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Water Resources Research

RESEARCH ARTICLE

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Key Points:

- A spatially distributed snow data assimilation approach for an energy balance snowmelt model coupled to distributed runoff model
- Assimilation of sparse SNOTEL observations improved snow water equivalent at points where observations were excluded
- Seasonal streamflow forecast volumes predicted on 1 April were improved by snow data assimilation

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Ensemble Streamflow Forecasting Using an Energy Balance Snowmelt Model Coupled to a Distributed Hydrologic Model with Assimilation of Snow and Streamflow Observations

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Abstract In many river basins across the world, snowmelt is an important source of streamflow. However, detailed snowmelt modeling is hampered by limited input data and uncertainty arising from inadequate model structure and parametrization. Data assimilation that updates model states based on observations, reduces uncertainty and improves streamflow forecasts. In this study, we evaluated the Utah Energy Balance (UEB) snowmelt model coupled to the Sacramento Soil Moisture Accounting (SAC-SMA) and rutpix7 stream routing models, integrated within the Research Distributed Hydrologic Model (RDHM) framework for streamflow forecasting. We implemented an ensemble Kalman filter for assimilation of snow water equivalent (SWE) observations in UEB and a particle filter for assimilation of streamflow to update the SAC-SMA and rutpix7 states. Using leave one out validation, it was shown that the modeled SWE at a location where observations were excluded from data assimilation was improved through assimilation of data from other stations, suggesting that assimilation of sparse observations of SWE has the potential to improve the distributed modeling of SWE over watershed grid cells. In addition, the spatially distributed snow data assimilation improved streamflow forecasts and the forecast volume error was reduced. On the other hand, the assimilation of streamflow observations did not provide additional forecast improvement over that achieved by the SWE assimilation for seasonal forecast volume likely due to there being little information content in streamflow at the forecast date prior to its rising during the melt period and this application of particle filter being better suited for shorter timescales.

1. Introduction

In many parts of the world, as it is in the intermountain United States, snow is a significant component of water resources. Hence, it is important to adequately model snow accumulation and melt in order to be able to forecast the quantity and timing of streamflow for purposes of water supply, energy production, flood control, maintaining the ecosystem, etc. In terms of complexity, snow models vary from lumped conceptual models to physically based, multidimensional models solving the energy and mass balance of the snowpack and spatial redistribution of snow such as due to wind (Anderson, 1976; Bartelt & Lehning, 2002; Clark et al., 2011; Jordan, 1991; Lehning et al., 2002; Mahat et al., 2013; Mahat & Tarboton, 2014; Mott et al., 2010; Pomeroy & Essery, 1999; Tarboton et al., 1995; You et al., 2014).

Currently, the U.S. National Weather Service (NWS) uses the SNOW-17 model (Anderson, 2006) for streamflow forecasts. SNOW-17 uses temperature as an index for energy exchanges at the snow surface, and it only requires two inputs: precipitation and temperature. The application of SNOW-17 to streamflow forecasting depends on the assumption that the calibrated relationship between temperature and snowmelt holds over the domain for which the model was calibrated. In addition, it relies on the fact that temperature is easy to measure and accurately forecast for a few days into the future in operational settings. While temperature-index snowmelt models work quite well if they are adequately calibrated, they prove insufficient when the weather conditions significantly deviate from those for which the models were calibrated (Anderson, 2006). In addition, conceptual models that rely on calibration of parameters based on historical data may be limited when there is a shift in hydrologic regime due to changes in climate, land cover, land use, urbanization etc. (Biederman et al., 2015; Broxton et al., 2015; Fowler et al., 2007).

Using physically based, energy balance snowmelt models for operational streamflow forecasting has been a goal of the U.S. NWS (Franz et al., 2008) as it offers the opportunity to overcome some of the shortcomings listed above. While physically based models reduce the uncertainty due to limited process representations and the overdependence on calibration in conceptual models, their application, on the other hand, entails added uncertainty arising from the additional input data requirements and uncertainty introduced by increased model complexity (Beven et al., 2015; Semanova & Beven, 2015).

In operational streamflow forecasts, assimilation of observed data is used to reduce forecast uncertainty by conditioning the forecasts on best possible model states at the time of the forecast (Clark et al., 2008; Franz et al., 2003; Pathiraja et al., 2016). In data assimilation (DA), observations are used to adjust and update model states balancing observation and model uncertainty represented by a statistical measure such as error variance. In snowmelt-driven streamflow forecasts, the updated model states that the forecasts are conditioned on include snowpack, soil moisture, and stream channel states.

Prior studies with respect to assimilation of observations in hydrologic models have focused on a specific process and data related to it. Examples of these include assimilation of soil moisture related data (Reichle et al., 2002), assimilation of data related to snow (Clark et al., 2006; Slater & Clark, 2006; Su et al., 2008), and assimilation of streamflow observations (Abaza et al., 2014; Clark et al., 2008). However, in a model that integrates multiple processes, there is an opportunity to assimilate multiple data types into the different model components with the potential to obtain improved outputs such as streamflow at basin outlet. The different observation types used in such multi-data assimilation complement each other where the limitation of one observation may be compensated by another observation type (Franz et al., 2014). It is also possible to apply different assimilation methods customized to different components of the integrated modeling system. For example, assimilation of streamflow using the ensemble Kalman filter (EnKF) or its variants may not be very efficient to update storage states such as snow water equivalent (SWE) or soil moisture. This is likely due to the nonlinearity of the relationship between the internal (watershed) model states and the streamflow at the outlet (Clark et al., 2008) that makes it difficult to compute the cross-covariances between states and outputs on which the EnKF relies (Rakovec et al., 2012).

Point observations such as those from Snow Telemetry (SNOTEL; <https://www.wcc.nrcs.usda.gov/snow/>) stations provide an opportunity to, through assimilation, update model SWE states to improve forecast initial conditions. However, SNOTEL observations are sparse, and an approach is needed to propagate information from these sparse sites to each model grid cell. Slater and Clark et al. (2006) interpolated normalized standard deviates of SWE to each grid cell, and then inferred grid cell SWE from an ensemble of historic model simulations at that grid cell. This interpolated SWE was treated as an observation and used in an EnKF to separately assimilate SWE at each grid cell (Slater & Clark, 2006). As an alternative to this treatment of an interpolation as an observation operator, there is the potential to use the EnKF to directly propagate information from observation sites to unobserved model grid cells through the spatial correlation of SWE. This can be done, for example, by augmenting the model grid SWE state vector with SWE states at observation locations and then having the EnKF observation function act on observation location elements of the augmented state vector.

In order to contribute toward the goal of adopting more physically based models in operational streamflow forecasting, and to evaluate the use of an energy balance snowmelt model as part of the modeling suite used in the NWS forecasting system, we integrated the Utah Energy Balance (UEB) snowmelt model into the Research Distributed Hydrologic Model (RDHM). RDHM already has implementations for the Sacramento Soil Moisture Accounting (SAC-SMA) and rutpix7 river routing models. In addition, we implemented two different DA methods to assimilate snow and streamflow observations to their respective model components and evaluated the potential improvement to forecast streamflow. The EnKF was used to assimilate point SWE from SNOTEL in UEB, and streamflow data were assimilated using the particle filter (PF) method to update SAC-SMA and rutpix7 model states. The snow DA method used state vector augmentation stated above in which the EnKF propagates information across watershed grids based on spatial correlation of SWE. The PF was selected for streamflow assimilation because, as stated earlier, the EnKF may struggle to accurately represent the cross-covariances between soil moisture and streamflow at the outlet.

This paper is organized as follows. In section 2, descriptions of the streamflow forecast scheme, the data assimilation methods, the study watersheds and model data, and the performance metrics are provided. Results and discussion are given in sections 3 and 4, respectively, followed by conclusions in section 5.

2. Data and Methods

2.1. Streamflow Forecast Scheme: Integrated UEB+RDHM Models

Figure 1 shows the ensemble streamflow forecasting scheme. Its major components are the UEB snowmelt model and its integration into the RDHM, the generation of ensemble forcing inputs, the snow and streamflow DA, and ensemble streamflow forecasting.

The UEB model represents the major physical processes critical for snow accumulation and ablation (Luce & Tarboton, 2010; Mahat et al., 2013; Mahat & Tarboton, 2012, 2014; Tarboton et al., 1995; You et al., 2014). As a single-layer model, UEB is parsimonious, avoiding some of the complexity and input needed for more detailed multilayered snowmelt models. This makes it a promising candidate for operational streamflow forecasting where computational time can be critical, and where there is interest in incrementally evaluating the improvements possible through adding better physical process representations.

RDHM is a modeling framework for gridded hydrologic simulation of watershed processes that comprises a platform for coupling different components and facilitating the transfer of data among different modeling components during run-time (Koren et al., 2004; The HL Research Distributed Hydrologic Model, 2008). Inside the integrated UEB+RDHM framework, the UEB model was run first. The rain + melt (Rmelt) output from UEB provides input to the SAC-SMA model (Burnash et al., 1973; Burnash & Singh, 1995), which simulates runoff that is subsequently routed to the basin outlet with the kinematic wave routing model rutpix7 (The HL Research Distributed Hydrologic Model, 2008) to generate streamflow.

The ensemble streamflow forecasting procedure is illustrated in Figure 2. A model run starts at the beginning of the water year, 1 October, and proceeds up to the “forecast time” using observed data for that year as input. The forecast time is the point when the streamflow forecasts are issued. The streamflow forecast is then run for a duration labeled “forecast period,” using input forcing data from all available historic years. This results in the ensemble of possible future traces depicted in Figure 2. In this study, the forecast period was from 1 April to 30 September. The forecast period is comprised of an optional “lead time” and a “forecast window.” The forecast window is the time span for which the forecast is sought after, while lead time is a period between the issuing of forecast and the start of the forecast window. Lead time provides water manager time to prepare to deal with the forecasted event. The forecast time for this study was chosen to be 1 April, and the forecast period and forecast window in this study were the same, between 1 April and 30 September (thus, the lead time was 0). The choice of 1 April for forecast time was based on the fact that for most watersheds in the western United States, the snowmelt season starts around this date. In addition, for the purposes of reservoir operations and other water allocation and management practices, the April–July streamflow volume is one of the primary variables of interest at the Colorado Basin River Forecast Center (CBRFC).

Figure 2 depicts a single simulation trace based on observed forcing data up to the forecast time as an illustration of the general idea. However, in this study we ran the model simulation between the start of simulation (1 October) and forecast time (1 April) using multiple traces that account for input uncertainty with assimilation of SWE and streamflow used to update model states. The objective of this was to arrive at a set of states that represent the best possible estimate of initial state, and its uncertainty, and to use this to initialize the forecast. The EnKF was used for assimilation of snow data, while the PF was used to assimilate streamflow observations at the watershed outlet. Forcing perturbations were used to represent uncertainty in input forcing to the EnKF. The implementations of the DA methods are described in section 2.3 below.

The ensemble simulation for the forecast period uses multiple realizations of future weather conditions to account for uncertainties in forecast weather forcing. Weather forcing ensembles can be obtained from numerical weather prediction models (Cloke & Pappenberger, 2009). Alternatively, long-term observations or reanalysis of historical weather forcing is taken to represent samples of the likely distribution of the future weather conditions (Day, 1985; Franz et al., 2003; Wood & Lettenmaier, 2008). The latter approach was used in this study.

Figure 1. Ensemble streamflow forecasting scheme with Utah Energy Balance (UEB) as Research Distributed Hydrologic Model (RDHM) component.

2.2. Study Watershed and Data

The study watershed used to evaluate the work in this paper is the Green River watershed above Warren Bridge (Figure 3). Observed SWE data from four SNOTEL stations shown in Figure 3 and summarized in Table 1 were assimilated in UEB. We evaluated the SWE assimilation at the observation points for the water year 2009 (1 October 2008 to 30 September 2009). The water year 2009 was selected because of the availability of gridded weather forcing data from the CBRFC for that year, at the start of this study. For streamflow forecast evaluation, that also incorporates SWE and discharge assimilation, we used the water years 2005 to 2009.

We used a 30-m digital elevation model (DEM) from the U.S. Geological Survey (USGS) to extract terrain variables slope and aspect. Canopy variables were generated based on the 2011 National Land Cover Database (Homer et al., 2015). We used precipitation and air temperature data from CBRFC. These datasets

were generated by the CBRFC from multiple sources including radar, satellite (in areas of data scarcity), and ground gages such as SNOTEL and NWS Cooperative Observer Network (COOP). The data were gridded to a resolution of 800 m, with elevation, slope, and aspect adjustments based on the PRISM (Parameter-elevation Relationships on Independent Slopes Model) interpolation (Daly et al., 1994, 2008). The data processing at CBRFC includes adjustments for elevation as well as bias correction.

Humidity and wind speed data were obtained from the North American Land Data Assimilation System (NLDAS) forcing datasets (Mitchell et al., 2004). The NLDAS datasets were downscaled, with elevation adjustment, following a downscaling methodology described by Sen Gupta and Tarboton (2016). In this downscaling, the DEM from NLDAS was used to represent the elevation of the NLDAS datasets, while the elevation from the USGS DEM at the center of the grid cell was the target elevation to which the forcing data were downscaled.

Solar and longwave radiation were parameterized based on air temperature and humidity in UEB (Tarboton et al., 1995; You et al., 2014). The parameters required for the generation of these radiation model inputs

Figure 2. Temporal organization of ensemble streamflow forecast procedure. Adapted from (Franz et al., 2003).

Figure 3. Study watershed: Green River above Warren Bridge.

were used from previous studies applying UEB in the western United States (Mahat & Tarboton, 2012; Sen Gupta & Tarboton, 2016). The sensitivity of UEB snowmelt simulations to radiative energy inputs has been quantified by others (e.g., Lapo et al., 2015; Raleigh et al., 2016).

The simulations were carried out on a grid with cells of size 0.25 Hydrologic Rainfall Analysis Project (HRAP) units. HRAP is a coordinate system used by the NWS for gridded data and modeling (Reed & Maidment, 1999). A 0.25 HRAP unit corresponds to a grid size of about 1,190 m. RDHM takes as an input

Table 1
SNOTEL Stations With SWE Data Used in the Study

Watershed	SNOTEL station	Elevation (m)	Latitude	Longitude
Green River above Warren Bridge	Kendall RS	2,359	43.25	−110.02
	Gunsight Pass	2,993	43.38	−109.88
	Loomis Park	2,512	43.17	−110.13
	New Fork Lake	2,542	43.12	−109.95

Abbreviations: SNOTEL: Snow Telemetry; SWE: snow water equivalent.

a connectivity file that specifies the model domain and the connectivity between grid cells that defines the path to the outlet for a given watershed. It is generated from DEM data. During runtime, RDHM resamples the forcing, terrain, and land cover data inputs at the centers of the grid cells in the connectivity file. Given this configuration and given that the terrain and land cover data were sampled from the 30-m resolution DEM, the UEB model at each 0.25 HRAP (~1,190 m) grid cell represents a point with 30-m support scale (footprint) and 1,190-m spacing.

This sampling scheme is premised on the assumption that these points at 1,190-m spacing aggregated over the watershed represent the distribution of snow and snowmelt input over the watershed. This assumption was tested by comparing the distributions of sample grid cells to the distribution of all 30-m grid cells in the domain. We found (in results not reported) that the distributions were comparable. Such subsampling was preferable to averaging inputs over the grid cell, especially for terrain and land cover data where averaging the slope and aspect of terrain may give erroneous values (flatten the terrain) and land cover classes cannot be averaged in the first place.

2.3. Data Assimilation Methods: EnKF and PF

In data assimilation, a model is run forward in time, up to a point when observations are available. Then the observations are used to adjust and update model states to reduce their uncertainty. These improved model states are then used to further propagate the model forward in time, to the point of another observation update, or to provide an initial condition to a forecast. During the assimilation, modeled and observed information is combined based on the relative magnitudes of their uncertainties (Lahoz et al., 2010). The resulting combined information from model and observation is expected to reduce the uncertainty of the predicted variable, by reducing the variance, compared to that of either the model or the observations by themselves. In addition, simulation model and state observations complement each other in that the observations often present a more accurate value of the state but at sparse temporal and spatial sampling intervals, while the simulation model represents spatially and temporally continuous system dynamics.

One of the most commonly used DA methods is the Kalman filter, in which model predicted and observed state values are linearly combined. The difference between observed and model predicted values, referred to as the innovation, is multiplied by a weighting factor and is added to the model predicted value to obtain the updated or assimilated value (Reichle, 2008). In the Kalman filter, the weighting factor, called the Kalman gain, is computed as the ratio of the variance of the model prediction error to the sum of variances of the observation and model prediction errors (Brown & Hwang, 2012).

The Kalman filter provides the optimal estimate in the least mean squared error sense, dependent on the assumption that the underlying distributions of both model prediction and observations are Gaussian and the system being modeled is linear (Drécourt, 2003). Methods that rely on linearization of process model equations such as the extended Kalman filter and the variance methods such as the 4-D VAR have been applied extensively over the years (Nichols, 2010). The requirement for linearization is a big challenge in terms of computational burden and the strong nonlinearities some environmental models exhibit. Alternative methods that do not require linearization of the model equations include those that derive from Monte Carlo sampling methods, such as the PF, and variants of the KF that also employ sampling methods such as the unscented Kalman filter and the EnKF (Liu et al., 2012).

The EnKF is a form of Kalman Filter that has been widely used in earth sciences and hydrology (Clark et al., 2008; Drécourt, 2003; Kumar et al., 2008; Liu et al., 2012). The EnKF relies on execution of Monte Carlo simulations to generate multiple realizations of model states that are assumed to be equally likely. The covariance computed based on the ensemble members represents the model error covariance from which the Kalman gain is computed (Evensen, 2003). The filter can be used for nonlinear processes and, while optimal filtering requires the distribution underlying the ensembles to be Gaussian, it has been shown that the EnKF provides sufficiently satisfactory, although suboptimal, performance for systems that deviate from Gaussian distribution or in systems where the underlying distribution is unknown (Reichle et al., 2002; Zhou et al., 2006).

The PF is a DA method that is similar to the EnKF in that it also relies on Monte Carlo simulation and generation of multiple realization of possible model states. However, in PF the particles (each particle representing a vector of state variables in state space) are not necessarily assumed to be equally likely. Rather, the probability distribution of the model states are represented by a set of particles (similar to

ensemble members in EnKF) and associated weights (Brown & Hwang, 2012; Grewal & Andrews, 2015; Labbe, 2015). In addition, in PF the update step does not involve computation of Kalman gain and adjustment of ensemble members. Instead, the particles' weights are updated based on distance of the corresponding state values from the observations. Particles closer to the observations are given higher weights and vice versa. Then the particle weights are used to select those that are close to the observations and generate more particles with similar characteristics while discarding particles that are too far away from observations.

2.4. Implementation of the EnKF in UEB

Hydrological and land surface processes are said to be “damped” (Reichle, 2008). Unlike atmospheric models, in which small errors in the initial conditions of states may be amplified as the process evolves forward, the primary sources of uncertainty in hydrological models are weather forcing inputs, model dynamics, and parameters (Reichle et al., 2002). The effect of errors in initial conditions diminishes over time. Hence, in this study, the ensemble realizations were generated by driving the model with ensemble forcing data obtained from perturbation of input forcing by adding randomly sampled small errors. This approach is similar to that taken by other snow DA studies (e.g., Slater & Clark, 2006). The errors for the forcing perturbation were sampled from a multivariate normal distribution generated across the grid cells in a watershed.

The UEB model state considered for assimilation is the SWE at each grid cell. The data used for assimilation in this study consisted of observed SWE at SNOTEL stations. Other UEB model states include the snowpack energy content and dimensionless age of snow surface (also known as snow surface condition). We considered only SWE for assimilation because updating the other state variables would require covariance/correlation between the observed SWE and the other states. For example, updating bulk snowpack energy based on observed SWE is only possible if the covariance between these two variables can be obtained. However, there is no clear covariance/correlation between the two. Depending on net energy inputs, snowpack energy content may increase or decrease while the snowpack water equivalent (SWE) remains the same. Therefore, the state variables other than SWE were allowed to evolve in the ensembles but were not updated.

Four SNOTEL stations in the study watershed and in the area surrounding it were used in this study. This sparsity is typical for watersheds such as this. One approach used to update the SWE over the whole watershed based on the few observation points is interpolation of SWE from the sparse SNOTEL stations across the model domain before assimilating it with the model simulated SWE at each grid cell. Instead of the direct interpolation of SWE, Slater and Clark et al. (2006) interpolated the normalized standard deviates of SWE (also known as z scores) before back-computing the assimilated SWE.

In this study, we used an approach that depends on the assumption that the SWEs between two grid cells in the study watersheds are correlated, and their covariance can be captured from the ensemble of simulated SWE by the energy balance snow model. This assumption arises from the following consideration: Spatial distribution of watershed snowpack depends on spatial variability of factors that include watershed topography, land cover, and weather forcing such as precipitation, temperature, humidity, wind, and radiation (Clark et al., 2011; Luce, 2000). If a distributed, energy balance snow model accounts for these variabilities, then one can expect the spatial variability of the snowpack states to be captured by such a model. It follows, then, that the ensemble of model simulations at a grid cell, if adequately sampled, represents the distribution of the model states in that grid cell. And, statistical measures such as the mean and standard deviation can be computed from such a distribution. Moreover, the distributions at any two grid cells can be used to compute the covariance between the states at the two grid cells. If one of the grid cells happens to have observations, the covariance so computed can be used together with the variance of the observation to apply the adjustment/update to the grid cell that does not have observed data because in Kalman filter the gain is proportional to the covariance of simulated distributions and the variance of observation.

The steps that were followed for implementation of the EnKF in UEB are presented below. In the equations that follow, all the variables with upper case, e.g., X , Y ... are matrices, and those with lower case, such as u , represent vectors. The subscripts refer to the time step while the superscripts differentiate between the prediction, also known as the background state, for example, x_k^b , prior to update, and the state after update, also called analysis, for example, x_k^a (Lahoz et al., 2010). Thus, given a model domain of N locations

comprising Ng centers of model grid cells and m measurement sites ($N=Ng+m$), the state vector at time step k , x_k^a is represented as

$$x_k^a = \begin{pmatrix} W_1 \\ W_2 \\ \dots \\ W_N \end{pmatrix} \quad (1)$$

where W is the UEB model SWE and W_i refers to SWE at location i . The m measurement sites do not necessarily coincide with grid cell centers and have their own parameters determined from the DEM, land cover, and their own downscaled inputs and are thus separate grid cells where the model is run. Following standard DA literature notation, observations of W at the m measurement grid cells are represented by the vector z_o .

$$z_o = \begin{pmatrix} z_1 \\ z_2 \\ \dots \\ z_m \end{pmatrix} \quad (2)$$

The general procedure followed at a given time step involves running the UEB model at all N grid cells in the watershed in ensemble mode and computing the model error covariances from the ensemble of states at each grid cell. This is followed by computing the Kalman gain from the model error covariances and the observation variances. The Kalman gain is then used with observations to adjust/update the simulated SWE. Steps 1, 2, and 3 below represent generation of ensemble UEB states and are applicable at all model times. Thus, the model evolves the ensemble of UEB states through time, regardless of whether there are observed data for assimilation or not. Steps 4 through 11 however are executed only at model time steps with observed data. Note also that the procedure below is applicable for the simulation time interval before the forecast time as there is no DA during the forecast period. Beyond the forecast time, each year of historical weather forcing data is used to generate model states for a forecast ensemble member.

1. Perturb meteorological forcing such as precipitation and temperature.

$$U_k = u_k * \theta_u, \theta_u = N(1, S_u) \text{ for all forcings except temperature} \quad (3)$$

$$U_k = u_k + \theta_u, \theta_u = N(0, S_u) \text{ for temperature} \quad (4)$$

where u_k is an input vector of forcing at all grid cells (size N). $U_k (N \times E)$ is the generated ensemble forcing. E is the ensemble size, and therefore, E forcing inputs were generated at each grid cell by perturbing the input forcing according to the covariance structure between grid cells represented by S_u . There are six UEB input forcing variables: precipitation (P), air temperature (Ta), wind speed (V), relative humidity (RH), solar radiation (Q_{si}), and atmospheric/longwave radiation (Q_{li}). The multiplier factors (or additive factor for temperature) θ_u were sampled from a multivariate Gaussian distribution with mean 1 (0 for temperature) and covariance S_u . For all the forcing variables except temperature, if this simulation results in a multiplier less than 0 (which happens with very small probability), the multiplier is set to 0 to preclude negative values that are possible with a Gaussian distribution. The covariance matrix, S_u , is computed based on the spatial correlation between the forcing variables in different grid cells and the standard deviation of each forcing. We assumed error correlation between grid cells that is exponentially decaying with distance. Such an assumption was adopted from prior studies because the error characteristics are difficult to measure or estimate (Liu & Gupta, 2007), leading us to follow the approach used in literature (e.g., Clark et al., 2008).

In addition to the spatial correlation that is an exponential function of distance between model grids, the correlations among the errors in precipitation, solar radiation, and longwave radiation were accounted for based on values from previous studies (Kumar et al., 2009; Kumar et al., 2014; Xue et al., 2018). For temperature, wind speed, and relative humidity, the forcing errors were assumed to be uncorrelated, because we have no information on their relationships with the other variables. Error variances were set, at what in our estimation was, toward their upper bound to give the forcing perturbations a large range and favor information from the observations over that from the model.

Following Clark et al. (2008) and Evensen (2003), the temporal correlation in forcing errors was modeled as

$$S_{t+1} = \rho S_t + \sqrt{1-\rho^2} w_t \quad (5)$$

where w is a spatially correlated random variable sampled from a standard normal distribution (zero mean and variance 1) and ρ is the temporal persistence parameter quantified as:

$$\rho = 1 - \frac{\Delta t}{\tau} \quad (6)$$

where Δt is the model time step and the decorrelation time parameter τ quantifies the rate at which forcing error correlation decays with time.

Parameters determining these correlations and perturbations are the standard deviation for the forcing variables, the spatial correlation length, and decorrelation time. These parameters were selected similar to values from the literature and with some trial and error adjustments so that the ensemble mean of model simulations with perturbed forcing and without DA is unbiased. The parameters used in this study for the generation of ensemble forcing are shown in Table 2.

Often, when running the EnKF, the initial states are also perturbed to get a distribution of initial states. In this study, all the simulations start at the beginning of the water year when there is no snow on the ground. Therefore, all ensemble members have the same initial state values of zero SWE.

2. Run ensemble of simulations using the perturbed forcing.

$$X_{k+1}^b = M_{k,k+1}(X_k^a, U_k) \quad (7)$$

where X_{k+1}^b ($N \times E$) is a matrix of UEB predicted/background states. $M_{k,k+1}$ represents the model run evolving the states from time step k to time step $k+1$. In other words, at each grid cell the model is run E times (with perturbed forcing) for time step k and produces an ensemble of state vectors of size E at the next time step $k+1$. All the remaining steps hereafter refer to the time step $k+1$; hence, the time subscript is dropped, and hereafter the matrix subscripts refer to matrix elements. The matrix for the ensemble of background states is thus

$$X^b = (x_1^b, x_2^b, \dots, x_E^b) \quad (8a)$$

where E is the ensemble size and the ensemble matrix is comprised of state vectors x_i^b giving SWE at each grid cell for each ensemble member:

$$x_i^b = \begin{pmatrix} W_{1i}^b \\ W_{2i}^b \\ \vdots \\ W_{Ni}^b \end{pmatrix} \quad (8b)$$

3. Compute ensemble mean $\bar{x}^b$

$$\bar{x}^b = \frac{1}{E} \sum_{i=1}^E x_i^b \quad (9)$$

4. Compute ensemble anomaly X' : subtract the ensemble mean vector from each column in the ensemble states matrix.

$$x_i' = x_i^b - \bar{x}^b \quad (10)$$

and form the anomalies matrix, X' , comprised of anomaly column vectors

$$X' = (x_1', x_2', \dots, x_E') \quad (11)$$

5. Compute model error covariance P_{xx} using the ensemble anomaly.

Table 2
Parameters of Forcing Perturbations for UEB Ensemble Generation

Forcing variable	Forcing perturbation error type	Error standard deviation	Correlation between variables					
			Ta	P	Q _{si}	Q _{li}	V	RH
Temperature (Ta)	Additive	1.2 °C	1					
Precipitation (P)	Multiplicative ^a	0.05 ^a		1	−0.8	0.5		
Short-wave radiation (Q _{si})				−0.8	1	−0.5		
Long-wave radiation (Q _{li})				0.5	−0.5	1		
Wind speed (V)							1	
Relative humidity (RH)								1

Note. Spatial correlation length = 16 HRAP ~ 76 km. Temporal decorrelation length = 6 hr.

^aFor all forcing except temperature the perturbation type is “Multiplicative” with error standard deviation of 0.05.

$$P_{xx} \approx \frac{1}{E-1} X' (X')^T \quad (12)$$

The model error covariance is a function of individual variances and covariances. For N grid cells, the matrix is symmetric and takes the following form:

$$P_{xx} = \begin{pmatrix} \text{var}(W_1) & \text{covar}(W_1, W_2) & \dots & \text{covar}(W_1, W_N) \\ \text{covar}(W_2, W_1) & \text{var}(W_2) & \dots & \text{covar}(W_2, W_N) \\ \dots & \dots & \dots & \dots \\ \text{covar}(W_N, W_1) & \text{covar}(W_N, W_2) & \dots & \text{var}(W_N) \end{pmatrix} \quad (13)$$

6. Map states into observation space.

$$X_h^b = f_h(X^b) \quad (14)$$

where X_h^b is the vector of observations that would be produced if the state was X^b and f_h is the “observation function” that describes how the quantity being measured relates to model state variables. The observation function links the model predicted state to the observed variable; the model state is said to be projected onto the observation space (Labbe, 2015). For nonlinear observation functions, a “forward model” that computes the observed quantities from model predicted states is required (Clark et al., 2008). For linear observation functions, a matrix called an observation operator H (of dimension $m \times N$) would be used to project model states to observation space.

$$X_h^b = HX^b \quad (15)$$

When the quantity observed is the same as a model state variable, then the matrix H will have 1s for grid cells that have corresponding observations and 0s for those that do not have an observation. This is the case for example when SNOTEL SWE observations are assimilated into a model that has SWE as a state variable. This is illustrated in Figure 4 for a hypothetical watershed where there are two SNOTEL stations with observations, resulting in an observation operator H as a matrix with zeros everywhere except for the elements corresponding to the two grid cells containing the SNOTEL stations.

In this study, we separately simulated the observation points with high-resolution input data. This was in part because the terrain variables used for the UEB simulation at the 1,190-m grid cell (obtained by sampling) may be different from those for the exact location of the SNOTEL station even if the station is within the grid cell. In addition, simulating observation points separately allows incorporation of observation points that fall outside the watershed boundary but are close enough to the watershed to provide data for assimilation (Figure 5). The observation operator thus selects from the matrix X^b the subset of states that are at observation points. The resulting matrix X_h^b consists of the ensemble of model states for all m observation points.

Figure 4. Illustration of the observation operator H for a hypothetical watershed with 59 grid cells (filled grid cells with different colors representing sub-watersheds) and two grid cells with observations. The observation operator is a 2 by 59 matrix where all but the two elements corresponding to the grid cells with observations have zero value.

Figure 5. Illustration of a hypothetical watershed with m (3 in this case) observation stations handled separately from the N_g (59) model grid cells (filled grid cells with different colors represent subwatersheds). In this case, there is no need for special observation operator; the state matrix in observation space consists of the ensemble of model states for the m (3) observation points.

$$X_h^b = \begin{pmatrix} W_{11}^b & W_{12}^b & \dots & W_{1E}^b \\ W_{21}^b & W_{22}^b & \dots & W_{2E}^b \\ \dots & \dots & \dots & \dots \\ W_{m1}^b & W_{m2}^b & \dots & W_{mE}^b \end{pmatrix} \quad (16)$$

7. Compute the cross covariance between model states and states in observation space, from their associated ensemble anomalies.

$$P_{xz} = \frac{1}{E-1} X' (X_h')^T \quad (17)$$

The ensemble anomaly in observation space X_h' is computed in a similar manner as X' (ensemble anomaly of model states). When the matrix H is used this reduces to

$$P_{xz} = \frac{1}{E-1} X' (X_h')^T = P_{xx} H^T \quad (18)$$

8. Compute the innovation: the difference between observation and model state in observation space.

$$d = Z_o - X_h^b \quad (19)$$

The matrix Z_o of dimensions $(m \times E)$ is obtained from the observation vector z_o by perturbing the observations with random errors sampled from a normal distribution with zero mean and observation error covariance R . The observation error covariance matrix R ($m \times m$) provides an estimate of uncertainty in measurements. Such perturbation of observations arises from the need to treat the observations as random variables and ensures that the update ensembles have sufficient variance (Burgers et al., 1998).

$$Z_o = z_o + \varepsilon_R, \varepsilon_R \sim N(0, R) \quad (20)$$

The R matrix is comprised of individual observation error variances. There is no known basis for correlation between errors at the measurement locations; hence the R matrix has no off-diagonal covariance terms.

9. Compute the innovation covariance P_{zz} , which is the sum of observation error covariance R and error covariance of model states in observation space X_h^b . The innovation covariance accounts for uncertainty in observation and uncertainty in process model—projected onto the observation space.

$$P_{zz} = \frac{1}{E-1} X_h' (X_h')^T + R \quad (21)$$

When the matrix H is used

$$P_{zz} = \frac{1}{E-1} X_h' (X_h')^T + R = H P_{xx} H^T + R \quad (22)$$

10. Compute the Kalman gain K from covariance matrices P_{xz} and P_{zz} .

$$K = P_{xz} P_{zz}^{-1} \quad (23)$$

The Kalman gain assigns proportional weights to the model predictions and observations based on their respective uncertainties (represented in

Figure 6. Correlation between Utah Energy Balance (UEB) simulated snow water equivalent (SWE) at two Snow Telemetry (SNOTEL) sites.

terms of their error covariances). A simple way to think about this is if the state and observation vectors were one dimensional, the covariance matrices would represent covariance and variance and the gain would be the ratio of these.

11. Update the states.

$$X^a = X^b + K d \quad (24)$$

Except for step 1, generation of the spatially and temporally correlated forcing perturbations, each model grid cell executes all the steps independently of other grid cells. Effectively each model grid cell and the vector of observations become a “model” to which the EnKF approach is applied. Therefore, the dimension of the EnKF model at each grid cell is one plus the number of observation points.

Steps 10 and 11 demonstrate that the Kalman gain and the resulting updates depend on the relative magnitude of the error covariances of the model and observations. It follows from this that a successful assimilation is only possible when there is a correlation between the model and observed variables. This is why we are not updating the state variables other than SWE (W) during assimilation, as we do not know if there is clear covariance/correlation between the observations of W and the other states. On the other hand, the same reasoning was used to justify assimilation of W measurements at an observation grid cell to simulated W at a different grid cell if there is a covariance/correlation between the simulated water equivalents at the two grid cells. Figure 6 shows a scatter plot of the UEB simulated SWE at two SNOTEL stations about 15 km apart demonstrating the strong correlation between the SWE at the two points during the snow accumulation season and motivating this assimilation approach to obtain the spatially distributed SWE.

The EnKF implementation for the assimilation of point SWE observations in UEB is summarized in Figure 7.

2.5. Implementation of the PF in RDHM (SAC-SMA + rutpix7)

The PF was implemented in RDHM to extend the DA beyond just snow (UEB) by using observed streamflow to adjust SAC-SMA and rutpix7 states. In PF, the vector of state variables representing a point in state space is referred to as a particle. Then as the model evolves and state variables change, the particles move forward in time. As stated earlier, the PF represents the probability distribution of the model states by a set of particles and associated weights. In this study, multiple realization of the SAC-SMA + rutpix7 models (X) and their associated weights (w) constitute the particles.

Figure 7. Summary of ensemble Kalman filter steps in Utah Energy Balance (UEB).

$$X = \{x_i\}_1^N; w = \{w_i\}_1^N \quad (25)$$

The steps for the implementation of the PF are summarized in Table 3. At the start of the simulation, the initial particles are generated by perturbing the initial SAC-SMA states with small errors sampled from normal distribution with zero mean. These initial particles are assumed to have uniform weights.

$$\{w_i\}_1^N = \frac{1}{N} \text{ at time step } t_k = 0 \quad (26)$$

After the SAC-SMA and rutpix7 models are run for all the particles with inputs of Rmelt (Rain + melt) output from UEB producing streamflow outputs, the weight of each particle is updated based on the likelihood function:

$$w_i \leftarrow w_i * \exp\left(\frac{-1}{2} (z - h(x_i)) R^{-1} (z - h(x_i))^T\right) \quad (27)$$

where z is observation, in this case discharge at the watershed outlet, with error covariance R . h is the observation function, in this case the RDHM model, projecting the model states onto observation space.

The weights are normalized so they sum to one.

$$w_i \leftarrow \frac{w_i}{\sum_{i=1}^N w_i} \quad (28)$$

The weight update assigns higher weights to those particles closer to the observation and vice versa. One consequence of this is that some particles may end up getting extremely small weights leading to a condition called “Particle degeneracy.” To mitigate this, particle resampling is employed to discard particles with negligible weights and multiply those with higher weights. The particle resampling uses the cumulative distribution of the particles, where the normalized particle weights represent the probability density (Arulampalam et al., 2002; Brown & Hwang, 2012). Resampling introduces another problem called

Table 3
Steps for Particle Filter Implementation in RDHM to Update SAC-SMA and Rutipix7 States

DA Step	Illustration ¹	Description
1. Initialize states and weights	$X_1 \quad X_2 \quad X_3 \quad \dots \quad X_{N-2} \quad X_{N-1} \quad X_N$ $\frac{1}{N} \quad \frac{1}{N} \quad \frac{1}{N} \quad \dots \quad \frac{1}{N} \quad \frac{1}{N} \quad \frac{1}{N}$	At the start of simulation all states have equal weights.
2. Run model	$X_i \leftarrow \text{RDHM}(X_i, \text{Rmelt})$	Run SAC-SMA and rutpix7 models with inputs of rain + melt from UEB to advance in time for each particle.
3. Update weights	$w_i \leftarrow w_i \cdot \exp\left\{\frac{-1}{2}(z-h(x_i))R^{-1}(z-h(x_i))^T\right\}$ Where z is observation with error covariance R $w_i \leftarrow \frac{w_i}{\sum_{i=1}^N w_i}$	At assimilation step of the PF, the particle weights are updated based on their proximity to the observed streamflow at outlet. Weights are then normalized to make all weights sum to 1.
4. Resample states	$X_1 \quad X_2 \quad X_3 \quad \dots \quad X_{N-2} \quad X_{N-1} \quad X_N$ $X_1 \quad X_2 \quad X_2 \quad \dots \quad X_{N-1} \quad X_{N-1} \quad X_{N-1}$ $\frac{1}{N} \quad \frac{1}{N} \quad \frac{1}{N} \quad \dots \quad \frac{1}{N} \quad \frac{1}{N} \quad \frac{1}{N}$	Weights are used as probability to resample particles. High weight particles are sampled more frequently (repeated) while low weight particles are sampled less frequently, and those with too little weight are discarded to avoid particle degeneracy.
5. Perturb particles	Add randomly generated small error to SAC-SMA states.	Randomly generated small error is added to each resampled particle to reduce particle impoverishment, i.e., loss of diversity and particles converging to common values.

Abbreviations: PF: particle filter; RDHM: Research Distributed Hydrologic Model; SAC-SMA: Sacramento Soil Moisture Accounting; UEB: Utah Energy Balance.

¹Sizes of the circles in the third column illustrate relative weights of particles—not to scale.

“Particle impoverishment” where the diversity of particles is lost in that the resampled particles’ set may consist of one or very few model realizations (Liu & Gupta, 2007). Perturbation of samples or “sample roughening” is introduced to generate particles that increase sample diversity (Crassidis & Junkins, 2011). In this study, sample roughening was performed with randomly generated small errors added to the SAC-SMA states.

To summarize, the PF proceeds by evolving the model states in time and updating the associated weights based on observations followed by resampling and (optional) perturbation of the particles.

The purpose of the DA prior to streamflow forecasting is to arrive at the best possible set of model states at forecast time (1 April) so that the uncertainty in the forecast streamflow is reduced. The EnKF SWE assimilation attempts to get the best snow state, while the purpose of the streamflow assimilation was to select the best possible SAC-SMA and rutipix7 states. One challenge in assimilation of streamflow to adjust soil moisture is that the observed discharge at a given time step is the result of integrated effect of the watershed processes at longer time span. Hence, it is often difficult to merely assimilate outlet discharge at a time step and expect “best” trajectories of states. To deal with this, the streamflow assimilation needs to account for possible lag between soil moisture states and discharge at outlet (Noh et al., 2011).

In this study, streamflow observations were available at daily frequency, and hence, we computed the weights (equation (27)) at daily steps. On the other hand, we tested different frequencies (daily, every 4 days, every 10 days, weekly, biweekly, and monthly) for the particle resampling and found that the biweekly resampling resulted in the best outputs, and thus, we used biweekly resampling. The challenge with this delayed resampling (not resampling at every assimilation step) is that the degeneracy mentioned earlier may get worse. The magnitude of the effect of degeneracy is measured by the “Effective sample size” (N_{eff} ; Arulampalam et al., 2002) computed as

$$N_{\text{eff}} = \frac{1}{\sum_{i=1}^N (w_i)^2} \quad (29)$$

Small N_{eff} signifies severe degeneracy (Arulampalam et al., 2002). In practice, resampling is carried out when N_{eff} falls below a threshold value (Moradkhani et al., 2005). In this study, the N_{eff} was computed at each step

and written out for inspection, but the resampling frequency was fixed to 2 weeks mentioned above as it resulted in the best outputs. Note after resampling and perturbation, the particle weights are reinitialized to uniform values, $1/N$ for N particles.

2.6. Evaluation and Performance Metrics

The SWE DA was run in the Green River Watershed above Warren Bridge for the whole 2009 water year with assimilation of observed SWE every 14 days. This includes assimilation in the accumulation period prior to 1 April and the ablation and melt period after 1 April. To evaluate the performance of the snow DA, we used “leave one out” validation. In the leave one out validation, one of the SNOTEL stations was excluded from assimilation and we examined how much the updated SWE at that station was improved by assimilation of observations from the other stations. This provided a way to quantify the likely improvement in estimated SWE at unmeasured grid cells across the watershed from the application of the spatially distributed snow DA.

The model simulated SWE at each observation location for cases with and without DA, and when the observation at that station is excluded (leave one out) were evaluated using the following performance metrics:

1. Root-mean-square error (RMSE) between observed and UEB modeled SWE at SNOTEL stations.
2. Nash-Sutcliffe efficiency (NSE) coefficient of UEB SWE as compared to observed SWE.
3. Normalized information contribution (NIC) from DA, in terms of RMSE and NSE.

The NIC from DA quantifies the extent to which the DA improves (or degrades) the model simulation. It is defined as the ratio of the improvement due to DA (over the simulation without DA) to the maximum possible improvement (Kumar et al., 2009; Kumar et al., 2014). NIC is defined in terms of error stats such as RMSE. We computed two values of NIC in terms of the RMSE and NSE as follows.

$$\text{NIC}_{\text{RMSE}} = (\text{RMSE}_{\text{NoDA}} - \text{RMSE}_{\text{DA}}) / \text{RMSE}_{\text{NoDA}} \quad (30)$$

$$\text{NIC}_{\text{NSE}} = (\text{NSE}_{\text{DA}} - \text{NSE}_{\text{NoDA}}) / (1 - \text{NSE}_{\text{NoDA}}) \quad (31)$$

The subscripts “DA” and “NoDA” in equations (30) and (31) refer to model with and without DA, respectively. In short, NIC_{RMSE} represents the reduction in RMSE divided by the maximum possible reduction, whereas NIC_{NSE} is the increase in NSE divided by the maximum possible increase. $\text{NIC} > 0$ implies improvement over no DA (Kumar et al., 2014).

The above evaluation deals with the SWE assimilation and its validation at observation points, which was limited by the few observation sites available. Next, we evaluated the effect of the DA on the integrated watershed response using the streamflow at the watershed outlet for the water years 2005 to 2009. In this case, the snow and streamflow DA was applied from 1 October to 1 April. Beyond 1 April, the UEB + RDHM model was run in forecast mode and there was no DA. The focus of this evaluation was on the streamflow forecast. Here the SWE assimilation frequency was also 14 days using the EnKF with all SNOTEL sites (no leave one out). Daily observations of streamflow were used to compute the PF sample weights (so the PF was run daily) with particle resampling and sample roughening done every 14 days. We evaluated ensemble streamflow forecasts for three simulation/reforecast scenarios:

1. no DA;
2. assimilation of SWE in UEB using EnKF; and
3. assimilation of SWE in UEB using EnKF and assimilation of streamflow with PF to update SAC-SMA and rtpix7 states.

For each scenario, the following evaluation metrics were calculated.

1. Daily streamflow error statistics for the whole water year: RMSE, NSE, mean absolute error (MAE), and correlation coefficient between simulation and observation (R).
2. Daily streamflow error statistics for the forecast period (April–September): RMSE, NSE, MAE, and R .
3. April–July volume error.

3. Results

3.1. Assimilation of SWE in UEB

Figure 8 shows plots of the ensemble SWE at the Loomis Park SNOTEL station for the 2009 water year, with assimilation every 14 days continuing for the full year, that is, both accumulation and melt periods. Plots are also shown for simulated SWE with no DA and the observed SWE at this SNOTEL station. This figure is representative of output at a UEB grid cell and demonstrates the behavior of the ensemble members before and after data is assimilated. Specifically, at the date of DA, the spread of ensemble members contracts toward the observations.

Figures 9–12 show the ensemble mean of SWE at each SNOTEL station used in this study. The plots include model outputs with and without DA, the SNOTEL observed SWE, and simulated SWE when observations at the SNOTEL station are excluded. In all four cases, the simulation without DA underestimates the SWE, when compared to observations. The simulation without DA also has a temporal shift from observations in some cases. After assimilation, the modeled SWE better tracks the observed SWE as demonstrated by the improved RMSE and NSE values. These error metrics were computed at the three hour model simulation time step (SWE observations were available at hourly steps). The major cause of underestimation of modeled SWE before DA is bias in precipitation. The SWE underestimation is drastic in Figure 10, for the Gunsight Pass SNOTEL station, and precipitation underestimation alone does not account for this bias. In this case, the terrain data subsampling may have picked the wrong values and resulted in poor radiation inputs. While DA is primarily applied to get state estimates that reduce random errors, in practice, it is often difficult to precisely separate systematic and random model errors (Ménard, 2010), and assimilation also reduces some model bias which appears to be the case here.

All NIC values, labeled “NIC_RMSE_DAll” and “NIC_NSE_DAll” in figures 9–12, are greater than zero indicating the DA improves estimation of the model SWE. For this case where data from all stations were assimilated, the NIC in RMSE value, averaged over the four stations, was 0.41 indicating there is about 41% decrease in RMSE due to DA. For the NSE criteria, the average NIC was 0.63; hence, about 63% of the possible maximum improvement in terms of NSE has been achieved through the SWE assimilation. A larger contribution in this value (improved NSE criteria) is coming from the Gunsight Pass and New Fork Lake SNOTEL stations, but the improvement in the other two stations is also significant. Overall, in all cases, the DA has improved the peak SWE (around 1 April) closer to the observed values, and this has a positive effect on melt period streamflow simulations/forecasts.

In the case of the leave one out validation, where the DA excludes observation at the particular station being evaluated, all locations except Kendall RS SNOTEL station showed improvement over no DA in terms of the RMSE and NSE, “NIC_RMSE_DAEclStn” and “NIC_NSE_DAEclStn.” As it can be seen from Figures 9–11, there is appreciable improvement in the modeled SWE from assimilation of data from the other stations, particularly during the accumulation period. While there is a degradation in performance at all stations during the snow ablation period, Figure 12 shows large degradation at the Kendall RS SNOTEL station. The average NIC values at the Kendall RS SNOTEL are negative indicating that the DA with leave one out degrades the SWE at this station. This degradation was primarily caused by the poor performance during the melt period. In this leave one out scenario, the update depends on the correlation of simulated SWE between the grid cell in question and the points where there are observations. This correlation breaks down during the melt season and is responsible for this melt season degradation in performance. This can be seen in Figure 12 where there is a big bump around 1 May in the Kendall RS SWE for the leave one out scenario, when the observed snow at this station has significantly declined but the nearby stations being used to update SWE have not declined as much. This indicates a possible weakness of the assimilation approach during the ablation period.

Figure 13 shows the same plots as in Figure 12 except that for this plot the SWE assimilation was stopped on 1 April. In this case, the simulated SWE traces beyond 1 April are closer to the observations for both assimilation cases (i.e., all stations included and leave one out). While the NIC values are still negative for the leave one out, their magnitude is much better than those in Figure 12. It is important to note here that the breakdown of correlations during the ablation period is likely to apply to the early season shallow snow conditions where intermittent accumulation and melt occurs at some locations. These early season errors possibly affect the performance of the assimilated SWE at some locations.

Figure 8. Snow water equivalent (SWE) at Loomis Park SNOTEL Station in Green River Watershed. Utah Energy Balance (UEB) simulated SWE without data assimilation, ensembles with the ensemble Kalman filter assimilation of SWE and their mean, and observed SWE at this SNOTEL station are shown. At the dates of each data assimilation, the spread of ensemble members contract toward the observations.

One of the strengths of the SNOTEL data is its high quality—compared to other operationally available data; however, the stations are sparsely distributed. The results shown here indicate that the model SWE at a given point is improved through assimilation of SWE at SNOTEL stations away from the grid point, due to the spatial correlation of snow, at least for the accumulation period. This serves as a measure of how estimates of SWE at grid cells across the watershed where there are no observations should also be improved, and this has a positive effect on watershed scale streamflow response at the outlet, evaluated in the next section.

3.2. Streamflow Forecast With Assimilation of SWE and Q in RDHM

Figures 14–16 show the 2009 water year outputs of daily streamflow forecast for the three modeling scenarios: (1) no data assimilation (No DA), (2) assimilation of SWE using the EnKF method (EnKF SWE), and (3)

Figure 9. Snow water equivalent at Loomis Park SNOTEL Station in Green River Watershed. The labels for the error statistics, at the top-right, refer to root-mean-square error (RMSE) with no data assimilation (RMSE_NODA), assimilation of observations from all four stations (RMSE_DaAll), and assimilation excluding data at this site (RMSE_DaExclStn). Similar terminology applies to NSE and NIC. The data assimilation outputs are from the ensemble Kalman filter assimilation of snow water equivalent and the plots shown are the ensemble mean for each case.

Figure 10. Same as Figure 9 but for the Gunsight Pass SNOTEL station.

assimilation of SWE using EnKF and streamflow observations using the PF method (EnKF SWE and PF Q). Note that in these results, ensembles were generated using perturbed observed forcing from 1 October to 1 April. Beyond the 1 April forecast time, the ensembles were generated using historical forcing. The DAs, when applicable, were run up to 1 April. The figures show individual ensemble traces of streamflow and their mean (ensemble mean). Plots also include the observed streamflow hydrograph at the USGS gage at the watershed outlet. Error statistics computed for the ensemble mean discharge at daily time steps are also shown in the figures. In addition, to focus on the forecast period (April–September), scatter plots of forecast (ensemble mean) versus observed discharge and the daily discharge error statistics for April–September are shown in Figure 17 for the three scenarios.

The April–July volume errors and their (ensemble) distribution are shown in Figure 18 for the 5 years (2005–2009). The box and whisker plots in Figure 18 were computed for each of the three scenarios using the April–July flow volume of individual ensemble members and then subtracting the measured April–July volume from each trace. For 2005, 2006, and 2008, results comparable to 2009, for which detailed results

Figure 11. Same as Figure 9 but for the New Fork Lake SNOTEL station.

Figure 12. Same as Figure 9 but for the Kendall RS SNOTEL station.

were presented above, were obtained. The assimilation of SWE generally improves the forecasted streamflow (compared to no DA), while it misses the shape of the hydrographs at the peaks as shown in Figure 15 for the 2009 water year. However, the PF assimilation of discharge does not add value beyond that achieved through SWE assimilation (Figure 16 for the 2009 water year). In general, the simulation with no DA has negative volume error, suggesting that without DA, forecast streamflow volumes are likely to be underestimated. The SWE assimilation reduces the volume error. For the water year 2007, however, the snow DA results in a volume error that is worse than for the case with no DA. In this case, the discharge assimilation performs better than the forecast with only SWE assimilation. By looking into the observed streamflow for all the 22 historical years (1989–2010), the streamflow for 2007 has the second lowest peak value, next to water year 1992, making it a dry year outlier. Based on these observations, it is possible that the snow DA may struggle for dry years with significantly shallower snow conditions than the historical average. This points to the need for further investigation with specific focus on low-flow years.

Figure 13. Same as Figure 12 but the data assimilation extends only up to 1 April 2009.

Figure 14. Ensemble streamflow forecast at Warren Bridge near Daniel for the water year 2009, with no data assimilation (NO-DA). Mean absolute error (MAE) and root-mean-square error (RMSE) have units of m^3/s .

The objective of this study was to contribute toward better operational streamflow forecasting through better representation of the spatial and temporal distribution of watershed snow states. Table 4 compares, for the water years 2005–2009, the April–July streamflow forecast volumes from the three DA scenarios of this work (the ensemble mean volume of each scenario) to the operational water supply forecasts of volume reported by the Natural Resources Conservation Service (NRCS) National Water and Climate Center and the observed streamflow volume for the study years. We can see that the model with no DA, that also did not employ parameter calibration, performs worse than the NRCS forecast in three of the 5 years. For these years, the assimilation of sparse SNOTEL observations resulted in a comparable or better forecast volume (ensemble mean) than the NRCS forecast. On the other hand, the DA considerably worsens the forecast

Figure 15. Ensemble streamflow forecast at Warren Bridge near Daniel for the water year 2009, with SNOTEL snow water equivalent (SWE) data assimilated every 2 weeks using ensemble Kalman filter (EnKF-SWE). Data assimilation applied between 1 October and 1 April. Mean absolute error (MAE) and root-mean-square error (RMSE) have units of m^3/s .

Figure 16. Ensemble streamflow forecast at Warren Bridge near Daniel for the water year 2009, with SNOTEL SWE data assimilated every two weeks using ensemble Kalman filter (EnKF) and assimilation of daily streamflow using particle filter (PF) with biweekly resampling (EnKF-SWE_PF-Q). Data assimilation applied between 1 October and 1 April. Mean absolute error (MAE) and root-mean-square error (RMSE) have units of m^3/s .

Figure 17. Scatter plots and error statistics of daily streamflow for the ensemble mean of April–September 2009 forecast discharge versus observed discharge at Warren Bridge near Daniel for the three scenarios no data assimilation (No DA), ensemble Kalman filter assimilation of snow water equivalent (EnKF-SWE), and assimilation of both snow and discharge (EnKF-SWE_PF-Q). Mean absolute error (MAE) and root-mean-square error (RMSE) have units of m^3/s . The green line is the 1:1 line.

Figure 18. April–July volume error of ensemble streamflow forecast at Warren Bridge near Daniel for the water years 2005–2009, for the three scenarios no data assimilation (No DA), ensemble Kalman filter assimilation of snow water equivalent (EnKF-SWE), and assimilation of both snow and discharge (EnKF-SWE_PF-Q).

volume for the low flow water year 2007. Note here that Table 4 shows that snow DA improves forecast volume in three out of 5 years, while Figure 18 shows 4 of the 5 years with improved forecast volume from snow DA. This apparent difference is due to the fact that Table 4 uses the ensemble mean of forecast volumes, while Figure 18 shows the distribution of the volume errors of the ensemble members, their interquartile range, and the median volume error. However, the results are generally consistent showing the sparse SNOTEL observations result in a better water supply forecast.

4. Discussion

The key observations from these results are as follows:

1. The EnKF snow DA generally results in better model states at the start of the forecast period, which is manifested in a better streamflow forecast (when compared to the forecast with no DA).
2. The assimilation of streamflow with PF does not add noticeable improvement to the streamflow forecast beyond that achieved by the SWE assimilation.

The PF Q did not add any more value beyond that achieved by the EnKF SWE likely due to the fact that prior to 1 April there has been little snowmelt, and hence, little streamflow response to serve as information to update model state and inform a forecast. It is also possible that this application of PF is better suited for shorter time scales. Other possible factors that might have affected the PF Q performance include insufficient particle size, inadequate representation of the impact of lag between soil moisture and streamflow, or other undetected errors. It is also possible, though unlikely, that the range of uncertainty due to soil moisture is narrower than that of the error distribution of the SWE ensemble and therefore the SWE assimilation compensates for the soil moisture error as well. Pinpointing the exact reason requires further investigation.

The large forecast volume error without DA could be attributed to a poorly calibrated model, noting that calibration is often used to reduce differences between observations and model simulations. In this study, we deliberately selected to not calibrate the UEB model because we wanted to maintain the transferability of its parameters across watersheds that have been applied in prior studies without calibration, primarily relying on the physical basis of the model. Furthermore, correcting the volume error by calibration would have required adjusting a precipitation or snow accumulation factor and we feel that it is better to leave this sort of empirical adjustment to be taken care of by assimilation based on observations current at the time of a forecast, rather than an uncertain calibrated adjustment factor.

Table 4
April–July Streamflow Forecast Volumes and Volume Errors (10^6 m^3) From UEB+RDHM (Ensemble Mean) and NRCS Water Supply Forecast

Water year	Observed ^a	^a	NRCS regression ^b	No DA	EnKF SWE	EnKF SWE and PF Q
2005	311.1	Forecast volume	271.4	243.9	368.6	365.3
		Volume error	−39.8	−67.2	57.5	54.2
2006	278.4	Forecast volume	326.9	257.1	322.6	344.5
		Volume error	48.5	−21.3	44.2	66.1
2007	179.4	Forecast volume	209.7	178.2	267.6	231.9
		Volume error	30.3	−1.2	88.2	52.5
2008	324.1	Forecast volume	283.7	228.8	356.9	369.1
		Volume error	−40.4	−95.3	32.8	45.0
2009	382.3	Forecast volume	302.2	270.4	376.1	399.6
		Volume error	−80.1	−111.9	−6.2	17.3

Abbreviations: EnKF; ensemble Kalman filter; No DA: no data assimilation; NRCS: Natural Resources Conservation Service; PF: particle filter; RDHM: Research Distributed Hydrologic Model; SWE: snow water equivalent; UEB: Utah Energy Balance.

^aUnits are in 10^6 m^3 . ^bSource: https://www.wcc.nrcs.usda.gov/ftpref/support/water/westwide/forecast_table/.

As with any model there are many uncertainties and possibilities for bias in the parameterizations. The more physically based the model the more universal the parameters should be, while a more empirical model requires more local calibration of parameters. Some of the possible sources of uncertainty and bias in UEB as applied here are in the parameterization of precipitation and temperature inputs produced by the CBRFC and in the estimation of radiation from the diurnal temperature range. It was beyond our scope to investigate all of these, but we do note that the parameters required for the generation of radiation model inputs were used from previous studies applying UEB in the western United States (Mahat & Tarboton, 2012; Sen Gupta & Tarboton, 2016) and the sensitivity of UEB snowmelt simulations to radiative energy inputs has been quantified by others (e.g., Lapo et al., 2015; Raleigh et al., 2016). UEB strives to move toward the physically based end of the continuum between physically based and empirical models and treats the radiation parameterizations as constant. While it would be ideal to examine each process independently (e.g., Clark et al., 2015), there is often insufficient data to do this and model evaluation has to be in terms of the weaker assessment of overall improvement in model forecasts. Assimilation of observations also moves model forecasts toward observations, adjusting and accounting for model errors.

The streamflow ensemble mean for all the three cases does not replicate the shape of the hydrograph at the peaks. While the observations show two peaks during the forecast period, the ensemble mean has a single smooth peak. This is to be expected due to the averaging of multiple ensemble members that were produced using historical weather inputs from all years with data available. Some of the individual ensemble members appear to have multiple peaks. This is due to the different weather patterns in different years. This indicates that while the total volume of discharge at the gage is more accurately captured, as shown in the April–July volume error in Figure 18, the ensemble streamflow generated from the historical forcing (assumed as representative of the possible distribution of future weather conditions) does not capture the actual shape of the hydrograph. To forecast the actual shape of the hydrograph in any 1 year requires a forecast of the specific weather pattern for that year. One implication of this result is that this DA is useful for water supply forecasting, but less useful for flood forecasting unless other factors such as input energy are also well quantified.

The ensemble model setup in this study was premised on the assumption that the major source of uncertainty in the model comes from the weather forcing. The ensemble forcing perturbation accounts for the spatial and temporal as well as intervariable correlations of errors in forcing such as precipitation. The parameters for generating ensemble forcing, such as the variance in precipitation and the spatial and temporal correlation lengths, were input to the model. Further study on the uncertainty in each weather forcing variable and its statistical characteristics such as the error standard deviation, for example, by analyzing forcing data from multiple sources, would be beneficial. Future study for accurate estimation of the spatial correlation length should look into its relation to the distance between the SNOTEL stations in a given watershed and other factors such as the effects of topography on precipitation shadows, ridges, and wind shadows that in turn affect the spatial correlation of snow.

5. Conclusions

In this study, we evaluated assimilation of SWE data from SNOTEL sensors into the UEB snowmelt model using the EnKF. The UEB model was then coupled to a distributed hydrologic model, RDHM, for streamflow forecasting. The streamflow forecasts were conditioned on updated snow and soil moisture states from assimilation of snow and streamflow data. We used the PF with observed streamflow to update SAC-SMA and rutpix7 states in RDHM.

Results from the SWE assimilation showed that taking advantage of the covariance between SWE at different grid cells, a measurement at one point can be used to update SWE at a grid cell away from the observation site without needing interpolation of observations. This suggested the potential for assimilation of SWE data from sparse SNOTEL stations to update SWE over the whole watershed, which we later evaluated through streamflow forecasts. The improvement in model SWE from assimilation was demonstrated with positive NIC (NIC from DA) values for RMSE and NSE.

The performance of the snow DA was much better during accumulation than ablation. This was likely due to the spatial correlations that resulted in data at one point having predictive capability at another point during accumulation diminishing during the energy driven melt process where melt timing is not synchronous. The spatial variability of snowmelt due to elevation and the effect of slope and aspect on radiation is not spatially correlated in the same way as snow accumulation and hence not readily captured by the DA method.

An important outcome of this study was that the ensemble streamflow forecasts with assimilation of SWE provided an improvement over forecasts with no DA. On the other hand, the assimilation of streamflow using the PF to update the SAC-SMA and rutpix7 states did not provide improvement beyond that achieved through the snow DA. Thus, the coupled UEB+RDHM model, with assimilation of snow observations introduced in this work, does have potential for and merit consideration for operational use. While the streamflow assimilation did not add to the improvements shown in this study, the coupled model with PF implementation provides a platform for further investigation.

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