Estimating Snow Water Storage in North America Using CLM4, DART, and Snow Radiance Data Assimilation

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ABSTRACT

This paper addresses continental-scale snow estimates in North America using a recently developed snow radiance assimilation (RA) system. A series of RA experiments with the ensemble adjustment Kalman filter are conducted by assimilating the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) brightness temperature $T_B$ at 18.7- and 36.5-GHz vertical polarization channels. The overall RA performance in estimating snow depth for North America is improved by simultaneously updating the Community Land Model, version 4 (CLM4), snow/soil states and radiative transfer model (RTM) parameters involved in predicting $T_B$ based on their correlations with the prior $T_B$ (i.e., rule-based RA), although degradations are also observed. The RA system exhibits a more mixed performance for snow cover fraction estimates. Compared to the open-loop run (0.171 m RMSE), the overall snow depth estimates are improved by 1.6% (0.168 m RMSE) in the rule-based RA whereas the default RA (without a rule) results in a degradation of 3.6% (0.177 m RMSE). Significant improvement of the snow depth estimates in the rule-based RA is observed for tundra snow class (11.5%, $p < 0.05$) and bare soil land-cover type (13.5%, $p < 0.05$). However, the overall improvement is not significant ($p = 0.135$) because snow estimates are degraded or marginally improved for other snow classes and land covers, especially the taiga snow class and forest land cover (7.1% and 7.3% degradations, respectively). The current RA system needs to be further refined to enhance snow estimates for various snow types and forested regions.

1. Introduction

Estimates of snow depth and snow water equivalent (SWE) are critical for climate studies and water resource management. Data assimilation (DA) has been identified as a powerful method to generate improved estimates by merging observations and model forecasts based on their uncertainties. As a DA method, radiance assimilation (RA) incorporates microwave brightness temperature $T_B$ observations into a land surface model (LSM) coupled with a microwave radiative transfer model (RTM). Previous studies successfully used RA at relatively small spatial scales (i.e., point scale, mesoscale, or basin scale). Durand and Margulis (2006) conducted a point-scale synthetic test, in which they demonstrated that RA can recover the true SWE and addressed the relative contributions of microwave-frequency channels to correcting the SWE estimates in

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the RA scheme. In their follow-on study (i.e., Durand and Margulis 2007), they also performed the mesoscale synthetic RA experiments and showed that RA can be an alternative to existing retrieval algorithms (e.g., Foster et al. 2005), which have limitations with respect to the characterization of SWE exceeding the 100-mm threshold (Dong et al. 2007). Durand et al. (2009), a point-scale snow RA study, assimilated (ground based) real microwave radiance observations and demonstrated that SWE estimated by the RA scheme is more accurate than that estimated by an empirical retrieval algorithm. Using the same dataset, Toure et al. (2011) showed that the additional use of horizontally polarized $T_B$ with a more elaborated representation of snowpack stratigraphy further enhances the snow RA performance. Andreadis and Lettenmaier (2012) also emphasized the importance of representing snowpack stratigraphy in snow models for improving snow estimates through RA. Using snow depth data from a 2002 Nome–Barrow snowpit transect, they demonstrated that significantly improved snow depth estimates can be obtained by using a multilayer snow model in the RA scheme. Che et al. (2014) tested the RA method in the eastern Siberian taiga area and showed that RA can enhance snow estimates during the snow accumulation period, but more efforts are needed for the snow-melting period. Dechant and Moradkhani (2011) successfully applied the RA method to the basin-scale SWE estimates and subsequent operational streamflow forecasts. Langlois et al. (2012) developed a two-step iteration scheme, in which the simulated snow grain size (first iteration) and SWE (second iteration) were corrected by minimizing the root-mean-square error (RMSE) between the estimated and observed $T_B$. They demonstrated that incorporating $T_B$ observations into a snow model coupled with RTM within the two-step iteration scheme considerably reduces uncertainties in the simulated SWE. However, continental-scale applications of RA require a substantial amount of further research because of various snow and vegetation cover conditions in the continental domain.

In this study, we address the feasibility of RA to improve snow estimates at the continental scale. This work builds on our previous research (Kwon et al. 2015) in which the Community Land Model, version 4 (CLM4; Oleson et al. 2010), is coupled with the Dense Media Radiative Transfer–Multi Layers (DMRT-ML; Picard et al. 2013) to predict $T_B$ from the snowpack. The observed $T_B$ from the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) is then assimilated using the ensemble adjustment Kalman filter (EAKF; Anderson 2001), which is an option in the Data Assimilation Research Testbed (DART; Anderson et al. 2009) developed by the National Center for Atmospheric Research (NCAR).

We hypothesize that the continental-scale RA performance in estimating snow depth and SWE can be improved through 1) simultaneous updates of all model physical states and RTM parameters involved in predicting $T_B$ and 2) a rule-based approach in which prior estimates are updated depending on their correlation with predicted $T_B$ within the ensemble. Kwon et al. (2015) emphasized that all physical states and parameters in the model used to estimate $T_B$ should be appropriately updated in RA to minimize errors related to them. Kwon et al. (2015) also showed that the $T_B$ signal can be dominated by snow and soil properties (in particular, snow grain size) instead of SWE (or snow depth). Such dominance in RA can degrade SWE (or snow depth) estimates because of undesirable correlations between the prior SWE (or snow depth) and $T_B$ estimates. A rule-based RA could ameliorate this issue.

The remainder of this paper is organized as follows. Section 2 describes the coupled RA system, the datasets, and the experimental design. Results are analyzed and discussed in section 3. Conclusions are enumerated in section 4.

2. Coupled radiance assimilation system, datasets, and experimental design

a. Coupled radiance assimilation system

The coupled CLM4, DART, and RTMs data assimilation system is hereafter referred to as the coupled RA system (see Fig. 1 for a schematic diagram of the system). CLM4 simulates snow and soil states (snow depth, snow layer thickness, snow temperature, soil temperature, and soil moisture) and snow characteristics (density, grain radius, and wetness). Whenever AMSR-E $T_B$
observations are available, CLM4 creates restart files for each ensemble member. The forecasted states and characteristics in the restart files are then read by DART and fed to an observational operator (i.e., RTMs), which converts the model states and snow characteristics to $T_B$. At the same time, DART reads AMSR-E $T_B$ observations and updates model states and snow characteristics by the assimilation process. These updated values in the restart files are used for subsequent model forecasts.

1) DART

Given its flexibility, DART has been coupled with various atmospheric and oceanic models (Anderson et al. 2009) and land surface models, including CLM4 (Zhang et al. 2014). In this study, we additionally incorporated RTMs as an observational operator to predict $T_B$.

DART involves a variety of ensemble-based assimilation algorithms. One of them, the EAKF (Anderson 2001), is applied in this study. In the EAKF, an updated (posterior) ensemble is generated by shifting the forecasted (prior) ensemble so that it has the same mean and standard deviation as those of the continuous posterior (Anderson et al. 2009). Anderson (2001) suggests that, in particular for a small ensemble size, the EAKF significantly outperforms the traditional ensemble Kalman filter (EnKF; Evensen 1994). More detailed descriptions of DART and the EAKF are available in Anderson et al. (2009) and Anderson (2001), respectively.

2) CLM4

CLM4 (Oleson et al. 2010) is the land component of the Community Earth System Model (CESM; Gent et al. 2011). CLM4 has 15 soil layers, up to five snow layers (depending on snow depth), and one canopy layer. CLM4 is advantageous for this study because it represents the snowpack as multiple layers and simulates snow thermodynamics. Durand et al. (2008) demonstrated that the use of a five-layer snow scheme of CLM4 provides more accurate $T_B$ calculations than a three-layer snow scheme. Furthermore, CLM4 is capable of simulating snow densification processes and melt–refreeze cycles, which are critical for RTMs to predict $T_B$. Therefore, CLM4 coupled with RTMs could potentially provide improved estimates of snow physical properties through RA.

As a community model, CLM has been extensively evaluated in a wide range of applications, and it evolves continuously from worldwide contributions. Recently, Kwon et al. (2015) linked CLM4 with two snow radiative transfer models, DMRT-ML (Picard et al. 2013) and the Microwave Emission Model of Layered Snowpacks (MEMLS; Wiesmann and Mätzler 1999). Kwon et al. (2015) also analyzed the error characteristics of these coupled models (CLM4–DMRT-ML and CLM4–MEMLS) from RA perspectives.

CLM4 computes snow depth, snow grain radius, and mass of liquid water and ice within the snowpack at every time step. SWE is the sum of snow liquid water and snow ice. Snow density (kg m$^{-3}$) is equal to SWE (kg m$^{-3}$) divided by snow depth (m). Therefore, updating all these snow variables separately in RA would violate their relationships in the model and cause excessive updating of snow mass. Zhang et al. (2014) updated SWE only through data assimilation. The updated SWE was redistributed to the mass of snow liquid water and ice, and snow depth was adjusted based on its physical relationship with SWE by using the prior snow density. This updating scheme was used in this study. Note that snow density was assumed to be unchanged during the adjustment process and this assumption may affect the assimilation results.

3) RADIATIVE TRANSFER MODELS

In the RA system, the RTM is an observational operator predicting $T_B$. Here, we used DMRT-ML to estimate microwave $T_B$ from the snowpack. DMRT-ML is a multilayer microwave emission model that calculates the microwave scattering and absorption coefficients of snowpack based on the Dense Media Radiative Transfer (DMRT) theory (Tsang and Kong 2001). To solve the radiative transfer equation, the model employs the discrete ordinate radiative transfer (DISORT) method (Jin 1994), which considers multiple scattering within and between the layers. DMRT-ML provides several combinations of reflectivity models and dielectric constant models for the snow-bottom interface [see Table 1 in Picard et al. (2013)]. To estimate the effect of the underlying soil on microwave emission, we used the rough bare soil reflectivity model by Wegmüller and Mätzler (1999) and calculated the soil dielectric constant based on Dobson et al. (1985). Snow and soil inputs required by DMRT-ML include snow layer thickness, density, wetness, snow grain radius, snow temperature, soil temperature, and soil water content, all of which are simulated by CLM4.

DMRT-ML has a stickiness parameter (Ding et al. 2001) that affects the size of the scatterers. Stickiness depends on snow type and is difficult to obtain from measurements (Picard et al. 2013). In this study, therefore, it is updated in the DA system.

It has been discussed in Brucker et al. (2011) and Roy et al. (2013) that snow grain radius defined as in CLM4 does not coincide with the effective snow grain radius in DMRT-ML because of the effects of the snow stickiness and the heterogeneity of snow grain size and shape.
Although the stickiness parameter in DMRT-ML was updated during the assimilation, some errors may be introduced by this discrepancy.

Brightness temperature at the top of the atmosphere (TOA) is modeled based on Durand and Margulis (2007). To consider the effects of atmosphere and vegetation, we used the atmospheric RTM by Ulaby et al. (1981) as implemented in Durand and Margulis (2007), and vegetation transmissivity was calculated from the optical depth of vegetation $\tau_c$ (Jackson and Schmugge 1991):

$$\tau_c = b' \lambda^x w_c / \cos \theta,$$

where $b'$ and $x$ are empirical coefficients; $\lambda$ is the wavelength (cm); $w_c$ is the vegetation water content (kg m$^{-2}$), which is estimated from the leaf area index (LAI) following Paloscia and Pampaloni (1988); and $\theta$ is the incidence angle (55° for AMSR-E). Empirical coefficients ($b'$ and $x$) depend on vegetation type and are also subject to update through RA in this study.

Brightness temperature is estimated for snow/soil columns within a CLM4 grid cell, and these column-based $T_B$ estimates are averaged, weighted by areas, for each grid cell. In CLM4, snow cover fraction (SCF) is estimated for each column and is used for calculating the ground albedo, but the surface energy fluxes are simulated for a column without distinguishing between snow-covered and snow-free areas within a column. Thus, in our current version of the RA system, $T_B$ is not calculated separately for snow-covered and snow-free areas based on SCF within a column. This may introduce some errors in snow estimates by the RA system for areas where SCF is less than 1.

b. Datasets

1) AMSR-E BRIGHTNESS TEMPERATURE OBSERVATIONS

In this study, AMSR-E/Aqua daily global quarter-degree gridded brightness temperature data (Knowles et al. 2006) were assimilated into model simulations. AMSR-E observes TOA vertically and horizontally polarized (V pol and H pol, respectively) microwave radiance at six frequencies: 6.925, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz. Durand and Margulis (2006) reported that the 36.5-GHz channel contains the most significant information with respect to snow RA. Theoretically, it has been shown that microwave radiance at the 18.7-GHz channel is sensitive to snow depth (e.g., Tsang et al. 2000). Therefore, two frequency channels (i.e., 18.7 and 36.5 GHz V pol) were used in our RA experiments. Horizontally polarized brightness temperatures were not assimilated because they are sensitive to ice layer properties (Mätzler 1987; Durand et al. 2008; Rees et al. 2010), which cannot be realistically represented by the five-layer snow model.

In Durand and Margulis (2006), the 18.7-GHz channel does not significantly contribute to correcting the SWE estimates because of competing relationships, that is, a negative relationship between snow depth and $T_B$ (based on sensitivity analysis) and a positive relationship between snow depth and $T_B$ (resulting from a negative relationship between snow depth and snow grain size). This issue is also emphasized in our previous error characterization study (i.e., Kwon et al. 2015). As we hypothesized, however, the simultaneous update of states and RTM parameters and the rule-based approach may be able to mitigate the problem. Although the lower-frequency channels (i.e., 6.925 and 10.65 GHz) provide valuable information for deep snowpack (Durand and Margulis 2006), they were not exploited in this paper because of the nontrivial computational demand of the continental-scale RA experiments. The RA system was run on the Texas Advanced Computing Center (TACC) Lonestar supercomputer and, on average, about 25 min were required for a 1-day assimilation of two frequency channels. Most of the computation time was used by the observational operator (i.e., RTM) to estimate the prior $T_B$. However, the use of these additional frequencies may further improve the snow RA performance.

For computational efficiency, AMSR-E $T_B$ observations (0.25° spatial resolution) were scaled up to the CLM4 grid (0.9° × 1.25°). Performing the assimilation at the CLM4 grid rather than the AMSR-E grid results in a tenfold difference in the computational burden. The observation error was assumed to be 2 K. The microwave emission from liquid water, which has an emissivity close to unity, dominates the signal from the snowpack (Clifford 2010), and thus $T_B$ observations of wet snow are assumed not to contain information about snow depth. Therefore, we used only nighttime $T_B$ observations.

2) ATMOSPHERIC ENSEMBLE FORCING

We constructed 40 ensemble members of CLM4 simulations at 0.9° × 1.25° spatial resolution using the coupled DART–Community Atmospheric Model, version 4 (CAM4), reanalysis (Raeder et al. 2012) as atmospheric forcing. Compared to traditional approaches that perturb each atmospheric forcing field separately to produce the ensemble (e.g., Andreadis and Lettenmaier 2006; Su et al. 2008), the use of the DART–CAM4 reanalysis offers the advantage of physical consistency between forcing fields. The standard deviations of the
atmospheric forcing fields across the 40 ensemble members used in this study are presented in Table 1. The resulting spatial distribution of the standard deviation of SWE and snow depth across the ensemble on 15 January 2003 is given in Fig. 2.

3) INDEPENDENT SNOW DATA SOURCES FOR VALIDATION

RA results were compared with two independent snow data sources, that is, the Canadian Meteorological Centre (CMC) daily snow depth analysis data and the Moderate Resolution Imaging Spectroradiometer (MODIS) SCF observations. The CMC product provides Northern Hemisphere daily snow depth (Brasnett 1999; Brown and Brasnett 2010) with approximately 24-km spatial resolution. These daily snow depth data have been used by previous studies (e.g., Su et al. 2010; Reichle et al. 2011; Zhang et al. 2014; Toure et al. 2016) as a reference for model evaluations over the Northern Hemisphere.

The 0.05° MODIS/Terra level-3 daily global snow cover products (MOD10C1; Hall et al. 2006) are used for additional validation of the RA results. For comparison purposes, we upscaled the original MOD10C1 data to the CLM4 grid (0.9° × 1.25°) using the Climate Modeling Grid (CMG) confidence indices (CIs) [see Riggs et al. (2006) for further information on CIs]. A higher CI indicates less cloud cover within a pixel and thus better-quality SCF estimates. Only CMG grid cells that have the CI greater than 20% and a nonzero daily percentage of snow cover were considered during upscaling.

c. Experimental design

Model initial conditions were generated through two steps. First, a single member of CLM4 was run from 1948 to 1998 using the standard forcing (Qian et al. 2006) in CLM4. Then 40 ensemble members of initial conditions were created by running the model from December 1998 to October 2002 using the DART–CAM4 atmospheric reanalysis. These initial conditions were used by the RA system for the assimilation process from November 2002 to February 2003. November 2002 was considered a burn-in period, and thus the assimilation results from December 2002 to February 2003 were analyzed. The assimilation was

### Table 1. Std devs of the DART–CAM4 atmospheric forcing fields across the 40 ensemble members. The calculated std dev of each forcing field was averaged over the land points in North America (25°–72°N, 50°–175°W) for the assimilation period. The max and min values of the std devs are also presented.

<table>
<thead>
<tr>
<th>Forcing field</th>
<th>Std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Direct near-infrared incident solar radiation</td>
<td>10.42</td>
</tr>
<tr>
<td>Direct visible incident solar radiation</td>
<td>8.64</td>
</tr>
<tr>
<td>Diffuse near-infrared incident solar radiation</td>
<td>4.30</td>
</tr>
<tr>
<td>Diffuse visible incident solar radiation</td>
<td>4.05</td>
</tr>
<tr>
<td>Downward longwave radiation</td>
<td>11.73</td>
</tr>
<tr>
<td>Convective rain rate</td>
<td>4.15 × 10⁻⁶</td>
</tr>
<tr>
<td>Large-scale (stable) rain rate</td>
<td>5.68 × 10⁻⁶</td>
</tr>
<tr>
<td>Convective snow rate (water equivalent)</td>
<td>6.76 × 10⁻⁷</td>
</tr>
<tr>
<td>Large-scale (stable) snow rate (water equivalent)</td>
<td>4.62 × 10⁻⁶</td>
</tr>
<tr>
<td>Zonal wind speed</td>
<td>0.74</td>
</tr>
<tr>
<td>Meridional wind speed</td>
<td>0.77</td>
</tr>
<tr>
<td>Air temperature</td>
<td>1.07</td>
</tr>
<tr>
<td>Specific humidity</td>
<td>2.52 × 10⁻⁴</td>
</tr>
<tr>
<td>Atmospheric pressure</td>
<td>89.84</td>
</tr>
</tbody>
</table>

FIG. 2. Spatial distribution of the std dev of (a) SWE and (b) snow depth across the ensemble on 15 Jan 2003 in the open-loop case without assimilation.
conducted for the entire spatial domain at once. CLM4 grid cells are laterally independent and thus there was no lateral exchange of information across grid cells.

We conducted three classes of experiments (Table 2): 1) open-loop run without assimilation, 2) default update in RA, and 3) rule-based update in RA. Ten subexperiments were set up to demonstrate the effect of the simultaneous update of snow and soil states and RTM parameters on the RA performance (Table 2). In the RA_{SW}, and RA_{SW-R} cases, only SWE-related states including snow depth were updated [see section 2a(2)]. Additional updates of snow grain radius (RA_{SR} and RA_{SR-R}), snow temperature (RA_{RT} and RA_{RT-R}), soil water content and temperature (RA_{RTS} and RA_{RTS-R}), and RTM parameters (RA_{RTP} and RA_{RTP-R}) were considered in the other eight subexperiments. All 11 experiments were driven by the 40 randomly chosen ensemble members of the DART–CAM4 reanalysis over North America from December 2002 to February 2003. In the RA cases, AMSR-E T_B observations at two frequency channels (i.e., 18.7 V pol and 36.5 V pol) were assimilated. All grid cells in CLM4 have the same time (UTC), whereas T_B has been observed by AMSR-E at the approximately the same local time (0130 LST for the descending pass) for each grid cell. Therefore, based on the method suggested in Zhao et al. (2016), each CLM4 grid cell was run for a different set of time indices, constructed such that the model simulations all end on their respective observation time index.

Note that the states and RTM parameters in the current RA system are not updated when one or more of the ensemble members in a grid cell have no snow. In addition, to avoid unacceptably large increments, T_B observations are not assimilated if the difference between the T_B observation and the ensemble mean of the estimated prior T_B is larger than three standard deviations from the square root of the sum of the observation error and prior ensemble variances.

Model parameter estimation in the DA system has already been demonstrated by several previous studies (e.g., Moradkhani et al. 2005; Vrugt et al. 2006; Dechant and Moradkhani 2011; Su et al. 2011). In our continental-scale RA experiments (RA_{RTP} and RA_{RTP-R}), we updated three RTM parameters, that is, snow stickiness in DMRT-ML and two empirical parameters (x and b') in the vegetation RTM. Initial values of the three RTM parameters were randomly generated for each grid cell and each ensemble member within the given ranges (i.e., 0.1 ≤ snow stickiness ≤ 0.5, −1.656 ≤ x ≤ −0.804, and 0.496 ≤ b' ≤ 0.744). The ranges of the parameters were arbitrarily determined on the basis of previous studies [e.g., Mätzler (1998), Tsang et al. (2008), Andreadis and Lettenmaier (2012), and Picard et al. (2013) for the snow stickiness and Jackson and Schmugge (1991) and Huang et al. (2008) for x and b'] and our experience (e.g., Kwon et al. 2015). More refined ranges of the parameters for continental-scale applications need to be established in dedicated studies. For all other RA cases, we used constant values of 0.2 (for stickiness), −1.23 (for x), and 0.62 (for b') for all grid cells and ensemble members during the simulation period.

In the rule-based approach, the rule is determined based on a sensitivity analysis. Only when correlations between the prior estimates of snow/soil states and RTM parameters and the prior T_B have the same signs as the sensitivity index are the priors updated. We analyzed the sensitivity of T_B to snow/soil states and RTM parameters, that is, SWE, snow grain radius, snow temperature, soil temperature, soil water content, snow stickiness (in DMRT-ML), and two empirical parameters (x and b' in the vegetation RTM), all of which are updated in the RA scheme. For the sensitivity analysis, a single-layer dry snowpack was assumed and ±10% perturbations were applied to default values of SWE (181.6 kg m⁻²), snow grain radius (251 μm), soil water content (0.1), snow stickiness (0.2), x (−1.23), and b' (0.62). In reality, snow temperature (270 K) and soil temperature (270 K) were perturbed by ±3 K. As mentioned previously, we assumed that the SWE update determines the snow depth update, whereas snow density is not changed during the assimilation. In addition,
SWE is not an input to DMRT-ML but snow depth is used to estimate $T_B$. Therefore, the SWE perturbation was assumed to be applied to snow depth, that is, the default snow depth (0.8 m) was perturbed by ±10% to estimate the sensitivity of modeled $T_B$ to SWE. Figure 3 shows the results of the sensitivity analysis. Brightness temperature is negatively sensitive to SWE, snow grain radius, and soil water content while it is positively sensitive to snow and soil temperature, snow stickiness, and $b'$ for both 18.7 and 36.5 GHz channels. The sensitivity of $T_B$ to $x$ is positive for 18.7 and negative for 36.5 GHz pol channels.

In general, $T_B$ at microwave frequencies decreases with increasing SWE (or snow depth) owing to volume scattering as shown in the sensitivity analysis results (Fig. 3). However, during the middle to late winter, a reversal of the behavior (i.e., a positive relationship between SWE and $T_B$) has been found in observations at the 36.5-GHz channel due to the microwave emission from the snowpack itself when SWE exceeds a threshold value (e.g., Mätzler et al. 1982; Rosenfeld and Grody 2000; Derksen et al. 2010; Langlois et al. 2012). The threshold SWE value depends upon local conditions such as snow grain size, stratigraphy, and dielectric properties, and thus it is spatially and temporally variable (Langlois et al. 2012), although the reported threshold values are between 120 and 180 mm (Derksen 2008). However, the threshold values have not been established for different locations in North America, and thus it is hard to consider this slope reversal phenomenon at 36.5 GHz channel in a continental-scale RA study. Furthermore, the observed positive relationship between SWE and 36.5 GHz $T_B$ exhibits some noise (Derksen et al. 2010). In our rule-based RA experiments, therefore, we assumed that $T_B$ is not an indicator of SWE (or snow depth) when they are positively correlated and thus no update of the prior SWE happened.

The use of a small ensemble size for the computational efficiency of the DA system can cause a large sampling error and subsequently lead to spurious large correlations between two uncorrelated variables (Anderson 2007). DART has a localization distance parameter, which can be tuned for different observation types. The localization process restricts the negative aspects of spurious correlations by restricting the impact of observations to nearby grid cells (Anderson et al. 2009). In DART, observations in a given grid cell affect model states of neighboring grid cells based on the regression coefficient multiplied by a distance weight factor (Gaspari and Cohn 1999), which decreases from 1 to 0 until their physical distance approaches 2 times the specified localization distance (Anderson et al. 2009). For the above-mentioned experiments, we used the localization distance of 0.03 rad according to Zhang et al. (2014). Here, we conducted additional RA experiments (with localization distances of 0.01, 0.05, 0.07, 0.1, 0.15, 0.2, and 0.3 rad) to find out the proper localization distance for the RA system used in this study.

We also tested the effect of inflation on the snow RA performance. In ensemble DA, the ensemble spread decreases as more information from observations is assimilated into the system. This may cause filter divergence (Anderson et al. 2009). Inflation helps the DA system to maintain adequate variability. In this study, the spatially and temporally varying adaptive inflation (Anderson 2009) in DART was applied to each CLM4 state variable and RTM parameter by increasing the variance (uncertainty) of the ensemble estimates while maintaining the ensemble mean before using the RTMs to compute $T_B$. The amount of inflation is determined
by a Bayesian estimator as described in Anderson (2009) and is updated with each new assimilation cycle. In the localization and inflation experiments, all model states and RTM parameters were simultaneously updated with and without the rule.

3. Results and discussion

In this section, we present the assimilation results using the coupled RA system. The RA results are assessed using the CMC daily snow depth analysis and MODIS SCF observations.

a. Simultaneous update of states and parameters

1) SNOW DEPTH ESTIMATION

Figure 4 shows the results of the open-loop case without assimilation. Compared to the CMC snow depth analysis data, CLM4 greatly overestimated snow depth for most of northern North America while the difference between the CMC and CLM4 snow depth is relatively small for the United States and southern Canada. This considerable overestimation of snow depth might be a consequence of systematic biases in the DART–CAM4 atmospheric reanalysis, especially the modeled precipitation. The necessity of applying a bias correction to atmospheric forcing in hydrological modeling has been emphasized in many studies (e.g., Sharma et al. 2007; Piani et al. 2010). However, in this paper, we did not employ the bias correction method because our main objective was to address the feasibility of the continental-scale snow RA by testing our developed approaches.

By updating only SWE-related snow states in RA (i.e., RA_{SWE}), we were not able to improve snow depth estimates (Fig. 5a). In Fig. 5, which shows the snow depth RMSE differences between the RA and open-loop cases, negative (or positive) values denote the improvement (or degradation) of the RA performance. Although compared to the open-loop run, the RA_{SWE} shows a minor improvement in snow depth estimates for some areas (42.2% of snow-covered grid cells), the snow
depth error is much greater for about 57.8% of snow-covered grid cells, especially for northeastern North America. This degeneration of the RA performance is much ameliorated in the RASR case by additionally updating snow grain size (Figs. 5b,f). As emphasized in Kwon et al. (2015), when snow grain radius is greatly biased, the \(TB\) error (which equals simulation minus observation) is contributed primarily by the snow grain radius error but not by the SWE error. In this case, we cannot expect a proper update of SWE in RA, even though SWE and \(TB\) show a high correlation. Accordingly, we might improve the RA performance by reducing the effect of the snow grain radius error on the \(TB\) error in the RASR case.

However, additional updates of snow temperature (i.e., RA\(_{SRT}\)) and soil temperature and water content (i.e., RA\(_{STTS}\)) did not significantly improve the RA performance (Fig. 5). As shown in Kwon et al. (2015), CLM4 provides a relatively accurate simulation of snow temperature. In addition, the ensemble spread of snow temperature was much smaller than that of other snow physical states, especially snow grain radius (Fig. 6). Table 3 shows the maximum and minimum ensemble members of the simulated snow grain radius and snow temperature and their corresponding \(TB\) estimates over the Rocky Mountains on 23 February 2003 when the ensemble spread of snow grain radius in Fig. 6 was relatively small compared to other days. We can see...
from Table 3 that compared to snow grain radius, the snow temperature uncertainty in the model could not significantly contribute to the uncertainty of the simulated $T_B$ despite the fact that the relative sensitivity coefficient implies nontrivial sensitivity to snow temperature (Fig. 3). As a result, the additional snow temperature update did not make a substantial difference in the RA performance between the RASRT and RASR cases. Meanwhile, the marginal improvement in the RASRTS case can be attributed to the fact that the effect of the underlying soil on microwave emission from the snowpack is insignificant over the region where snow depth is relatively deep and mostly overestimated by the model (Fig. 4a).

In the RASRTSP case, we achieved noticeable improvement in the snow depth estimation in particular for the northeastern and western parts of Canada (Figs. 5e,i). This implies that the update of parameters in the DA system is a large-scale alternative where parameter optimization is difficult. Figure 7 shows the spatial distributions of the parameter ensemble mean updated in the RA system. The figure shows that the parameter values were not significantly changed during the simulation period after they approached certain values for each grid cell.

2) SCF ESTIMATION

In contrast to the snow depth estimation, the SCF bias of the open-loop run was very small for most of Canada while SCF was greatly overestimated or underestimated over the United States, including Alaska (Fig. 4b). CLM4 estimates SCF from the simulated snow depth and density using the snow cover parameterization developed by Niu and Yang (2007), which is based on monthly averaged snow depth and density using the snow cover parameterization developed by Niu and Yang (2007), which is based on monthly averaged snow depth and SCF and thus may not be applicable to the simulation at a daily time scale (Swenson and Lawrence 2012). Therefore, the large SCF
bias in the United States may result from this snow cover parameterization because the snow depth bias was marginal for the same region (Fig. 4a). Using the coarse spatial resolution (0.9° × 1.25°), the model cannot explicitly consider the effect of topography on the SCF estimation, especially in mountainous regions, and this might also lead to the large SCF bias. The SCF RMSE was almost zero for deep snowpack regions in northeastern North America (Fig. 4b), where snow depth was greatly overestimated (Fig. 4a) and SCF is saturated (i.e., 100% SCF).

Overall, for more than half (about 51.8%) of snow-covered grid cells in the United States, the SCF estimation in RA was better than the open-loop run, whereas it was degraded for other regions (about 48.2% of snow-covered grid cells), including southwestern Alaska (Fig. 5). Unlike the snow depth estimation, the improvement of the RA performance resulting from the simultaneous update was not that obvious.

The results in Fig. 5 show that RA is effective in improving the snow depth estimation for areas where SCF approaches 100%. As reported by previous DA studies using SCF observations (e.g., Rodell and Houser 2004; Andreadis and Lettenmaier 2006; Su et al. 2008; Zaitchik and Rodell 2009; De Lannoy et al. 2012; Zhang ...

**Fig. 7.** Spatial distributions of the ensemble mean of the RTM parameters (i.e., snow stickiness in DMRT-ML and x and b′ in the vegetation RTM) on 15 Dec 2002, 1 and 15 Jan 2003, and 28 Feb 2003.
et al. 2014), SCF DA does not work when the ground is fully covered with snow because satellite SCF data cannot detect additional snow mass or snow depth variations. The results in this paper imply that RA may be able to complement the SCF DA if both SCF and $T_B$ observations are simultaneously assimilated because RA can improve snow depth estimates for areas where SCF is already saturated.

b. Rule-based RA

1) Snow Depth Estimation

In the rule-based RA, the states and RTM parameters were updated when the signs of their correlations with the prior $T_B$ coincided with those of the sensitivity indices (Fig. 3). Like the default RA, the performance of the RA system in the rule-based RA cases was also enhanced via the simultaneous update of states and RTM parameters (Fig. 8). The additional update of snow grain radius (i.e., $R_{ASR-R}$) greatly reduced the snow depth error in the central to southern parts of Canada (Fig. 8f). However, the effects of the updates of snow temperature (i.e., $R_{ASRT-R}$) and soil temperature and water content (i.e., $R_{ASRTS-R}$) on the RA performance were insignificant (Figs. 8g,h). The snow depth RMSE largely diminished in the southern and western parts of Canada by additionally updating the RTM parameters (i.e., $R_{ASRTSP-R}$; Fig. 8i).

Compared to the default RA cases, snow depth estimates in the rule-based RA were more accurate in many areas of North America, especially northeastern Canada (Fig. 9). However, the rule-based RA performed worse
Fig. 9. (a)–(c) Snow depth and (f)–(j) SCF RMSE differences between the RA cases with a rule-based update and with default update.
than the default RA in midlatitudes of Canada, particularly in the RASWE-R case (Fig. 9a).

The RA performance deteriorates in two possible cases: 1) the prior SWE (or snow depth) is positively correlated with the prior $T_B$, and SWE (or snow depth) and $T_B$ are overestimated and underestimated, respectively; and 2) the prior SWE and $T_B$ show a negative correlation but both SWE (or snow depth) and $T_B$ are overestimated because of the effects of other factors, such as a greatly underestimated snow grain radius. Ideally, the prior SWE (or snow depth) should have a negative correlation with the prior $T_B$ based on the sensitivity analysis results. However, a positive correlation between the prior SWE and $T_B$ can happen when the $T_B$ signal is dominated by snow density, when SWE (or snow depth) is negatively correlated with snow grain radius (Kwon et al. 2015), when SWE exceeds a threshold value (e.g., 120–180 mm), after which the microwave emission becomes the dominant process of the $T_B$ signal from the snowpack (see section 2c), or when imprecise values of the RTM parameters are used.

In the first possible case of degeneration, the RA system tries to raise $T_B$, and as a result SWE (or snow depth) is further overestimated. This may be the principal reason for the degraded performance of the rule-based RA in midlatitudes of Canada as shown in Fig. 8a. This problem was partly resolved by additionally updating snow grain radius (Fig. 8f) and RTM parameters (Fig. 8i); however, RA still degraded the snow depth estimates compared to the open-loop run for the region (Fig. 8e).

2) SCF ESTIMATION

Compared to the open-loop run, the rule-based RA improved the SCF estimates for many areas in the United States, including Alaska (Fig. 8). Although the SCF estimation error of the RASWE-R case was larger than that of the open-loop run in the coastal areas of northern Canada (Fig. 8j), the RA performance for those areas was reinforced by additionally updating snow grain size (Figs. 8k,o). However, like the default RA cases, the improvement of the SCF estimates by simultaneously updating states and RTM parameters was not significant (Figs. 8o,r). The rule-based RA outperformed the default RA over Alaska and the western and eastern coastal areas of North America (Figs. 9f,j), but overall both the default and rule-based RA showed comparable performance in estimating SCF over the United States (Fig. 9j).

c. Localization and adaptive inflation

The results of the localization and inflation experiments are shown in Fig. 10. Using the optimal parameter values, the prior ensemble estimates become more consistent with the assimilated observations and thus the magnitude of the innovations would reduce (Dee 1995). Therefore, here we analyzed the prior $T_B$ RMSE

![Fig. 10](image-url)

**Fig. 10.** The prior $T_B$ RMSE of the RA cases with localization distances of 0.01, 0.03, 0.05, 0.07, 0.1, 0.15, 0.2, and 0.3 rad. The RMSE values were averaged over North America. The solid and hollow symbols represent the default and rule-based RA cases, respectively. The red triangle symbols denote the results of RA using the adaptive inflation and the localization distance of 0.01 rad (0.68), which are plotted slightly displaced laterally from their original position for clearness.
calculated using AMSR-E $T_B$ observations. As shown in Fig. 10, the rule-based RA was superior to the default RA with respect to $T_B$ estimations and the localization distance of 0.01 rad provided the smallest $T_B$ RMSE for both the default and rule-based RA. The localization distance (0.01 rad) obtained here is smaller than that from Zhang et al. (2014) (0.03 or 0.05 rad) using MODIS SCF observations. This can likely be explained by high spatial heterogeneity of various factors (i.e., snow depth, snow temperature, snow density, snow grain size, snow wetness, soil temperature, soil water content, and vegetation) influencing $T_B$ over snow-covered regions. As previously mentioned, the distance weight factor approaches zero at twice the localization distance. Therefore, using the localization distance of 0.01 rad (0.6°), the $T_B$ observation did not affect the update of longitudinally adjacent grid cells while it had an impact on latitudinally adjacent grid cells because the RA system was run at $0.9° \times 1.25°$ spatial resolution. This implies that in RA, more improved estimates would be obtained by removing the impact of adjacent grid cells on each other’s update in DART.

In the inflation experiments, the localization distance of 0.01 rad was used. Adaptive inflation further improved $T_B$ estimations for the default RA (see the solid red triangle in Fig. 10) while the $T_B$ RMSE of the rule-based RA with inflation was almost the same as that without applying inflation (see the hollow red triangle in Fig. 10).

The RA performance in estimating snow depth was analyzed for snow classes and land covers (Tables 4, 5). Here, our focus was 1) on comparing the performance of the default and rule-based RA cases for each snow class and land-cover type when all model states and RTM parameters are simultaneously updated and the optimized localization distance are applied and 2) on examining the added impact of applying the adaptive inflation method on snow depth estimates. For all RA cases in Tables 4 and 5, the localization distance of 0.01 rad was used. In the RA$_{SRTSP}$/INF and RA$_{SRTSP-R}$/INF cases, adaptive inflation was additionally applied. Snow cover was classified into six classes (i.e., tundra, taiga, alpine, maritime, prairie, and ephemeral) as defined in Sturm et al. (1995) (Fig. 11a) and land cover was classified into five groups (i.e., bare soil, forest, shrub, grass, and crop) using CLM4 plant functional types (PFTs; Fig. 11b). Tables 4 and 5 exhibit that the rule-based RA outperforms the default RA in estimating snow depth and the rule-based RA without inflation (i.e., RA$_{SRTSP-R}$) provides the most improved snow depth estimates (0.168 m RMSE, 1.6% improvement). Compared to the open-loop run (0.171 m RMSE), the default RA (i.e., RA$_{SRTSP}$) degraded snow depth

<table>
<thead>
<tr>
<th>Cases</th>
<th>Open loop</th>
<th>RA$_{SRTSP}$</th>
<th>RA$_{SRTSP-R}$</th>
<th>RA$_{SRTSP}$/INF</th>
<th>RA$_{SRTSP-R}$/INF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tundra</td>
<td>0.2383</td>
<td>0.2478 (3.99%,$p=0.000$)</td>
<td>0.2108 (7.11%,$p=0.000$)</td>
<td>0.6372 (167.39%,$p=0.000$)</td>
<td>0.5499 (130.76%,$p=0.000$)</td>
</tr>
<tr>
<td>Taiga</td>
<td>0.1758</td>
<td>0.1839 (4.01%,$p=0.034$)</td>
<td>0.1819 (7.11%,$p=0.000$)</td>
<td>0.4027 (106.77%,$p=0.000$)</td>
<td>0.3651 (113.76%,$p=0.000$)</td>
</tr>
<tr>
<td>Maritime</td>
<td>0.1521</td>
<td>0.1497 (0.0%,$p=0.000$)</td>
<td>0.1493 (0.0%,$p=0.000$)</td>
<td>0.1719 (13.02%,$p=0.000$)</td>
<td>0.1730 (13.02%,$p=0.000$)</td>
</tr>
<tr>
<td>Prairie</td>
<td>0.0770</td>
<td>0.0793 (3.57%,$p=0.000$)</td>
<td>0.0766 (3.57%,$p=0.000$)</td>
<td>0.1780 (3.57%,$p=0.000$)</td>
<td>0.1780 (3.57%,$p=0.000$)</td>
</tr>
<tr>
<td>Alpine</td>
<td>0.1288</td>
<td>0.1312 (1.25%,$p=0.000$)</td>
<td>0.1312 (1.25%,$p=0.000$)</td>
<td>0.1763 (1.64%,$p=0.000$)</td>
<td>0.1763 (1.64%,$p=0.000$)</td>
</tr>
<tr>
<td>Total</td>
<td>0.1708</td>
<td>0.1748 (0.0%,$p=0.000$)</td>
<td>0.1748 (0.0%,$p=0.000$)</td>
<td>0.2383 (3.99%,$p=0.000$)</td>
<td>0.2383 (3.99%,$p=0.000$)</td>
</tr>
</tbody>
</table>

Table 4: The snow depth RMSE of each case for snow classes as defined in Sturm et al. (1995). The RMSE was calculated across the time series for each grid cell and then averaged over all grid cells in each snow class. The localization distance of 0.01 rad was used for all RA cases. Adaptive inflation was applied in the RA$_{SRTSP}$/INF and RA$_{SRTSP-R}$/INF cases. In parentheses are also given in parentheses. The boldface numbers highlight the improvement of estimates by radiance assimilation compared to the open-loop run.
estimates for most snow classes and land covers, except for the maritime snow class and crop land cover.

The overall effects of applying adaptive inflation are 122.19% (in the default RA; i.e., RASRTSP/INF) and 113.76% (in the rule-based RA; i.e., RASRTSP-R/INF) increases in the snow depth RMSE (Tables 4, 5). One possible reason is that the current inflation scheme in DART would not be able to consider the physical relationships between snow/soil states updated simultaneously in the RA system. As a result, inflation would result in the abnormal update of model states in this RA study. However, because adaptive inflation is a helpful method to improve the DA performance, future RA studies need to address this issue for the proper use of the method.

The rule-based RA without inflation (i.e., RASRTSP-R) was effective only for the tundra (11.5% improvement, \( p < 0.05 \)) and maritime (1.8% improvement, \( p > 0.05 \)) snow classes, but it degraded the snow depth estimates for other snow classes, in particular for the taiga snow class (7.1% degradation, \( p < 0.05 \); Table 4). Compared to the CMC data, the RA system still highly overestimated snow depth over Canada, especially in the taiga region (Fig. 12), although the snow depth estimates were improved by applying our new approaches.
Figure 13 shows that in the regions of the taiga snow class (marked by a rectangle in Fig. 11a), more than about 60% of available TB observations were not assimilated even though the mean TB RMSE (6.3 K) and total spread (4.8 K) were comparable to those for other snow classes. One plausible reason is the poor performance of our coupled RA system for forested areas (Table 5). Table 5 shows that compared to the open-loop run, in the RASRTSP-R case, the snow depth estimation was degraded (i.e., 7.3% increase in the RMSE, p < 0.05) for the forest land-cover type while it was enhanced for all other land-cover types. Significant improvement of the snow depth estimates in the rule-based RA (i.e., RASRTSP-R) was observed for bare soil (13.5%, p < 0.05; Table 5, Fig. 14). Although the RASRTSP-R improved the snow depth estimates for shrub, grass, and crop land-cover types, it was marginal and insignificant (p > 0.05) as shown in Fig. 14. We used a simple empirical equation to estimate the vegetation effect on TB at the TOA [see Eq. (1)]. Although the empirical coefficients in the equation were updated in the RA system, it may not be enough to accurately represent the vegetation effect. The use of more sophisticated vegetation RTMs, applicable to a large scale, would further improve the RA performance for vegetated areas.

One thing that should be noted is that the RA system tends to underestimate snow depth over the Rocky Mountains in the United States (Fig. 12). Especially, as well as the CMC snow data, the model predicted no snow for the Sierra Nevada where snow constitutes a significant part of the water budget throughout the winter (Kirchner et al. 2014). Orographic processes are the primary control on the accumulation and evolution of snow across the mountains (Mott et al. 2014). However, our RA system using a coarse spatial resolution (0.9° × 1.25°) does not explicitly take into account the orographic effect on snow in mountainous regions, although CLM4 tries to describe the horizontal spatial heterogeneity of the land surface by a nested sub-grid hierarchy such as land units, snow/soil columns, and PFTs. Because TB is also influenced by topography (Flores et al. 2009), our RA results may involve some errors in mountainous regions. To improve the performance of the RA system over mountainous areas, further studies need to be explored with respect to the use of higher spatial resolution for large-scale applications of the RA method.

4. Conclusions

In this study, we aimed to demonstrate the feasibility of the RA system (i.e., coupled CLM4, DART, and RTMs) to enhance snow estimation at the continental scale. Based on our previous work (Kwon et al. 2015), we developed and demonstrated new approaches: the simultaneous update of all model states and RTM parameters (involved in estimating TB) based on the rule in which the prior estimates are updated only when their correlations with the simulated TB have the same signs as the sensitivity index. AMSR-E TB at 18.7 and 36.5 V pol were assimilated into the RA system and the results were assessed using the CMC daily snow depth and MODIS SCF observations. In total, 11 experiments were conducted over North America from December 2002 to February 2003, and their performances were compared to each other.

The results in this paper show that RA performance is improved by both the simultaneous update and rule-based update. The additional updates of snow grain radius and RTM parameters greatly improved the snow depth estimates over North America while the improvement by updating snow temperature, soil temperature, and soil water content was not significant. For both the default and rule-based RA cases, the additional updates of states and RTM parameters could not obviously improve the SCF estimates.
The rule-based RA was more effective in estimating snow depth than the default RA when only SWE-related snow states were updated. Simultaneously updating all states and RTM parameters, the degradation of the performance of both the default and rule-based RA was mitigated, and eventually the default RA showed comparable performance to the rule-based RA. This indicates that the updates of all states and RTM parameters can reduce the $T_B$ errors related to them and consequently lead to considerable improvement of the relationship between SWE (or snow depth) and $T_B$. The results also demonstrate that the parameter update in

![Fig. 13. Time series of the prior $T_B$ RMSE (black curve) and total spread (red curve) in the RASRTSP case (rule-based RA without inflation) for six snow classes. The blue circles and plus signs represent the number of $T_B$ observations that are available and assimilated, respectively. The values were calculated for the regions marked by rectangles in Fig. 11a.](image-url)
the DA system can be an alternative way of optimizing parameter values on a large scale.

The effects of the localization and inflation on the RA performance were additionally tested. The smallest $T_B$ RMSE was achieved using the localization distance of 0.01 rad for both the default and rule-based RA, and the $T_B$ estimation of the default RA was further enhanced by applying adaptive inflation. The results show that the rule-based RA is superior to the default RA in estimating snow depth, and the most improved performance is achieved by the rule-based RA without adaptive inflation. However, even in the best performance RA case, the overall improvement (1.6% decrease in the RMSE) of snow depth estimates was not significant ($p = 0.135$) because snow estimates were degenerated or marginally improved for other snow classes and land covers, particularly for the taiga snow class and forest land cover (7.1% and 7.3% increase in the RMSE, respectively).

Further improvement in performance of the RA system may be possible by addressing the following issues. First, a more refined method, estimating the vegetation effect on $T_B$ at the TOA, should be employed in the RA system. Second, other frequency channels need to be tested with respect to their performance in estimating snow through RA. In this study, among the six AMSR-E frequencies, only two frequencies, that is, 18.7 and 36.5 GHz V pol, were assimilated. However, as discussed in section 2c, our current approach (i.e., rule-based update) may lead to some errors for SWE greater than the threshold value (i.e., ~120–180 mm) because of the slope reversal phenomenon at the 36.5-GHz channel. The use of other frequency channels may be able to further improve the RA performance. Third, in this study, we assumed that the uncertainties in the model simulations are primarily caused by the uncertainties in the atmospheric forcing. Introducing additional uncertainties resulting from model structures and/or parameterizations, especially the snow grain size parameterization as in Durand et al. (2009), would likely improve the performance of the RA system. Finally, as mentioned in section 3c, a higher spatial resolution must be used for mountainous regions. However, it requires considerably increased computational demands for a large-scale RA. A compromise between the spatial resolution (and subsequent RA performance) and computational efficiency may be a key issue to be discussed in future studies.

**FIG. 14.** Time series of snow depth (m) for land covers: (a) bare soil, (b) forest, (c) shrub, (d) grass, and (e) crop. The localization distance of 0.01 rad was used for the RA cases.
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