Feasibility Test of Multifrequency Radiometric Data Assimilation to Estimate Snow Water Equivalent

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ABSTRACT

A season-long, point-scale radiometric data assimilation experiment is performed in order to test the feasibility of snow water equivalent (SWE) estimation. Synthetic passive microwave observations at Special Sensor Microwave Imager (SSM/I) and Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) frequencies and synthetic broadband albedo observations are assimilated simultaneously in order to update snowpack states in a land surface model using the ensemble Kalman filter (EnKF). The effects of vegetation and atmosphere are included in the radiative transfer model (RTM). The land surface model (LSM) was given biased precipitation to represent typical errors introduced in modeling, yet was still able to recover the true value of SWE with a seasonally integrated rmse of only 2.95 cm, despite a snow depth of around 3 m and the presence of liquid water in the snowpack. This ensemble approach is ideal for investigating the complex theoretical relationships between the snowpack properties and the observations, and exploring the implications of these relationships for the inversion of remote sensing measurements for estimating snowpack properties. The contributions of each channel to recovering the true SWE are computed, and it was found that the low-frequency 10.67-GHz AMSR-E channels contain information even for very deep snow. The effect of vegetation thickness on assimilation results is explored. Results from the assimilation are compared to those from a pure modeling approach and from a remote sensing inversion approach, and the effects of measurement error and ensemble size are investigated.

1. Introduction

Because of the large latent heat of vaporization of water and its high albedo, snow cover plays a key role in the global energy balance. Additionally, it is well known that many arid regions depend upon the seasonal snowpack as a primary source of water. These facts have motivated the study of snow, including both efforts to invert remote sensing observations to obtain estimates of snow quantity (e.g., Chang et al. 1987; Aschbacher 1990; Hallikainen and Jolma 1992), and increasingly sophisticated snow characterization within land surface models (LSMs; e.g., Sun et al. 1999; Stiegitz et al. 2001). Recently, because of difficulties associated with retrieval algorithms, many researchers have begun incorporating a priori information into regression relationships that predict snow water equivalent (SWE) as some function of brightness temperature measured via satellite (e.g., Foster et al. 2005; Tait 1998). This amounts to merging meteorological, atmospheric, vegetation, or terrain information with the remotely sensed data. Data assimilation is an ideal framework for merging remote sensing observations, and this sort of a priori information, because it is not site-specific, allows for simultaneous assimilation of remote sensing observations at different frequencies and provides an explicit method to account for atmospheric and vegetative effects, as well as a means of weighing the uncertainty of meteorological data (such as precipitation measurements), uncertainty in model parameterizations, and uncertainty in the remote sensing observations. The objective of this study is to assess the feasibility of estimating snowpack properties using the ensemble Kalman filter (EnKF) to assimilate multifrequency remote sensing observations. A secondary objective is to gain insight into which remote sensing frequencies contain the most information about SWE in this data assimilation context.

This data assimilation feasibility study is arranged as
follows. Section 2 gives a brief review of related SWE estimation studies, including the direct inversion of remote sensing observations, modeling of snowpack evolution in LSMs, and direct insertion data assimilation methods. Section 3 describes the methods utilized in this study, including a description of the “off-the-shelf” LSM and radiative transfer models (RTMs). Description of the ensemble modeling approach and the ensemble Kalman filter are then given. The design of the feasibility experiment is described in section 4. The results obtained are reported and discussed in section 5. Finally, conclusions are presented in section 6.

2. Background and motivation

a. The inversion of remote sensing observations

Much work has been done to estimate SWE by directly inverting remote sensing observations. Chang et al. (1987), Ashbacher (1990), and Hallikainen and Jolma (1992), for instance, have developed linear relationships from remote sensing, radiative transfer models, and in situ observations. One difficulty with direct inversion is the well-known saturation effect (Sturm et al. 1993; Kelly et al. 2003); for every frequency, there is a certain threshold after which an increase in SWE does not result in any further changes in brightness temperature. This effectively limits the usefulness of these retrieval algorithms to shallow snow (Chang et al. 1987), though remote sensing observations are also insensitive to SWE less than 10 mm. A second difficulty is the many-to-one nature of the SWE–brightness temperature relationship. Armstrong et al. (1993), for instance, demonstrated that retrieval is made difficult without an accurate estimate of snow grain size.

A number of papers have been published that attempt to incorporate knowledge of the snow age and canopy properties into an SWE inversion scheme. Foster et al. (2005) pointed out that most errors are due to inaccurate grain diameter information and vegetation and proposed adjustments for the Chang et al. (1987) algorithm for each of these factors. Tait (1998) used a priori meteorological and geographic data to classify pixels and performed separate regressions on each. Pulilainen et al. (1999) included snow grain size in a modified least squares objective to develop a linear brightness temperature difference index relationship with SWE, using radiative transfer model output for inversion. Davis et al. (1993) and Tedesco et al. (2004) used radiative transfer model output to train a neural network to predict SWE from microwave observations. These last two methods implicitly characterize dependence of the brightness temperature on the snow parameters. Other work treats the grain diameter explicitly, modeling its evolution with time. Kelly et al. (2003), for instance, assumed a simple grain diameter evolution scheme and developed nonlinear inversion relationships. Wilson et al. (1999) used remote sensing observations to update the snow states in a hydrologic simulation using an inversion scheme based on radiative transfer model output. Similarly, Chen et al. (2001) used a neural network to update snow states in a hydrology model. These last two approaches are in line with suggestions to incorporate as much a priori information (i.e., meteorological data) as possible in using remote sensing observations to estimate SWE.

b. Snow schemes in LSMs

Snow models are routinely used independently of remote sensing techniques to estimate SWE. Physical snow models (e.g., Koren et al. 1999; Jordan 1991) must be used in data assimilation schemes rather than simplified conceptual snowpack models, since estimates of several snowpack variables are required to drive the radiative transfer model (see below). According to the results of the Program for Intercomparison of Land Surface Parameterization Schemes Phase 2(d) [PILPS 2(d)] project there is a large degree of variation among the different physical models arising from the uncertain model parameters and model structure (Slater et al. 2001). Xue et al. (2003) found that parameterizations of albedo and snow compaction mechanisms have a significant effect on model performance. Furthermore, the well-known problem of accurately gauging precipitation (e.g., Gray and Male 1981) degrades SWE estimates. Indeed, Pan et al. (2003) reported a significant low bias in modeled SWE in all four models investigated in the North American Land Data Assimilation System (NLDAS) when compared to in situ observations. Specifically, they found a low bias between 51% and 78% when estimates were compared to SWE measured by in situ snowpack telemetry (SNOTEL) gauges; this was attributed to a low bias in precipitation data. These uncertainties have led some authors to assimilate in situ SWE observations into snow models.

c. Snow data assimilation

Data assimilation is the science of merging observations with a model. Various data assimilation methodologies have been used in a number of hydrologic applications, including the estimation of soil moisture in LSMs (Reichle et al. 2002; Margulis et al. 2002). Most data assimilation work done with snow has focused on the assimilation of in situ observations of snow depth. Liston et al. (1999) used a direct-insertion method for updating snow depth, where the snow observation re-
places the modeled value during a coupled land–atmosphere simulation. Rodell et al. (2004) also used a direct-insertion method for updating snow cover. Sun et al. (2004) used the extended Kalman filter (EKF) with SWE observations to update a three-layer LSM. J. Jin and N. Miller (2005), personal communication) implemented a direct-insertion scheme into a snow model driven by a mesoscale atmospheric model. B. Cosgrove et al. (2005, personal communication) explored some issues introduced through forcing biases in the direct insertion of SWE observations into an LSM. SWE values used in some of these direct insertion schemes are derived from retrieval algorithms and are therefore subject to significant errors due to the limitations mentioned above. Despite the usefulness of these methodologies, most snow data assimilation has been limited to direct-insertion schemes that do not take into account the uncertainty in the observations. Assimilation of passive microwave remote sensing observations to update a modeled estimate of SWE has not been reported in the literature.

**d. Motivation and science questions**

General application of a data assimilation methodology requires only assumptions about the measurement and model input uncertainty, and implicitly accounts for the many-to-one problem, which causes difficulties in retrieval algorithms. Each channel in these multifrequency observations has a different relationship to the SWE, and each of these relationships is constantly evolving in time as the snowpack ripens. Furthermore, each channel is attenuated to different extents by the vegetation, atmosphere, and clouds, since atmospheric and vegetative transmissivity is a function of frequency; low-frequency channels may also be affected by radio-frequency interference (RFI). Our ultimate goal is to assimilate both passive microwave observations at frequencies between 6.925 and 89 GHz [available from Special Sensor Microwave Imager (SSM/I) and Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) sensors] and broadband albedo [available from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor]. These albedo observations are currently used in inversion schemes to estimate surface grain diameter (e.g., Klein and Stroeve 2002; Nolin and Dozier 2000). Though passive microwave observations have a coarse spatial resolution, their long measurement history makes them attractive for operational use. Though not addressed here, the problem of coarse spatial resolution will be considered in a follow-on study. The current work is a feasibility study using point-scale synthetic observations in order to test a new approach and to gain a better understanding of how multifrequency observations may be exploited for SWE estimation. We hope to address several questions through this work: Can incorporation of radiometric observations overcome significant biases in forcing data for snow hydrology models? Can a data assimilation methodology be used to estimate snowpack properties for very deep snow? Will the presence of some liquid water in the snowpack corrupt the estimate? Which channels contribute the most to correcting the estimate? How useful are the high-frequency measurements given atmospheric attenuation? How does the snow signal attenuation by vegetation affect the estimation accuracy?

**3. Models and methods**

Assimilation of remotely sensed observations using the EnKF involves 1) the propagation of the state vectors by an LSM in between observations, and 2) the update of the state vector at the measurement time based on predicted observations of the state from a radiative transfer model. The LSM and RTMs utilized in this study are discussed next, followed by a full description of the EnKF methodology.

**a. Land surface model adaptation**

For this study, we use the Simple Snow–Atmosphere–Soil (SAST) transfer model, which is an intermediate-complexity, three-layer energy-balance snow scheme (Sun et al. 1999). It has been verified against data on at least three continents and compared against a more complex snow physics model with favorable results (Jin et al. 1999). The SAST prognostic variables include enthalpy (related directly to snow temperature and density), snow water equivalent, and snow depth. The model takes into account compaction due to destructive metamorphism, overburden, and snow melting (Sun et al. 1999). In this study, we use the SAST code integrated into the Simplified Simple Biosphere (SiB) LSM code (Xue et al. 1991), which is the Simplified Simple Biosphere version 3 (herein referred to as SiB3). The default grain diameter and albedo parameterizations described in Sun et al. (1999) are not detailed enough for this study. Because of the sensitivity of microwave emission and albedo to grain size (Armstrong et al. 1993; Nolin and Dozier 2000), a prognostic estimate of the grain size is required. Hence, we incorporated the dynamic grain diameter model of Jordan (1991) into SiB3. Specifically, it is assumed that the dry snow grain diameter evolves at each time step based on the flux of water vapor through the snowpack according to...
\[ \frac{\partial d}{\partial t} = \alpha_1 \frac{U_v}{d}, \quad (1) \]

where \( d \) is the grain diameter, \( U_v \) is the water vapor diffusing through the snowpack, and \( \alpha_1 \) is a constant. Applying the chain rule to Fick’s law, we obtain an expression for the vapor flux as a function of the temperature gradient of each snow layer,

\[ U_v = -D_{es} C_{kt} \frac{\partial T}{\partial z}, \quad (2) \]

where \( D_{es} \) is the effective vapor diffusion coefficient for snow, \( C_{kt} \) is the variation of equilibrium vapor density with temperature, and \( \partial z \) is the snow layer thickness; the thickness of the three layers in SSiB3 is determined based on the rules described in Sun et al. (1999). The effects of this layering assumption on the assimilation results may be investigated in a future study. The rate of grain diameter growth for wet snow is parameterized based on another constant \( \alpha_3 \) and the liquid water in the snowpack (Jordan 1991).

The SSiB3 albedo parameterization was modified to include a dependence upon the grain diameter based on the SNTHERM (a one-dimensional energy and mass balance model) albedo parameterization (Jordan 1991), which is similar to the albedo estimate given in Marks and Dozier (1992). The MODIS albedo observations contain useful information about the surface grain diameter, which will be exploited based on this SNTHERM parameterization. Based on the modified SSiB3 model, the state variables used in this study are snow depth and ground surface temperature in addition to snow density, temperature, grain size, and volumetric water content in the three snowpack layers, for a total of 14 state variables. The relationship between the SSiB3 states and the other remotely sensed data is the subject of the next section.

b. Radiative transfer models

Three radiative transfer models must be employed in order to predict the satellite observation. The emission models of the snowpack, vegetation, and atmosphere are discussed in turn. The emission of microwave radiation from snowpacks has been investigated extensively. The two general approaches have been electromagnetic wave theory and radiative transfer theory. For this study, we have chosen the Microwave Emission Model of Layered Snowpacks (MEMLS; Wiesmann and Mätzler 1999a). MEMLS is a multilayer model based on radiative transfer theory but accounts for multiple-scattering effects within the snowpack by using a spatial correlation function to model snow structure (Mätzler et al. 2000; Mätzler 1997). It may be applied to coarse-grained snow, such as refrozen crusts and depth hoar (Mätzler and Wiesmann 1999; Mätzler 1998). The model description for computing scattering and absorption coefficients has been tested on many snow samples (Wiesmann and Mätzler 1998) and validated against actual snowpacks (Wiesmann and Mätzler 1999a). The relationship between snow grain size modeled by SNTHERM and the MELMS snow correlation length has been explored (Mätzler 2002). Furthermore, it is readily available and well documented (Wiesmann and Mätzler 1999b). MEMLS is also easily coupled with a software package developed by Tigerstedt and Pulliainen (1998), which helps account for the vegetative and atmospheric attenuation effects. Finally, it has been successfully tested with SNTHERM output (Wiesmann et al. 2000), which in many ways is the foundation for the SAST model (Sun et al. 1999). In addition to the approach taken by MEMLS, there are other schools of thought in the field of modeling the microwave emission from snow, most notably the dense media radiative transfer theory (DMRT) of Tsang (1987). The two methods have not been compared sufficiently to definitively determine the better approach. In any case, the modularity of the EnKF framework would easily allow for the incorporation of the DMRT or other emission models of snowpacks in future studies.

The vegetation is modeled according to Wegmuller et al. (1995), following the approach given in Tigerstedt and Pulliainen (1998). The reflectivity and transmissivity of individual leaves is based on the geometrical optics approach, taking into account the inhomogeneity of the electric field within the vegetation. The clear-sky atmosphere is modeled according to Ulaby et al. (1981) as implemented in Tigerstedt and Pulliainen (1998). Absorption by oxygen and water vapor are computed assuming a typical exponential relationship for water vapor and pressure profiles, and a simple expression for the temperature profile. From Tigerstedt and Pulliainen (1998), the expression for the predicted top-of-atmosphere (TOA) brightness temperature is

\[ T_{b,TOA} = T_{b,a}^1 + (T_{b,space} T_{a} + T_{b,asv}) (1 - e_{asv}) T_{a} + T_{b,asv} T_{a}, \quad (3) \]

where \( T_{b,a}^1 \) is the upward emitted atmospheric brightness temperature, \( T_{b,space} \) is the space brightness temperature, \( T_{a} \) is the atmospheric transmissivity, \( T_{b,a} \) is the downward emitted atmospheric brightness temperature, and \( e_{asv} \) and \( T_{b,asv} \) are the combined emissivity and brightness temperature of the soil, snow, and vegetation scene, respectively; the latter of these may defined as.
\[ T_{b,ssv} = t_v T_{b,ss} + (1 - t_v) T_{s} + (1 - t_v) T_{f}(1 - e_{as}) t_v \]

where \( t_v \) is the transmissivity of the vegetation canopy, \( T_{b,ss} \) and \( e_{as} \) are the brightness temperature and emissivity of the soil and snowpack computed by MEMLS, respectively, and \( T_s \) is physical temperature of the vegetation. Note that the radiative transfer properties of both the atmosphere and vegetation vary as a function of frequency. For more detailed descriptions of the models used to compute these parameters, the reader is referred to Wegmuller et al. (1995) and Ulaby et al. (1981).

c. Ensemble modeling

Before discussing the EnKF method, it is important to touch on a related area, that of ensemble modeling. In an ensemble modeling approach the forcing data, initial conditions, and key model parameters are treated as random variables. Then a number of simulations are run in parallel with various combinations of perturbed random input variables, which reflect the uncertainty in these model inputs. Since a primary end goal of this work is to estimate SWE, we treat precipitation as an uncertain random variable as well as several crucial parameters including the coefficient for the growth of snow grains \( \alpha_f \) in (1). The first benefit of this method is that the estimate of the state variable (usually the mean across the ensemble) can be complemented with the variance across the ensemble, giving a measure of the uncertainty of the estimate. The second benefit is that the statistical information required by Kalman filtering theory can be estimated solely from the forward model output without needing to linearize the forward model. To obtain a distribution of realistic initial conditions for filtering, an ensemble of model runs was performed until there was a significant snowpack. The final states of these simulations were used as initial conditions for the tests described below.

d. The ensemble Kalman filter

The EnKF technique has been used in a number of different applications, including estimation of soil moisture (e.g., Margulis et al. 2002) and correcting LSMs due to uncertainty in precipitation data (Crow 2003). The assimilation of remote sensing observations into an LSM using the EnKF involves two steps. During the propagation step, the LSM computes the evolution of an ensemble of state variables from the initial conditions until the time when an observation is available; by using an ensemble approach, no complex adjoint or tangent model needs to be derived. The evolution of the vector of states \( y \) for one replicate \( k \) at time \( t \) is expressed by

\[ y_{k,t} = A(y_{0,k}, u_{k,t}, \alpha_k), \]

where \( A() \) is the model operator, \( y_{0,k} \) is the initial condition, \( u_{k,t} \) represents the forcing (meteorological) data for replicate \( k \), and \( \alpha_k \) is the time-invariant model parameter vector for replicate \( k \).

The second step specified by the EnKF methodology is the update step in which we seek the optimal a posteriori estimate of the state variable based on the a priori estimate and the observation. If we represent the a posteriori or updated state variable as \( y_k^+ \) and the a priori or prior state variable as \( y_k^- \), then the Kalman update equation at the measurement time (time subscripts omitted for simplicity) is given by

\[ y_k^+ = y_k^- + K[z_{obs} - M(y_k^-) + u_k], \]

where \( K \) is the Kalman gain, \( z_{obs} \) is the observation vector, containing all remote sensing observations at the measurement time, \( M(y_k^-) \) is the measurement operator that predicts the observation at the top of the atmosphere based on the state variables and the three RTMs. The \( u_k \) term is random error that prevents the introduction of correlations among the replicates (Burgers et al. 1998). The Kalman gain specifies the optimal linear update of the state variables (Houtekamer and Mitchell 1998) and is given by

\[ K = C_{yz}(C_{zz} + C_{\epsilon y})^{-1}, \]

where \( C_{yz} \) is the cross covariance of the states with the measurements of the states derived from the radiative transfer model, and \( C_{zz} \) is the covariance of the measurements of the states. Both of these covariances are computed from the ensemble. The measurement error covariance is specified and given by \( C_{\epsilon} \). The propagation and update steps given by (5) and (6) are applied to each ensemble member and are applied sequentially forward in time so that a given posterior estimate is conditioned on all previous observations.

4. Experimental design

A necessary first step in a new application of data assimilation methodology is a synthetic experiment that allows for testing the feasibility of the approach. A synthetic experiment is essentially a test in a controlled environment where the “true” state is known. In this study, we use the model in a lumped framework and focus on the complicated interactions between snow states and multifrequency observations in order to address the science questions above. A later study will
apply the method for a spatially distributed case over a large basin.

The experimental setup is especially designed to evaluate whether errors in forcing data may be overcome by assimilating radiometric observations using the EnKF. To this end, point-scale forcing data were obtained from the Mammoth Mountain Energy Balance Station (MMEBS) for the 1993/94 winter (Davis et al. 1984) in order to drive the SSiB3 model. We must make some assumptions regarding the error statistics of these nominal forcing data. Because of the common occurrence of undercatch in snow precipitation datasets (Pan et al. 2003) and especially in mountainous terrain (Groisman and Legates 1994), we included a positive bias when computing the precipitation for the true simulation: It was specified that, on average, the measured value was 50% of the actual precipitation. The measured precipitation data were corrupted with biased, multiplicative, time-correlated, lognormal forcing error based on an assumed coefficient of variation of 0.75, and a correlation time scale of 6 h in order to obtain the precipitation for the true simulation. This mimics the situation in which the measured value is biased by gauge undercatch. Furthermore, the true value of the $\alpha_i$ parameter controlling grain growth in (1) was also randomly perturbed.

To provide a benchmark for evaluating the filter estimate, we run the model in “open loop” mode, that is, without the benefit of the observations. The open-loop simulation is given the nominal forcing data and parameter values, so that it receives, on average, only 50% of the true simulation precipitation. The EnKF replicates also receive an average of 50% of the true precipitation as well as randomly perturbed grain growth parameter values.

In this test, the collection of observations used in the assimilation are brightness temperatures at several passive microwave frequencies (available from SSM/I and/or AMSR-E) as well as broadband albedo (available from MODIS), all computed synthetically at a single point. Snow states generated by SSiB3 are used to synthetically generate passive microwave and albedo observations. The observations are corrupted assuming that the standard deviation of the passive microwave measurement error and the broadband albedo measurement error can be characterized as white Gaussian noise with a standard deviation of 2 K and 5%, respectively; these error standard deviations were also used in the filter for the values of $C_m$ in (7). We chose an ensemble size of 100 replicates to represent the pdf of the state and measurement variables. The AMSR-E instrument on the Aqua platform has equatorial crossover times around 1 A.M. and 1 P.M. daily. For simplicity, it is assumed that all microwave observations are available at 1 A.M. and the albedo observations at the 1 P.M. overpass. There are seven SSM/I channels including 19.35, 22.235, 37.0, and 85.5 GHz at vertical and horizontal polarizations, except the 22.235-GHz channel, which has only the vertical polarization. AMSR-E has 12 channels, including 6.925, 10.65, 18.7, 23.8, 36.5, and 89 GHz, all at both horizontal and vertical polarizations. All 14 snow states are updated at each measurement time, and the snow water equivalent may then be computed from the snow depth and snow density.

5. Results and discussion

Implementing the methodology described above, the EnKF was run under a variety of conditions for this lumped model test using forcing data from the MMEBS for the 1993/94 winter. Results below are grouped by the subset of frequencies assimilated; results from assimilation of observations at SSM/I frequencies will be discussed first, followed by results from assimilation of AMSR-E frequencies and results from simultaneous assimilation of AMSR-E frequencies and broadband albedo. For each frequency subset, we will first review the basic filter results of the EnKF estimate of the SWE, which is of primary interest. Then we will consider three secondary issues, including 1) which frequencies made the biggest contribution to the updates, 2) what information was contained in those measurements, and 3) explanation of a low bias observed late in the winter for very deep snow. All of these initial tests are for the bare snow case. The impact of vegetation on these results is discussed below. Sensitivity tests examining the effects of the measurement error and the ensemble size on the EnKF estimate are presented at the end of this section.

a. Performance of EnKF using SSM/I frequencies

The snow depth and snow density (for the bottom snow layer) estimated from the assimilation of synthetic passive microwave observations at SSM/I frequencies are shown in Fig. 1. The true snow depth grows rapidly in the first two weeks of December, and is approximately 1 m until February. Snow events during February increase the depth to over 3 m, after which the snow compacts (due to destructive metamorphism) to approximately 2 m. The sharp drops in the bottom-layer snow density are due to precipitation events. (Throughout the text, the bottom layer is denoted by a “1” subscript and the surface layer by a “3” subscript). As expected, the result of the precipitation bias leads to underestimation of snow depth in the open-loop case. It is
immediately clear that the EnKF estimate greatly improves upon the biased open-loop model run for both snow depth and density. These states are used together with the upper-layer densities (not shown) to compute the SWE, discussed below.

Two additional state variables, grain diameter (Fig. 2) and the volumetric liquid water content of the snowpack (Fig. 3), are shown. Accurate estimates of these variables are required in order to accurately predict the observations using the RTM. From Fig. 2, it is clear that the grain diameter estimates are qualitatively much closer to the truth than the open-loop values throughout the winter. For much of the snow season, there is no liquid water present in the snowpack, and the bottom layer (not shown) is dry throughout the snow season. Liquid water for two weeks late in the snow season is shown in Fig. 3. An important advantage of the EnKF, over retrieval methods, is that the SWE estimate does not degrade significantly when liquid water is present in the snowpack, since some ensemble members should have some liquid water present, and this will be reflected in the ensemble of predicted observations. Furthermore, if a measurement contains little or no SWE information, the update is, by definition, small so that the posterior estimate is equal to the prior estimate.

From the depth and density state variables, the SWE is computed and shown in Fig. 4. The estimate follows the truth closely through mid-February, after which there is a low bias. Both 20 February and 2 March illustrate a good update (where the estimation error is reduced) and a “nonupdate” (where the estimation error stays constant), respectively, and are discussed below. From Table 1, the ensemble mean estimate has a season-averaged bias of 3.37 cm, and rmse of 4.0 cm, which is an 85% reduction of the open-loop rmse of 27.1 cm.

In addition to comparing the EnKF performance to the open-loop case, it is instructive to use the synthetic measurements at the SSM/I channels to compare results to a well-known retrieval algorithm for estimating snow depth. Figure 5 shows the SWE computed by the EnKF and the Chang et al. (1987) algorithm. Since the retrieval methodology was only designed to work for snow with a depth less than 1 m, we compare the results for the months of December and January only. Though not applicable during February and March, the retrieval algorithm provides a good benchmark for the effectiveness of the EnKF estimate. The rmse for the Chang algorithm is 13.8 cm, compared to an rmse of 3.2 cm for the EnKF estimate. Furthermore, the retrieval algorithm does not capture the temporal changes in the snowpack over this period, highlighting an important advantage of the EnKF over retrieval algorithms in general.
One way in which these synthetic tests can potentially be very useful is in objectively evaluating which observations contain the most information in the context of this synthetic experiment. Based on the EnKF update Eq. (6), we can evaluate the information contributed by each channel to the state estimate explicitly. Decomposing the update equation at a given time into the update to each state $i$ due to each measurement $j$ for each replicate $k$, we have

$$y^+(i,k) = y^-(i,k) + \sum_{j=1}^{n_m} \delta y(i,j,k),$$

where, $n_m$ is the number of measurements, and $\delta y(i,j,k)$ is the state variable update or innovation and is given by

$$\delta y(i,j,k) = K(i,j)[z_{obs}(j) - z^-(j,k) + v(j,k)],$$

where $z^-(j,k)$ indicates the predicted observations, i.e. the output of the measurement model.

The error in each state $i$ that is corrected due to each channel $j$ at each replicate $k$ can now be computed. We can define a correction factor based on the prior error and the posterior error based on update due to only one measurement as

$$\kappa(i,j,k) = |y^-(i,k)| - |y^+(i,j,k)|,$$

where $y^-$, $y^+$ refer to the prior and posterior error in each state variable relative to the true state. The most important property of the $\kappa$ metric is that it is greater than 0 whenever the update based on channel $j$ has reduced the absolute value of the error in state $i$, and less than 0 otherwise. To examine the contribution of

![Fig. 3.](image1.png)

**Fig. 3.** Dimensionless liquid water content of the snowpack for the upper layers—(top) layer 3 and (bottom) layer 2—estimated by EnKF methodology for two weeks in March. The truth is the solid line, the open loop is the dotted line, the faint dotted lines are individual replicates, and the EnKF estimate (ensemble mean) is the dashed line. No liquid water was present in layer 1, the bottom layer ($\theta_i = 0$).

![Fig. 4.](image2.png)

**Fig. 4.** Snow water equivalent estimate obtained by assimilating synthetic observations corresponding to SSM/I frequencies. The truth is the solid line, the open loop is the dotted line, and the EnKF estimate is the dashed line. The vertical lines show the update times on 20 February and 2 March, which are discussed in detail.

![Fig. 5.](image3.png)

**Fig. 5.** True SWE and results from the EnKF and a common microwave inversion algorithm. The truth is the solid line, the Chang et al. (1987) algorithm is the dotted line, and the EnKF estimate is the dashed line.

![Table 1.](image4.png)

**Table 1.** The bias and rmse of the SWE estimate for assimilating different synthetic observations and for the open-loop simulation.

<table>
<thead>
<tr>
<th></th>
<th>Bias (cm)</th>
<th>Rmse (cm)</th>
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</thead>
<tbody>
<tr>
<td>Open loop</td>
<td>25</td>
<td>27.1</td>
</tr>
<tr>
<td>SSM/I</td>
<td>3.36</td>
<td>4.0</td>
</tr>
<tr>
<td>AMSR-E</td>
<td>2.04</td>
<td>3.16</td>
</tr>
<tr>
<td>AMSR-E and MODIS</td>
<td>1.20</td>
<td>2.60</td>
</tr>
</tbody>
</table>
Table 2. The correction factor $\kappa$ for snow water equivalent in cm, averaged over the ensemble and summed over all the updates for the SSM/I frequencies ($H$ = horizontal and $V$ = vertical).

<table>
<thead>
<tr>
<th>Frequency</th>
<th>$V$</th>
<th>$H$</th>
<th>$V$</th>
<th>$H$</th>
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<th>$H$</th>
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<tr>
<td>19.35</td>
<td>0.97</td>
<td>0.75</td>
<td>1.7</td>
<td>13.49</td>
<td>13.26</td>
<td>-2.9</td>
<td>-3.62</td>
<td></td>
</tr>
<tr>
<td>37.0</td>
<td>1.24</td>
<td>1.24</td>
<td>1.59</td>
<td>3.81</td>
<td>2.47</td>
<td>1.83</td>
<td>1.62</td>
<td></td>
</tr>
<tr>
<td>89.0</td>
<td>-1.69</td>
<td>-1.88</td>
<td>-2.51</td>
<td>-0.49</td>
<td>-0.65</td>
<td>-5.63</td>
<td>-5.56</td>
<td></td>
</tr>
</tbody>
</table>

In each channel, the correction factor for the snow water equivalent across the entire ensemble of replicates during each update was averaged at each update time. These mean correction factor values were then integrated over the entire winter and compiled in Table 2. In addition, the “best” update (the maximum value of $\kappa$) and the “worst” update (the minimum value of $\kappa$) for each frequency are shown.

From Table 2, the 37.0-GHz channels contributed an integrated sum of 13.49 and 13.26 cm for the vertical and horizontal polarizations, respectively. The 19.35- and 22.235-GHz channels made a combined contribution of only 3.42 cm. This is somewhat surprising since these channels are sensitive to snow depth (e.g., Tsang et al. 2000) and are not significantly attenuated by the atmosphere. This result is discussed with the AMSR-E assimilation results below. The 89-GHz channel overall led to the degradation of the SWE estimate. The sum of the contributions over the vertical and horizontal channels was -2.9 and -3.62 cm; however, as in the case of the 19.35- and 22.235-GHz channels, the high-frequency channel led to important onetime updates. More significantly, these channels made important contributions to correcting the grain diameter. Both of the 89-GHz channels contributed an integrated total of over 1 mm toward correcting the error in the grain diameter in both of the upper two snowpack layers (not shown), more than the other channels combined. Without accurate estimates of the grain diameter, the information in the 37-GHz channel would not have been useful for correcting the SWE estimate.

Returning to Fig. 4, there is clearly a low bias in the EnKF estimate that grows worse late in the winter. One reason for this is the well-known saturation effect of brightness temperature as a function of increasing snow depth (Sturm et al. 1993); stratigraphic effects may also result in saturation of the signal. Another possible explanation is due to the fact that there is liquid water present in upper two snowpack layers on some days (Fig. 3). Even very small amounts of liquid water also effectively cause the brightness temperature to saturate, in which case it no longer contains any information about the SWE. To further diagnose the reason for this low bias, we may first ask what conditions lead to a good update. From the Kalman update Eq. (6), we can hypothesize that, in general, a good update will occur 1) whenever the Kalman gain adequately represents a linear relationship between the state variable and one or more observation variables and 2) whenever the true state and synthetic measurement may be adequately modeled by that same relationship.

We may test this by first considering a good update to snow depth on 20 February due to the 37-GHz H SSM/I channel on 20 February. The “x” symbols represent the ensemble members, the triangle represents the uncorrupted synthetic observation, and the diamond represents the observation with random measurement error. The square represents the prior estimate, and the circle represents the posterior estimate. The solid line represents the model sensitivity of the measurement to the state, the dotted line is the “ideal” update trajectory (in the limiting case where there is no measurement error), and the dash-dot line is the actual update trajectory specified by the Kalman gain (including measurement error). A vertical update trajectory corresponds to no information in the measurement.

Fig. 6. The update to the snow depth due to the 37.0-GHz H SSM/I channel on 20 February. The “x” symbols represent the ensemble members, the triangle represents the uncorrupted synthetic observation, and the diamond represents the observation with random measurement error. The square represents the prior estimate, and the circle represents the posterior estimate. The solid line represents the model sensitivity of the measurement to the state, the dotted line is the “ideal” update trajectory (in the limiting case where there is no measurement error), and the dash-dot line is the actual update trajectory specified by the Kalman gain (including measurement error). A vertical update trajectory corresponds to no information in the measurement.
there is a small but significant positive correlation (the correlation coefficient is 0.48) in the ensemble members between the brightness temperature and the snow depth, which satisfies our first condition for a good update. Note that the true state and both the true brightness temperature and the synthetic observation lie within the range of this relationship, satisfying our second condition for a good update.

The gain or slope of the Kalman update Eq. (6) is the “direction” or trajectory in which the filter updates the prior estimate. The “ideal” update trajectory, which is the update trajectory calculated with zero measurement error, and the actual update trajectory, which is the update trajectory calculated with the actual measurement error, are also shown in Fig. 6. The actual update trajectory shows graphically the effect of the EnKF in updating the state variable by computing the posterior state estimate for different differences between the observation and predicted observation; the ideal update trajectory shows the effect of the measurement error on the actual update. For the limiting case of infinite measurement error, the actual update trajectory reduces to a vertical line, implying that there is no information about the state in the observation. For comparison purposes, we can estimate the true sensitivity of the measurement to the state variable by considering a single replicate, perturbing the snow depth, and recomputing the predicted brightness temperatures (solid line). In this case, we can see that this measurement channel is entirely saturated, such that the measurement contains no information about the snow depth directly. In fact, the observation contains crucial information about the SWE based on an indirect relationship of the grain diameter to the snow depth. This is the cause of the surprising positive relationship between the snow depth and brightness temperature, which is somewhat unexpected since most authors have reported a negative correlation between brightness temperature and snow depth (e.g., Chang et al. 1987), although some studies have reported positive relationships (e.g., Rosenfeld and Grody 2000). In this case, however, the positive correlation is due to 1) the fact that this channel is saturated with respect to snow depth, 2) the strong dependence of the 37-GHz brightness temperatures on the snowpack grain diameter, and 3) the strong inverse relationship between the snow depth and the grain diameter in the lower snow layer, which is shown in Fig. 7. This relationship derives from Eqs. (1) and (2), where it is shown that the grain diameter growth is proportional to the temperature gradient across the snowpack. For given boundary condition temperatures, a deeper snowpack will be associated with a smaller average temperature gradient across the snowpack, where a shallow snowpack will be associated with a larger temperature gradient across the snowpack. This relationship between snow depth and grain diameter was observed in physical snowpacks by Armstrong et al. (1993). These types of indirect relationships are implicitly taken into account using data assimilation schemes such as the EnKF but are extremely difficult to incorporate into retrieval algorithms.

Another question is why we do not observe a good update due to the 37-GHz H channel to correct the low bias observed in Fig. 4. To address this, we may consider the update on 2 March late in the season. The state and measurement scatterplot is shown in Fig. 8. Consider the ideal update trajectory, which is sufficient
to correctly update the snow depth in the positive direction. For the actual measurement error of 2 K, however, the update trajectory is nearly vertical, indicating no update. The reason for this change is that the standard deviation of the predicted measurement across the ensemble is only 0.8 K. If the measurement error is of similar magnitude to (or bigger than) the measurement variance, we cannot expect a good update. Therefore, to the list of necessary conditions for a good update developed above, we may add that 3) the brightness temperature covariance must be greater than the magnitude of the measurement error variance.

**b. Performance of EnKF using the AMSR-E frequencies**

From Fig. 9, the EnKF SWE estimate using the AMSR-E frequencies has improved somewhat over the SSM/I case. The estimate is excellent throughout December, January, and February. Near the end of February, however, we see the same low bias in the snow water equivalent that we observed previously. Nevertheless, the addition of the low frequency 6.925- and 10.65-GHz channels apparently improves the estimate inasmuch as the rmse from Table 1 for the estimate is only 3.16 cm, which is 0.74 cm or 19% less than the rmse for the estimate using the SSM/I frequencies.

From Table 3, the 37-GHz channels made the biggest overall contributions toward correcting the estimate of SWE. The lower frequency channels made a large contribution as well, with the 6.925 and 10.65 H channels being the next most important. While the 85-GHz channels made two of the most important contributions at a single update (1.76 and 1.80 cm in the horizontal and vertical channels, respectively), their overall effect was to degrade the estimate with respect to SWE. However, as in the SSM/I case, these channels made the most important contributions to estimation of the grain diameters (not shown), which is critical information for estimating SWE.

We can investigate the information contained in these lower frequencies in more detail by considering a good update on 9 February. We would expect that the lower-frequency 10.65-GHz V channel is not saturated even for these deep snowpacks. In fact, in Fig. 10 it is clear that the negative correlation between the snow depth and brightness temperature is effectively modeled by a linear relationship, and that the actual update trajectory, though much steeper than the ideal trajectory, still represents the relationship between the states and measurements. It should be noted that the true state lies far outside the trend. Nevertheless, we still observe a good update, since the effect of the difference between the truth and the relationship shown in the replicates is to force a large positive update in snow depth, partially correcting the usual low bias in the estimate.

This raises the question as to why the information in the 10.65-GHz measurement is not exploited to correct the late season bias. Figure 11 shows the scatterplot of the snow depth and 10.65-GHz V channel on 9 March. It is clear that there is some (small) negative linear correlation in the data, satisfying the first condition for a good update. It can also be seen that the true state and corrupted measurement lie in the general range of the scatterplot data, which satisfies the second condition for a good update. Note, however, that the 35-cm spread in the snow depth corresponds to less than a 4 K

**Table 3.** The correction factor $\kappa$ for snow water equivalent in cm, averaged over the ensemble and summed over all the updates for the AMSR-E frequencies.

<table>
<thead>
<tr>
<th></th>
<th>6.925 V</th>
<th>6.925 H</th>
<th>10.65 V</th>
<th>10.65 H</th>
<th>18.7 V</th>
<th>18.7 H</th>
<th>23.8 V</th>
<th>23.8 H</th>
<th>36.5 V</th>
<th>36.5 H</th>
<th>89.0 V</th>
<th>89.0 H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum</td>
<td>0.19</td>
<td>1.37</td>
<td>4.9</td>
<td>1.05</td>
<td>0.88</td>
<td>0.94</td>
<td>1.34</td>
<td>1.49</td>
<td>10.2</td>
<td>6.38</td>
<td>-2.3</td>
<td>-2.16</td>
</tr>
<tr>
<td>Max</td>
<td>0.58</td>
<td>0.55</td>
<td>1.02</td>
<td>1.06</td>
<td>0.88</td>
<td>0.99</td>
<td>0.81</td>
<td>0.65</td>
<td>3.62</td>
<td>2.56</td>
<td>1.8</td>
<td>1.76</td>
</tr>
<tr>
<td>Min</td>
<td>-0.57</td>
<td>-0.84</td>
<td>-0.1</td>
<td>-0.51</td>
<td>-1.39</td>
<td>-1.31</td>
<td>-1.69</td>
<td>-0.65</td>
<td>-0.94</td>
<td>-2.51</td>
<td>-4.33</td>
<td>-4.32</td>
</tr>
</tbody>
</table>
spread in the brightness temperature. In other words (similar to the case shown for the 37-GHz H in Fig. 8 above), the variance in the predicted measurements is on the order of the measurement error variance, which violates our third condition for a good update. Note that the incremental update evident in Fig. 11 was not due to the 10.65 GHz, but to one of the other channels.

The results concerning the contribution of each measurement channel cited from Tables 2 and 3 raises a further question as to why the 18.7- and 23.8-GHz channels do not contribute more to the estimate. The 18.7-GHz channel has been shown theoretically to be sensitive to snow depth (e.g., Tsang et al. 2000), so it was expected that they would make a significant contribution. Consider the update on 13 December in Fig. 12. It seems that in the 18.7-GHz channel, the signal is sensitive both directly to the snow depth, and indirectly to the grain diameter; importantly, the grain diameter is inversely related to the snow depth. Evidence of the first relationship is given in the sensitivity calculations for one replicate shown in the solid line, which demonstrates a negative relationship between snow depth and the measurement. The second relationship seems evident from the scatterplot, showing a positive correlation between the depth and the measurement, especially for depths above ~0.9 m. It is hypothesized that the resulting scatterplot is a composite of these two competing relationships (one positive relationship and one negative relationship), and that a linear update is inadequate to extract any information about the snow depth from such a signal.

c. Impact of addition of MODIS broadband albedo

We now consider assimilation of synthetic passive microwave observations at AMSR-E frequencies and broadband albedo observations simultaneously. From Table 1 the bias is reduced from the AMSR-E case by 41% or 0.84 cm and the rmse is 0.56 cm or 18% less than the estimate made without the albedo observations. These results support the idea that there is a synergistic benefit between assimilation of both passive microwave and visible/NIR observations. Furthermore, the spatial resolution of the MODIS observations has a nominal value of 500 m, while the AMSR-E observations have resolutions ranging between 5 and 60 km. We hypothesize that the MODIS albedos will contribute to accurate grain diameter and SWE estimates at relatively high spatial resolution in the spatially distributed case. This hypothesis will be tested in follow-on work.
d. Effects of vegetation

It is well known that vegetation severely attenuates passive microwave signals (e.g., Foster et al. 2005). For this reason, we repeated the assimilation of AMSR-E frequencies with different thicknesses of vegetation, with wet biomass values ranging from 1.0 to 3.0 kg m\(^{-2}\).

The results can be seen in Fig. 13; it is clear that with thicker vegetation, measurements contain less information about SWE, and the filter results begin to converge to the open-loop results. The bias and rmse of the SWE for each of these simulations is shown in Table 4; even for a wet biomass of 1.0 kg m\(^{-2}\), the rmse has already more than doubled over the no-vegetation case. However, even for thick vegetation with a wet biomass of 3.0 kg m\(^{-2}\) the rmse value of 18.51 cm is still 26% less than the open-loop rmse of 25 cm.

e. Sensitivity study

To evaluate the effect of the measurement error on the performance of the filter, we performed parallel runs assimilating synthetic AMSR-E measurements only using measurement errors of 1, 2, and 4 K in brightness temperature. From Table 5, even with the higher 4 K error, the rmse is still significantly better than both the open-loop rmse (27.1 cm) and the early winter retrieval rmse (10 cm) cited above. The rmse in the case of 4 K standard error is 6.36 cm, which is 3.2 cm or twice as large as the rmse with 2-K error. The bias is nearly 3 times as large if the error is 4 K, so the results are quite sensitive to measurement error.

We may also examine the effect of ensemble size on the filter performance. The estimate of SWE based on assimilation of AMSR-E frequencies was computed for various numbers of replicates, and the results are shown in Table 6. It is clear that ensemble sizes of less than 25 lead to higher error, as the rmse of the 5-replicate run is 6.98 cm. The rmse of the 50- and 100-replicate runs are 2.91 and 3.16 cm, respectively, so that we can see there is a threshold, between 25 and 50 replicates, above which there are diminishing returns.

6. Conclusions and future work

A new method for estimating SWE using synthetic multifrequency remote sensing observations was tested. The EnKF radiometric data assimilation scheme was used to recover the true snowpack states (most notably SWE). It is applicable to deep snow with liquid water present. The EnKF run was performed using artificially biased meteorological forcing data, such that the average ensemble replicate received only half the precipitation that the true state received. The results are very encouraging, in that the synthetic microwave observations using all 12 AMSR-E channels contained sufficient information to recover the true SWE to within an rmse of approximately 3 cm compared to the maximum SWE of 80 cm and maximum snow depths of greater than 3 m. A method for evaluating the contribution of each channel during an update was developed, and the integrated contribution of each channel was deter-

**Table 4.** The bias and rmse of SWE estimates are shown for various vegetation thickness.

<table>
<thead>
<tr>
<th>Wet biomass (kg m(^{-2}))</th>
<th>Bias (cm)</th>
<th>Rmse (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.04</td>
<td>3.16</td>
</tr>
<tr>
<td>0.9</td>
<td>8.02</td>
<td>8.59</td>
</tr>
<tr>
<td>1.9</td>
<td>12.42</td>
<td>13.16</td>
</tr>
<tr>
<td>2.9</td>
<td>17.29</td>
<td>18.51</td>
</tr>
</tbody>
</table>

**Table 5.** The rmse and bias of the SWE estimate for different assumed values of the standard deviation of the measurement error.

<table>
<thead>
<tr>
<th>(\sigma_{\text{err}})</th>
<th>Bias (cm)</th>
<th>Rmse (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 K</td>
<td>0.80</td>
<td>2.22</td>
</tr>
<tr>
<td>2 K</td>
<td>2.04</td>
<td>3.16</td>
</tr>
<tr>
<td>4 K</td>
<td>5.68</td>
<td>6.36</td>
</tr>
</tbody>
</table>

**Table 6.** The bias and rmse of the SWE estimate based on assimilation of AMSR-E frequencies for different numbers of replicates, \(n_r\).

<table>
<thead>
<tr>
<th>(n_r)</th>
<th>Bias (cm)</th>
<th>Rmse (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>6.33</td>
<td>6.98</td>
</tr>
<tr>
<td>25</td>
<td>3.08</td>
<td>3.66</td>
</tr>
<tr>
<td>50</td>
<td>1.14</td>
<td>2.91</td>
</tr>
<tr>
<td>100</td>
<td>2.04</td>
<td>3.16</td>
</tr>
</tbody>
</table>
mined. It was confirmed that in the context of this data assimilation experiment, at least some passive microwave channels (e.g., the 10.65-GHz channel) still contain valuable information even in the case of deep snow. Despite being saturated with respect to snow depth directly and attenuation due to atmospheric absorption, the 36.5-GHz channel adds significant information to the SWE estimate through an indirect relationship with the bottom-layer grain diameter. The 18.7- and 23.8-GHz channels add much less information than the 10.65-GHz channel in this experiment. Assimilating albedo observations in addition to passive microwave measurements improved the rmse by nearly 20%; furthermore, it is anticipated that these albedo observations will play a significant role in refining the surface grain diameter estimate in the spatially distributed case. A thin layer of vegetation more than doubles the SWE rmse; but even when subject to thick vegetation, the filter estimate is much improved over the open-loop case.

The effects of measurement error and ensemble size on the EnKF efficiency in terms of the rmse of the SWE were also evaluated. The filter performance is quite sensitive to assumed measurement error, and there is a minimum number of replicates (approximately 50) that are needed in order to achieve accurate results and above which there are diminishing returns on the added computational expense of the ensemble propagation. The next logical step in this research is to apply this methodology to a spatially distributed test case. For the distributed case, the various resolutions of the different microwave frequencies and the MODIS albedo will all come into play, leading to additional potential synergism between observations. Another possible extension of this work would be to assimilate active remote sensing observations, which generally have higher spatial resolution and are beginning to be utilized in inversion schemes for estimating SWE (Marshall et al. 2004). Ultimately, we anticipate the assimilation of real AMSR-E, SSM/I, and MODIS observations. The ensemble methodology could eventually be applied to the very relevant problem of estimating snow mass in remote regions of the world where the need to drive hydrologic models using meteorological forcing data derived from remote sensing instruments requires careful accounting of additional input uncertainties (e.g., Margulis et al. 2006).

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REFERENCES
Davis, R., J. Dozier, and D. Marks, 1984: Micrometeorological measurements and instrumentation in support of remote sensing observations of an alpine snow cover. Western Snow Conf., Sun Valley, ID, 161–164.


