Ensemble Kalman Filter, Common Land Model, Snow Depth, Snow Hydrology

1. INTRODUCTION

Snow plays an important role in energy and water cycles by modifying turbulent and radiative exchange between the ground and atmosphere, especially over large areas of the mid-latitudes. Snow is also a vital water resource globally, particularly in semi-arid regions, where a significant amount of water comes from seasonal snowmelt in mountainous regions. It has been estimated that one-sixth of the global population lives in areas where the seasonal cycle of snowmelt-driven runoff dominates temporal patterns of streamflow (Barrett et al., 2005). Consequently, accurate estimation and monitoring of snow properties, such as snow coverage and water equivalent, have important implications for water resources management.

Current model-based forecasting approaches can predict snow properties (such as snow cover, snow density, snow depth, snow temperature, and SWE) evolution in time and space, but accuracies of the modeled snow variables depend on model physics, model parameters and atmospheric forcing data (Essery et al., 2004 and 2009; Feng et al., 2008). Though ground observations is a very useful and reliable way to monitor snow properties evolution such as snow courses and automated measurement devices (snow pillow), they are unable to capture fully the considerable spatial and temporal variability in snow properties over large areas. Remote sensing offers an opportunity for observation of snow properties, like areal extent and water equivalent, over larger areas (Schmugge et al., 2002). Various snow cover products are currently produced through optical remote sensing sensors such as Geostationary Operational Environmental Satellites (GOES), Advanced Very High Resolution Radiometer (AVHRR), and Moderate-Resolution Imaging Spectrometer (MODIS) (Hall et al., 2002; Maurer et al., 2003). However, these snow cover data are easy to be contaminated by cloud, which results in spatially and temporally discontinuous snow cover data. Additionally, optical remote sensing lacks any information about snow depth or snow water equivalent (SWE) which is much useful for hydrological application. Passive microwave remote sensing is also an important means to detect snow properties. These sensors are not restricted by weather conditions and can retrieve snow depth and SWE (Chang et al., 1987, Kelly et al., 2003). However, the existing snow retrieval algorithms still are limited by several problems such as snow stratigraphy, forest cover, liquid precipitation and wet snow, which affect the microwave emission characteristics and make it difficult to accurately extract values of snow properties (Grody and Basist, 1996; Pulliainen and Hallikainen, 2001; Foster et al., 2005). Data assimilation provides a framework for optimally merging information from remotely sensed observations and hydrologic model predictions (McLaughlin, 1995). Snow data assimilation studies are generally increasing frequency in recent years, such as direct insertion of snow observations (snow depth, SCF, or SWE) into land surface models (Rodell & Houser ,

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2004；Sun et al., 2004), assimilating satellite-based SCF to improve SWE by snow depletion curve (Clark et al., 2006；Durand et al, 2008), and assimilating directly passive microwave brightness temperature data (Durand et al, 2009). They demonstrated capabilities of data assimilation method in updating snow properties by assimilating different satellite observations related to snow properties.

The objective of this study is to explore the feasibility of an EnKF method that assimilates daily 0.05° MODIS snow cover fraction (SCF) data (MOD10C1) into the common land model (CoLM) land surface model in Xinjiang province.

2. METHODS

2.1 Land Surface Model

In snow data assimilation, a land surface model (LSM) is used as the forward operator to simulate snow variables evolution. The LSM used in this study is the Common Land Model (CoLM). CoLM was developed for community use by a grassroots collaboration of scientists who have an interest in making a general land model available for public use and further development. It combines the best features of three existing LSM's that are modular and well documented three existing successful and relatively well documented and modular land models: the Biosphere-Atmosphere Transfer Scheme (BATS) (Dickinson et al, 1993), Bonan's Land Surface Model (LSM) (NCAR, 1996), and the 1994 version of the Chinese Academy of Sciences Institute of Atmospheric Physics LSM (IAP94) (Dai et al, 2003). CoLM has one vegetation layer, 10 unevenly spaced vertical soil layers, and up to 5 snow layers (depending on snow depth). The detailed description of model structure, physical parameterizations, and model parameters are represented in Dai et al (2001).

2.2 Ensemble Kalman Filter

Kalman filter (Kalman, 1960) is a widely used optimal sequential data assimilation algorithm for dynamics and measurement processes with Gaussian error statistics. For nonlinear dynamics, the extended Kalman filter (EKF) can be used, which is based on the first order linearization and is very unstable to deal with strongly nonlinear problems (Miller et al., 1999). The main assimilation algorithm used in this study is the ensemble Kalman filter (EnKF), which was first proposed by Evensen (1994). It uses an ensemble of model realizations to evaluate necessary statistics. EnKF is suitable for handling nonlinearities and large dimensions and is easy to implement. Here we provide only a brief algorithm summary needed to understand the implementation of EnKF. Consider a vector that is comprised of the state variables of interest (e.g. SWE, snow depth, or snow cover fraction) X. The model state equation can then be written as

$$X_{i,t+1}^{f} = M(X_{i,t}^{a}) + w_i \qquad w_i \sim N(0,Q) \qquad (1)$$

Here, ***M(.)*** is model operator and represents land surface model (CoLM) in our case. It is applied to propagate the model state variables. The superscripts 'a' and 'f' refer to state variables of analysis and forecast, respectively. $X_{i,t+1}^{f}$, is the forecasted state variable of each member at the time t+1; $X_{i,t}^{a}$ is the analyzed state variable of each member at the time t; $\boldsymbol{Q}$ is model error covariance at time t; $\boldsymbol{w_i}$ is model error vector, which conforms to Gaussian distribution with zero mean and covariance matrix $\boldsymbol{Q}$. The observation equation can be written by

$$Y_{i,t+1} = H(X_{i,t+1}^{f}) + v_i \qquad v_i \sim N(0,R) \qquad (2)$$

Where, ***H(.)*** is observation operator used to relate model state variables to observations. It need not be linear. $\boldsymbol{Y_{i,\,t+1}}$ is simulated observation of each member at the time t+1; $\boldsymbol{R}$ is observation error covariance; $\boldsymbol{v_i}$ is random error vector of observation with zero mean and covariance matrix $\boldsymbol{R}$. In our case, observations are MODIS SCA. The algorithm starts with the generation of an ensemble of model state variables by perturbing first guest state variables X_{t_0}. Each ensemble member of state variables is propagated with Eq. (1) until observation becomes available. At the time of observation, each ensemble member of forecast state variables is then updated with the following equations.

$$X_{i,t+1}^{a} = X_{i,t+1}^{f} + K_{t+1}[(Y_{t+1}^{o} + v_i) - H(X_{i,t+1}^{f})] \qquad (3)$$

$$K_{t+1} = P_{t+1}^{f} H^{T} (H P_{t+1}^{f} H^{T} + R)^{-1} \qquad (4)$$

Where K_{t+1} is Kalman gain matrix at time t+1; P_{t+1}^{f} is the forecasted background error covariance matrix at time t+1, which is sampled from the ensemble of model state and perturbed measurement vectors; $H(X_{i,t+1}^{f})$ is the simulated MODIS SCA of each member at the time t+1.

2.3 Assimilation strategy of SFC

In this study, we choose a very simple scheme to assimilate MODIS SFC product as follows. (1) To update snow depth of each ensemble member using satellite SCF. When MOD10C1 SCF is greater 10%, the snow depth will be increased to 2cm for those realizations with snow depth less than 2cm. (2) to adding new snow layer. When MOD10C1 SCF is greater 10% while the model is without snow, a new snow layer with 2cm will be added to model grid. (3) To removing wrong snow properties. When MOD10C1 SCF is less than 10%, the modeled snow layers will be removed.

3. EXPERIMENT DESIGN

3.1 Study area description

In this work, the Xinjiang province in west China is selected as study area, which extends from 33° to 49° N and from 72° to 97° E (Fig. 1). Mountains, plains and deserts are the three major geomorphologic units. Influenced by the Siberian circulation, snowfall is very frequent during winter and spring in the northern of study area, which is one of three snow centers in China, and Snow disasters often occur during November to March. The average snow depth is 60 cm, with a maximum of 1–2 m in the mountainous areas. Disasters caused by heavy snow frequently result in the death of animals and people, and destroy traffic and telecommunication devices (Liang et al., 2008). Therefore, this area is very suitable for validating our snow data assimilation scheme.

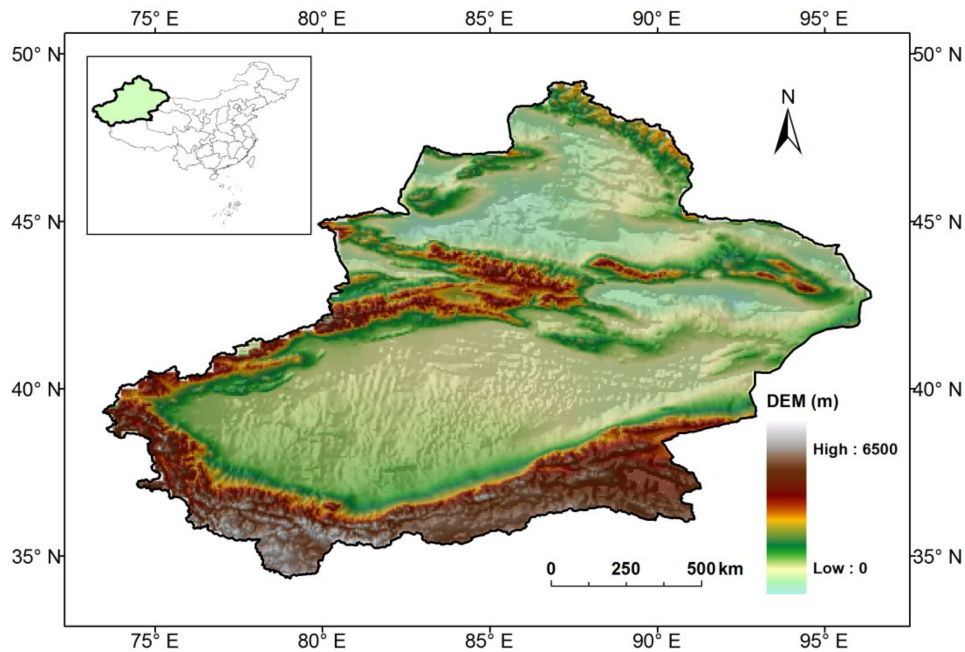

Fig. 1 The study area of Xinjiang province, China

3.2 Model implementation

In this work, CoLM is run with 0.05° model grid resolution. The model parameters are related to soil and vegetation characteristics in CoLM, so the USGS land use/land cover map and FAO soil texture dataset are chosen. The 3-houly atmospheric forcing data were drawn from the Global Land Data Assimilation System (GLDAS) forcing database at 0.25° spatial resolution. Then the forcing data are convert to hourly 0.05° using the method proposed by Liston and Elder (2006). The simulation period is from 2002 to 2004.

3.3 Observation data

The dataset we used is MODIS/Terra Snow Cover Daily L3 product (MOD10C1) with a spatial resolution of 0.05 degree, which is based on 500-m Terra/MODIS observations (Hall et al. 2002). Snow percentage in each grid cell is calculated using 500 m totals of the number of snow observations and count of land observations in that cell at the time of the satellite overpass (approximately 10:30 A.M. local time).

4. RESULTS

In order to investigate the feasibility of our snow assimilation scheme, two snapshot results are randomly chosen in day 330 of 2002 and day 30 of 2003. Fig. 2 and Fig. 3 present results between the modeled and assimilated snow properties (snow fraction, snow depth, and SWE) in Day 330 of 2002 and Day 30 of 2003 respectively. From MODIS snow and cloud results, we see that cloud contamination is very serious in the study area, which results that it is difficult to identify snow by MOIDS product under thick cloud condition. In day 330 of 2002, half of study area is covered by cloud and only a limited snow can be seen by MODIS along mountainous regions. Snow distribution in spatial pattern is much different between MODIS snow fraction and the simulated snow fraction by CoLM. After assimilation, snow distribution is more reasonable in study region. It not only merges the available snow fraction information from MODIS in current time but also uses the previous snow information from CoLM. Snow under thick cloud also can be seen after assimilating MOIDS snow fraction data. Snow depth and SWE are also updated and more reasonable comparing to the corresponding simulations. In day 30 of 2003, the study area is cover by more heavy cloud and snow can only be seen in the northern and southeast regions from MODIS snow/cloud fraction product. The snow fraction, snow depth and SWE are also improved obviously after assimilation in comparison with results of simulations.

5. CONCLUSIONS

In this work, we developed a simple snow data assimilation scheme which is used to assimilated satellite-based snow cover fraction data and this scheme was tested in Xinjiang province, West China. Due to cloud containment, snow cover fraction data is discontinuous in space and time, and high-quality snow fraction data is very seldom in study region. Data assimilation was proved to be a very useful and practical way to merge remote sensing data into land surface model to improve snow properties estimation. The snow distribution in spatial pattern was much reasonable via assimilating MODIS snow cover fraction data comparing to the corresponding simulation. This method can reduce cloud effect on snow cover extension and produce more accurate and continuous snow cover fraction data. Unfortunately, the quantity of snow depth and SWE was not compared in this study. In future, we will collect in-situ snow depth measurements distributed in this area to validate the assimilated snow depth and SWE. Additionally, we will also develop new scheme to simultaneously assimilate MODIS snow cover fraction and passive microwave brightness temperature.

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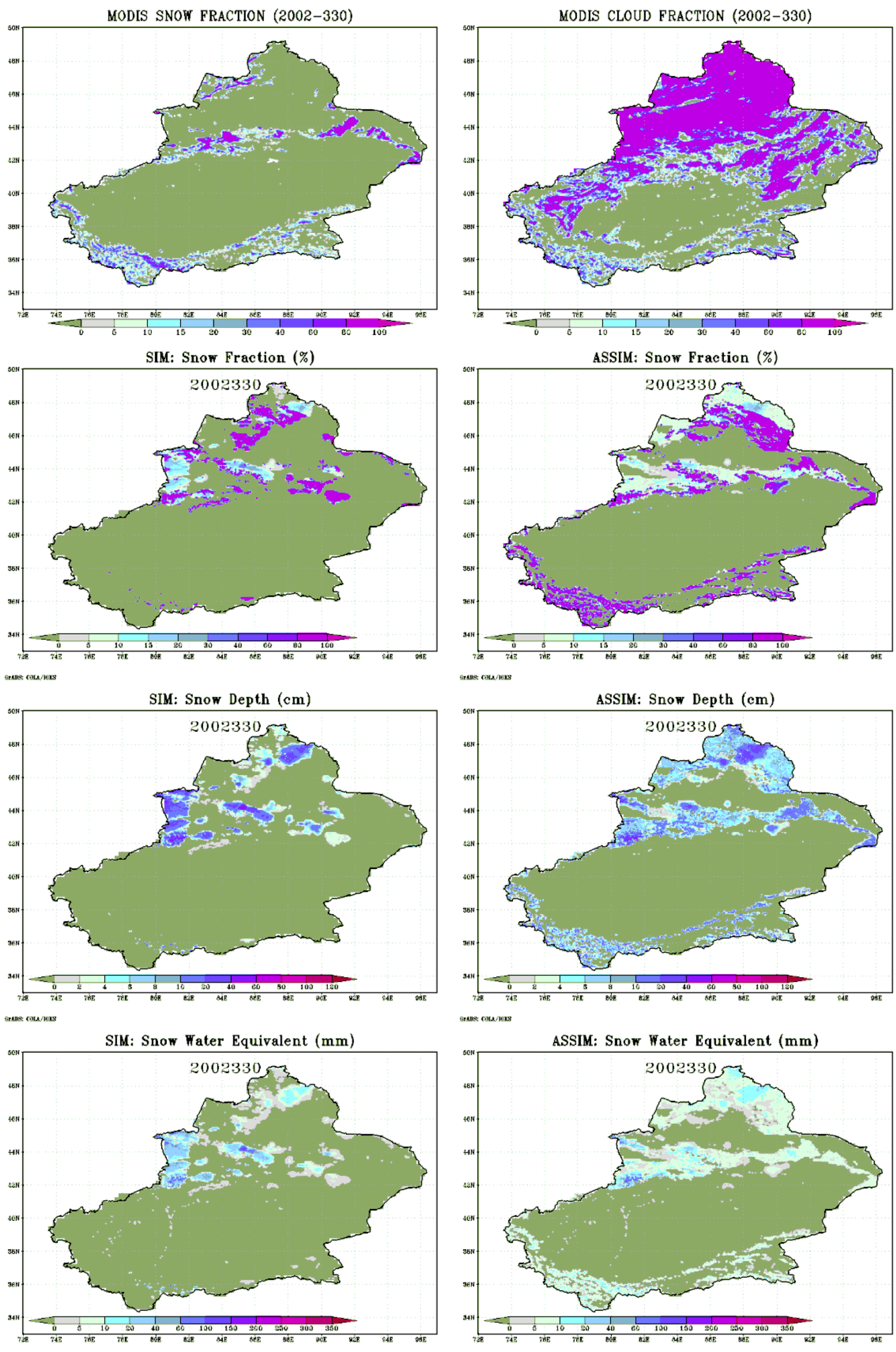

Fig. 2 Comparison between the modeled and assimilated snow properties in Day 330 of 2002.

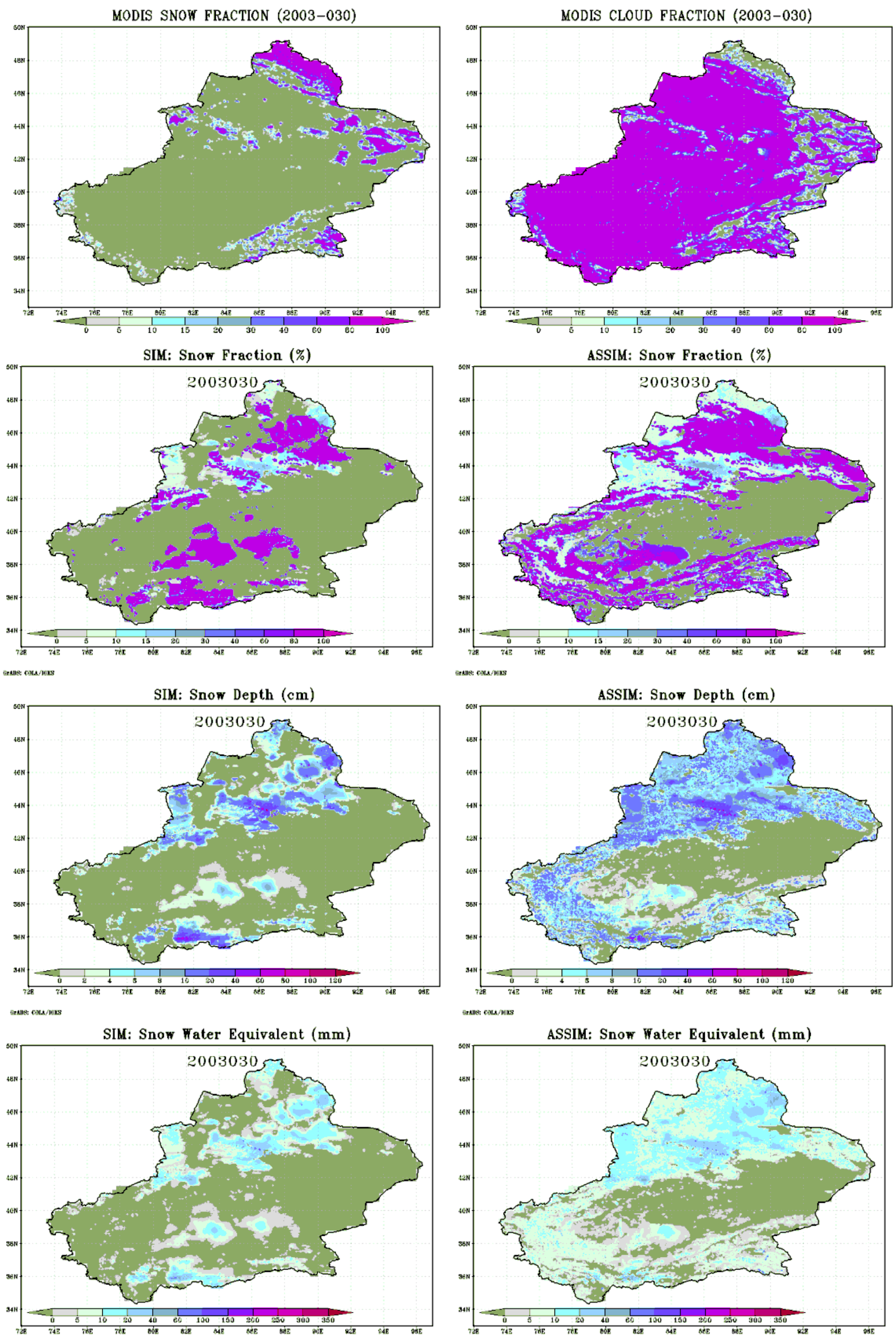

Fig. 3 Comparison between the modeled and assimilated snow properties in Day 30 of 2003.