# Snow Data Assimilation

**Andrew G. Slater[1] and Martyn P. Clark[2]**

*[1] National Snow & Ice Data Centre (NSIDC), University of Colorado*
*[2] National Institute of Water and Atmospheric Research (NIWA), New Zealand*

## 1. Introduction

Snow acts as a water store, an insulator and a reflector thus is an important surface condition which can aid predictability in numerical weather prediction (NWP) or hydrologic forecasting. The aims of the modeling system, whether for purposes such as streamflow forecasting or NWP, will play a role in the applicability of data and assimilation methods. Here we discuss the state of snow data assimilation. Motivations for data assimilation is given in Section 2, Section 3 gives examples of using station data for assimilation. Assimilation of snow covered area information is discussed in Section 4 while Section 5 mentions other potential information sources such as passive microwave data and albedo data.

## 2. Why assimilate snow data?

For hydrologic forecasting, snow assimilation largely revolves around aiding knowledge of the mass of snow, which in turn translates to the volume of water in a basin. In snow dominated regions, a vast amount of streamflow forecast skill can be gained if information on the state of the snowpack is available. Interests such as reservoir operations and flood forecasting can directly benefit from knowledge of the volume and distribution of snow within catchment areas.

With regard to NWP, in the very short term the largest impact of snow may concern the albedo of the land surface. Of all the land surface covers, snow has the ability to be highly variable in time and space. The surface energy balance of a region can change dramatically with a dusting of snow as albedo can change from 0.15 to over 0.9 in a matter of hours [Viterbo &Betts, 1999]. The presence of snow can also provide an energy sink at the surface. Surface temperature will have an upper bound at the melting point as the latent heat of fusion has to be overcome in order for melt to occur and allow temperatures to climb higher. Considering slightly longer timescales, the volume and distribution of snow will impact the thermal and hydrologic state of the subsurface. Due to its ability to act as an insulator, the depth and density of snow plays a significant role in the penetration of the freezing wave into seasonally frozen ground and permafrost. The degree of freezing governs the ability of soil to act as a cold content storage where this energy sink can be released in later seasons. Knowledge of cold content storage has the capability to aid predictability. The extent of freezing can also impact the hydrologic regime of the soil by altering the ability of water to infiltrate soil [Slater *et al.*, 1998][Viterbo *et al.*, 1999]. Lastly, the volume of snow can dictate the amount of moisture available to the soil; in turn, knowledge of soil moisture aids predictability.

---

[1] Andrew Slater, National Snow and Ice Data Center, University of Colorado
Boulder, CO, 80309-0449, USA, Email: aslater@kryos.colorado.edu

## 3. Assimilation of Snow Data from Stations

The Ensemble Kalman Filter (EnKF) is a flexible and easy to implement tool for assimilation, but requires many assumptions to be met in order to be used effectively, and therein lies the difficulty. [Slater & Clark, 2006] undertook a snow data assimilation study in which real data was used to update a conceptual model, SNOW-17. The aim of this study is to improve the model's estimate of snow water equivalent (SWE) by merging the uncertainties associated with meteorological forcing data and SWE observations within the model. This is done with a view to aiding the estimation of snowpack initial conditions for the ultimate objective of streamflow forecasting via a distributed hydrologic model. In order to provide a test of this methodology, we perform experiments at 53 stations in Colorado. In each case we mimic the situation of an unobserved location, using the data at any given station only for validation; essentially these are withholding experiments. Both the ensembles of model forcing data and assimilated data were derived via interpolation and stochastic modeling of data from surrounding sources. Through a process of cross validation we explicitly estimate the error for the ensemble of model forcing data and assimilated observations using the method of [Clark & Slater, 2006]. We apply an ensemble Square Root Kalman Filter to perform assimilation on a 5-day cycle. Improvements in the resulting SWE are most evident during the early accumulation season and late melt period. However, the large temporal correlation inherent in a snowpack results in a less than optimal assimilation and the increased skill is marginal. Once this temporal persistence is removed from both the model and assimilated observations during the update cycle, we produce a result that is, within the limits of available information, consistently superior to either the model or interpolated observations (Figure 1).

The method described above is successful as the station density for snow and meteorological observations is sufficient; this is not the case globally, thus ECMWF applies a Cressman analysis using SYNOP data. Any assimilation scheme must bow to the capabilities of data availability.

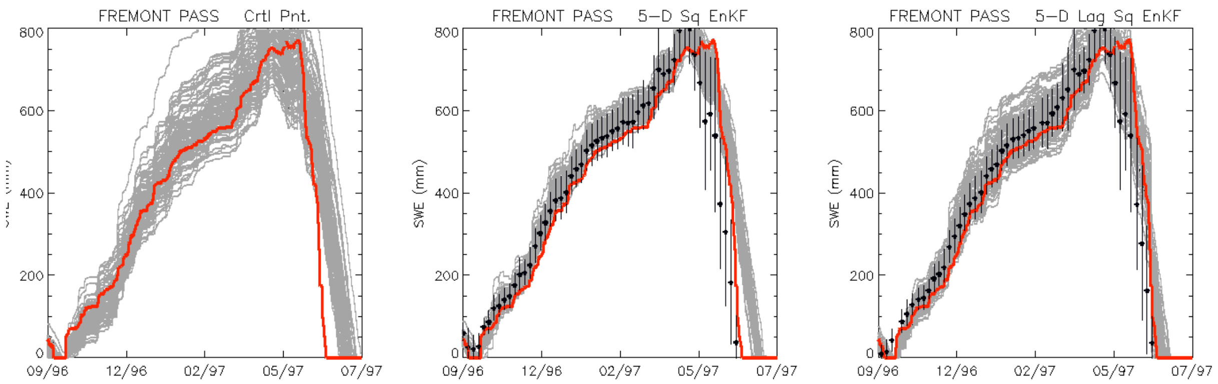


*Figure 1: Example of model control simulations (left), assimilation runs using the ensemble square root kalman filter (EnSRF) with updates every 5 days (middle) and an EnSRF case which accounts for the temporal correlation of model and observation within the assimilation scheme. The ensemble of model simulations is given in light gray, truth is given in the thick red line. The mean of the assimilated SWE is given by the dark squares complete with one standard deviation shown in the thin dark lines. Periods shown are from 29th September to July 31st of respective water years. Note that the ensemble spread is maintained when temporal correlation is accounted for. From Slater & Clark [2006].*

# 4. Use of Snow Covered Area Information

Snow covered area (SCA) is a reasonably reliable product, particularly at a larger scale, and is available via visible imagery from sensors such as MODIS or AVHRR. While presence of snow may aid albedo calculations, conversion of SCA to SWE is an over-determined problem, meaning that there are many possible solutions. Several investigators have tried applying universal snow depletion curves with the result that snow accumulation is often degraded under assimilation, though if the model melt is delayed, SCA assimilation can improve matters. [Clark *et al.*, 2006] describe a data assimilation method that uses SCA observations to update hydrologic model states in a mountainous catchment in Colorado. The assimilation method uses SCA information as part of an EnKF to alter the sub-basin distribution of snow as well as the basin water balance. This joint parameter/state updating method permits an optimal combination of model simulations and observations, as well as propagation of information across model states. Sensitivity experiments are conducted with a fairly simple snowpack / water balance model to evaluate impacts of the data assimilation scheme on simulations of streamflow. However, the form of the snow model applied was chosen with SCA assimilation in mind, in which snow total accumulation and ablation are tracked as state variables rather just SWE and the SCA-SWE relationship is described by a statistical distribution, following the method of [Liston, 2004]. The assimilation of SCA information results in minor improvements in the accuracy of streamflow simulations near the end of the melt season (Figure 2). The small impact from SCA assimilation can be explained because a significant portion of snow melts before any bare ground is exposed, and because the transition from 100% to 0% snow coverage occurs fairly quickly. Both of these factors are basin-dependent. We expect satellite SCA information to be most useful in basins where snow cover is ephemeral. The data assimilation strategy presented in this study did improve the accuracy of the streamflow simulation, indicating that SCA is a useful source of independent information that could be used as part of an integrated data assimilation strategy.

# 5. Alternative and Potential Information Sources

Snow cover area (SCA) and albedo products are relatively robust, but the current suite of global snow water equivalent (SWE) products is unreliable. Figure 3 shows that the standard SWE products from passive microwave data is inaccurate over Eurasia when compared to several model simulations (which compare favorably with station based estimates of SWE [Slater *et al.*, 2007] ). Sensitivity to snow grain size, interference of vegetation canopies, presence of liquid water, fluctuations in snow temperature and several lesser factors all contribute to the difficulty of SWE retrieval using a global algorithm. One potential way forward is the use of multi-sensor, radiance based assimilation. For example, the high resolution visible imagery could be used to help interpret the larger footprint view of passive microwave signals and algorithms dependent upon the snow crystal and depth regimes (rather than a single global inversion) could lead to better characterisation of snow mass distribution. The use of model states, such as underlying snow/soil temperatures, could aid the measurement model or microwave retrieval algorithm. Use of anomaly space, rather than absolute snow mass may also be more fruitful for interpreting microwave signals of snow across the globe. These suggestions are merely speculative.

Gravitational anomalies, such as from the GRACE satellites, can map snow mass considerable better than current passive microwave methods (S.Swenson, *pers. comm.*). However, data is best available at the monthly time scale and at large (600x600km) spatial scales, thus precluding it for use in

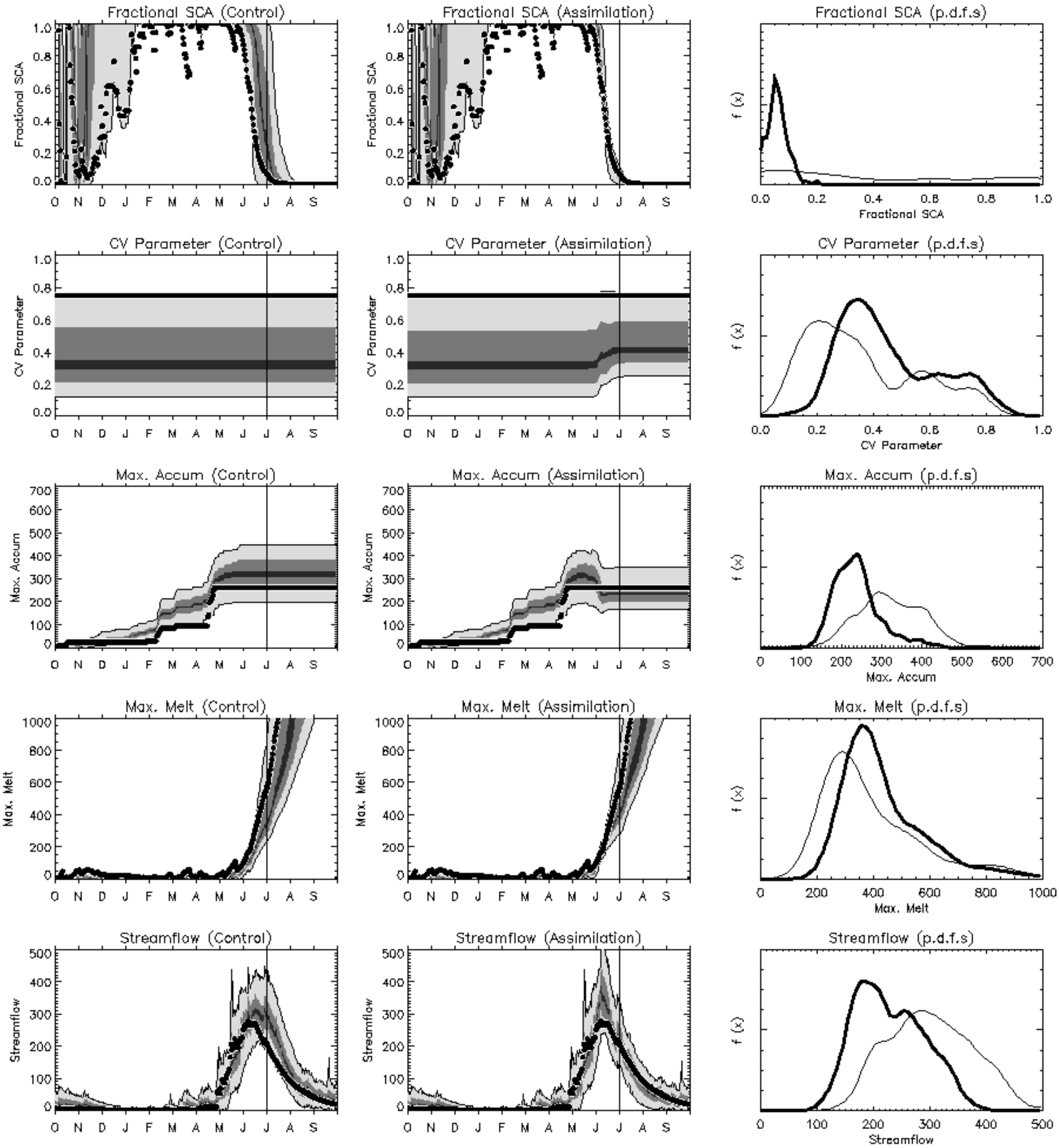


*Figure 2: Example ensemble simulations of model states and streamflow for water year 1995. The left column shows results for the "control" ensemble, the middle column shows results for the "assimilation" ensemble, and the right column shows example p.d.f.s for July 1st (light line is control, dark line is assimilation). Synthetic observations from the "truth" simulation are shown as dots, and the shading depicts percentiles from the ensemble (0.05, 0.25, 0.45, 0.55, 0.75, 0.95). The assimilated variable was SCA, which was propagated across various states and parameters. From [Clark et al., 2006]*

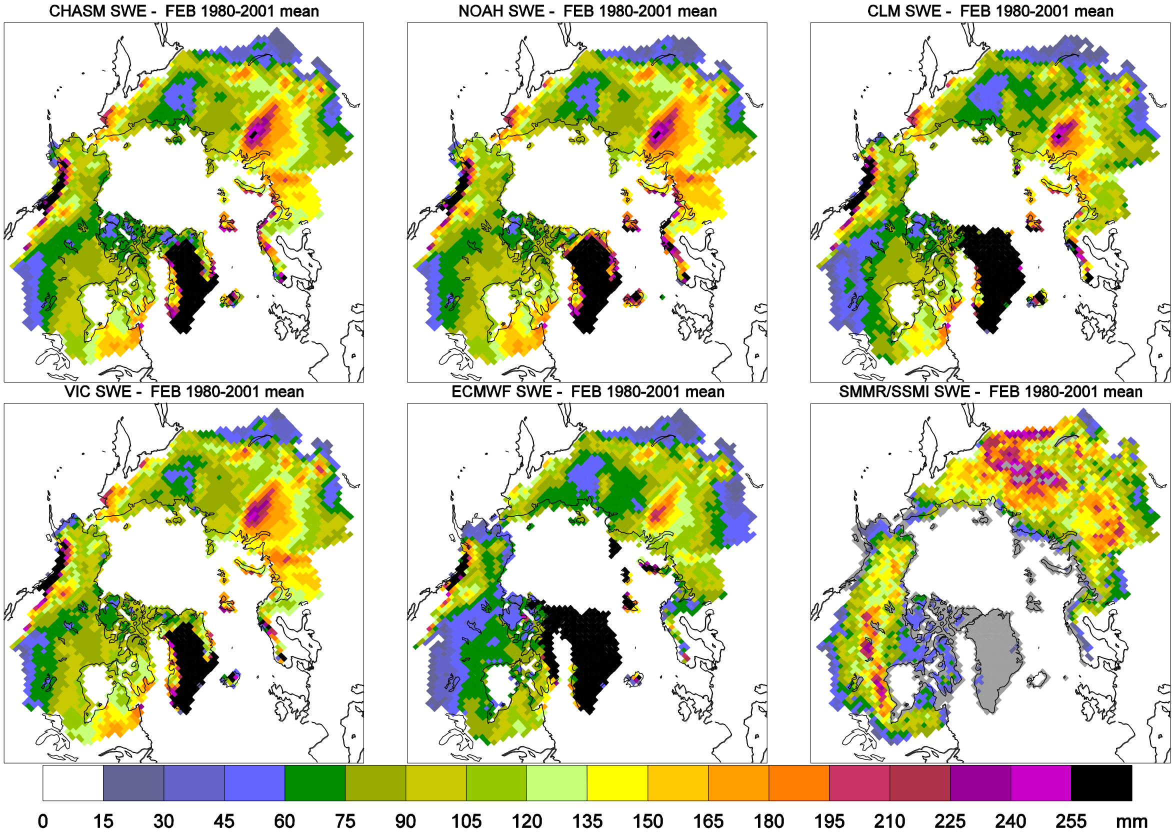


*Figure 3: Mean monthly snow water equivalent (February 1980-2001) from land surface models driven by ERA-40 data, along with the global scale passive microwave (SMMR and SSM/I) snow product. The image demonstrates problems with microwave inversions over much of Eurasia. Follows from [Slater et al., 2007]*

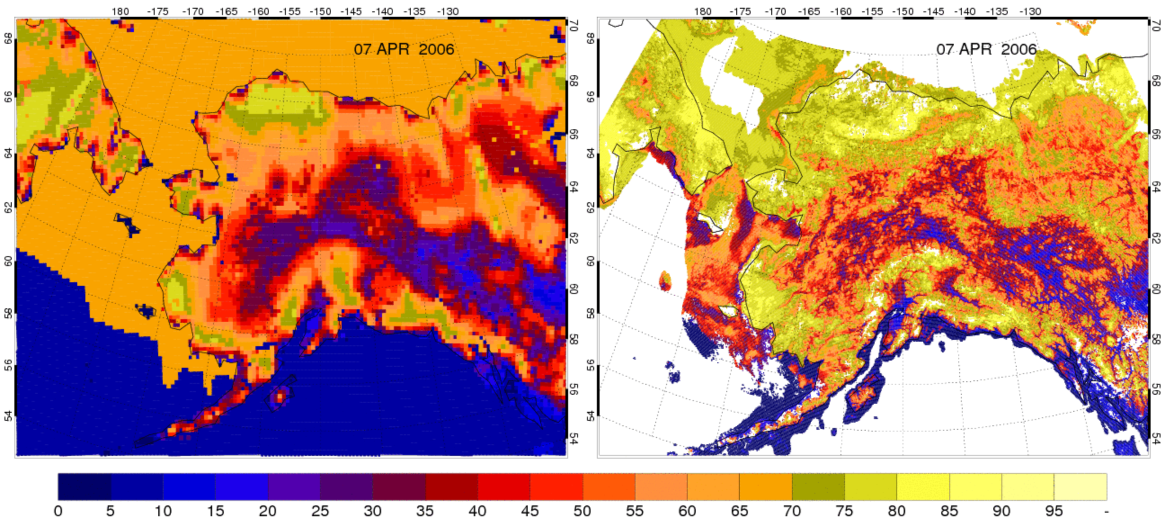


*Figure 4: Mean terrestrial albedo for the 8 days following 7th April, 2006 from the WRF model (left) and from the MOD43C combined Terra/Aqua MODIS product. Slater et al., in prep.*

operational NWP. Albedo data is available from the MODIS sensors as an 8-day average product and is seen to be reliable barring the problems of cloud cover. The assimilation of albedo has considerable potential and has the advantage that it is a direct mapping to an easily understood model variable that can have a significant impact on the surface energy balance of the NWP model if errors exist in parameterization of snow albedo or fractional cover (Figure 4). Methods for albedo assimilation are yet to be established, but the authors envisage simple rule based implementation to begin with. This will be tested as part of the "Arctic System Reanalysis Project", though may not be part of the final product.

## 6. Reference:

Clark, M.P. and A.G. Slater (2006) Probabilistic quantitative precipitation estimation in complex terrain. *J. Hydrometeor.*, **7**: 3-22.

Clark, M.P., A.G. Slater, A.P. Barrett, L.E. Hay, G.J. McCabe, B. Rajagopalan, and G.H. Leavesley (2006) Assimilation of snow covered area information into hydrologic and land-surface models. *Adv. Water Resources*, **29**: 1209-1221.

Slater, A.G., A.J. Pitman and C.E. Desborough (1998) Simulation of freeze-thaw cycles in a general circulation model land surface scheme. *J.Geophys.Res – Atmos.*, **103**: 11303-11312.

Slater, A.G. and M.P. Clark (2006) Snow data assimilation via an ensemble Kalman filter. *J. Hydrometeor*, 7: 478-493.

Slater, A.G., T.J. Bohn, J.L. McCreight, M.C. Serreze and D.P. Lettenmaier (2007) A multimodel simulation of pan-Arctic hydrology. *J.Geophys.Res - Biogeoscience*, **112**: G04S45, doi:10.1029/2006JG000303.

Viterbo, P. and A. Betts (1999) Impact on ECMWF forecasts of changes to the albedo of the boreal forests in the presence of snow. *J.Geophys.Res – Atmos*, **104**: 27803-27810.

Viterbo, P., A. Beljaars, J. Mahfouf and J. Teixeira (1999) The representation of soil moisture freezing and its impact on the stable boundary layer. *Q.J.Roy.Meteor.Soc.*, **125**: 2401-2426.