Quantifying the Added Value of Snow Cover Area Observations in Passive Microwave Snow Depth Data Assimilation

SUJAY V. KUMAR,[*,+] CHRISTA D. PETERS-LIDARD,[+] KRISTI R. ARSENAULT,[*,+] AUGUSTO GETIRANA,[+,#] DAVID MOCKO,[*,+,@] AND YUQIONG LIU[+,#]

[*] *Science Applications International Corporation, McLean, Virginia*
[+] *Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, Maryland*
[#] *Earth System Science Interdisciplinary Center, University of Maryland, College Park, College Park, Maryland*
[@] *Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, Maryland*

(Manuscript received 30 January 2015, in final form 2 April 2015)

ABSTRACT

Accurate determination of snow conditions is important for several water management applications, partly because of the significant influence of snowmelt on seasonal streamflow prediction. This article examines an approach using snow cover area (SCA) observations as snow detection constraints during the assimilation of snow depth retrievals from passive microwave sensors. Two different SCA products [the Interactive Multisensor Snow and Ice Mapping System (IMS) and the Moderate Resolution Imaging Spectroradiometer (MODIS)] are employed jointly with the snow depth retrievals from a variety of sensors for data assimilation in the Noah land surface model. The results indicate that the use of MODIS data is effective in obtaining added improvements (up to 6% improvement in aggregate RMSE) in snow depth fields compared to assimilating passive microwave data alone, whereas the impact of IMS data is small. The improvements in snow depth fields are also found to translate to small yet systematic improvements in streamflow estimates, especially over the western United States, the upper Missouri River, and parts of the Northeast and upper Mississippi River. This study thus demonstrates a simple approach for exploiting the information from SCA observations in data assimilation.

1. Motivation

Snow conditions on the land surface are key components of the global hydrological cycle, and they play a critical role in the determination of local and regional climate. The contribution to the moisture conditions from snow is vital in supporting agriculture and in determining water management practices. Data assimilation techniques are considered an effective approach to combine the information from remotely sensed snow measurements and model forecasts to produce accurate and spatially and temporally consistent estimates of snow conditions.

Primarily, there are two types of spaceborne remotely sensed measurements of snow processes: 1) snow cover area (SCA) is typically measured using visible or infrared satellite sensors, exploiting the high reflectance of snow-covered areas compared to areas with no snow cover; and 2) passive microwave (PM)-based measurements of snow depth and snow water equivalent (SWE). Measurements made in the visible spectrum provide observations at high spatial resolution, but they are limited to cloud-free conditions (Hall et al. 2002). On the other hand, PM measurements tend to be at spatially coarser resolutions and have large errors over areas with dense vegetation cover and proximity to open water, but they can observe under cloudy and nighttime conditions. They are also not sensitive to thin snow packs and are prone to signal saturation in areas of deep snowpack (Dong et al. 2005), such as the western United States.

As both SCA and snow depth observations are viable sources of information to improve model snow estimates, there have been a number of studies that have examined the assimilation of these measurements (Rodell and Houser 2004; Andreadis and Lettenmaier 2006; Su et al. 2008; De Lannoy et al. 2012; Arsenault et al. 2013; Liu et al. 2013; Kumar et al. 2014). The SCA measurements provide either binary observations (i.e.,

Corresponding author address: Sujay Kumar, Hydrological Sciences Laboratory, NASA GSFC, Code 617, Greenbelt, MD 20771.
E-mail: sujay.v.kumar@nasa.gov

DOI: 10.1175/JHM-D-15-0021.1

they simply specify the presence or absence of snow) or fractional snow cover information derived from normalized difference snow index (NDSI) relationships (Salomonson and Appel 2004). The typical strategy to assimilate SCA observations has been to use rule-based direct insertion approaches or to use snow depletion relationships to translate the SCA information into the model prognostic states such as SWE. The PM snow depth observations, on the other hand, provide quantitative information on the snowpack properties and therefore do not require such indirect approaches (De Lannoy et al. 2012; Liu et al. 2013).

In a more recent study, Kumar et al. (2014) examined the impact of assimilating bias-corrected PM data over the continental United States. Though improvements from data assimilation were obtained in the snow depth fields, these enhancements did not always translate to downstream improvements in runoff and streamflow. Most notably, degradations in streamflow simulation skills due to PM snow depth assimilation over the basins in the western United States were observed. In this article, we examine the added impact of using visible SCA observations as additional constraints during PM snow data assimilation, as an extension of the Kumar et al. (2014) study.

2. Approach

In this study, we employ a modeling domain over the continental United States, at ⅛° spatial resolution, similar to the domain configuration used in Kumar et al. (2014). The Noah land surface model, version 3.3 (Ek et al. 2003), is used in the simulations, forced with surface meteorology data from phase 2 of the North American Land Data Assimilation System (NLDAS-2) project (Xia et al. 2012). Version 3.3 of Noah includes several snow physics–related enhancements that are described in Barlage et al. (2010). The simulations are run with a 30-min time step for the 32-yr time period 1979–2011. The initial conditions are generated by running the LSM from 1979 to 2011 twice and then reinitializing the model in 1979. Routed streamflow estimates from the gridded runoff fields from the Noah LSM are generated using the Hydrological Modeling and Analysis Platform (HyMAP; Getirana et al. 2012) model.

The data assimilation integrations employ a 1D ensemble Kalman filter (EnKF) approach to assimilate PM snow depth retrievals. An ensemble size of 30 is used in the simulations with perturbations applied to both meteorological fields and model prognostics fields to simulate uncertainty in the model estimates. Note that compared to the previous study (Kumar et al. 2014) that employed an ensemble size of 12, here we use a larger ensemble size to reduce the effects of sampling density limitations. Based on the parameters used in Kumar et al. (2014), multiplicative perturbations are applied to the precipitation and downward shortwave radiation fields with a mean of 1 and standard deviations of 0.3 and 0.5, respectively. In addition, downward longwave radiation fields are perturbed with additive noise (with a standard deviation of 50 W m^{-2}). The Noah LSM variables for SWE and snow depth are perturbed with multiplicative noise with a mean of 1 and standard deviations of 0.01 and 0.02, respectively. As described in Kumar et al. (2014), the microwave retrievals [from three different sensors: Scanning Multichannel Microwave Radiometer (SMMR; used from January 1979 to July 1987), Special Sensor Microwave Imager (SSM/I; used from August 1987 to June 2002), and Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E; used from July 2002 to October 2011)] are bias corrected using in situ snow depth measurements from the Global Historical Climatology Network (GHCN) and the Snowpack Telemetry (SNOTEL) data prior to assimilation. These PM snow depth products are available at approximately 25-km spatial resolution. Similar to Kumar et al. (2014), the standard deviation of the observation error is assumed to be 20 mm after the bias correction of the snow depth products.

In this article, we build upon the Kumar et al. (2014) study by introducing a number of additional constraints to evaluate the added impact of SCA observations. Figure 1 shows a flowchart of SCA databased constraints used in the PM snow depth assimilation. Overall, the SCA observations are used as the default for identifying the presence or absence of snow. If an SCA observation is missing at a location, then no passive microwave data are assimilated. If an SCA observation indicates the absence of snow (zero snow cover), then the passive microwave snow depth observation is determined to be zero and is assimilated. Conversely, if the SCA observation indicates nonzero snow cover but PM data indicate no snow, then the PM data are not assimilated. The nonzero snow depth amounts indicated by the PM data are only assimilated if the corresponding SCA data also indicate nonzero snow presence. We use two different sources of SCA observations: 1) the Interactive Multisensor Snow and Ice Mapping System [IMS; Ramsay (1998), available from 1997] from the National Oceanic and Atmospheric Administration (NOAA) and 2) the Moderate Resolution Imaging Spectroradiometer [MODIS; Hall et al. (2006), available from 2000]. IMS data are a blend of visible data from geostationary and polar-orbiting satellites and passive microwave data and are available at approximately 24-km

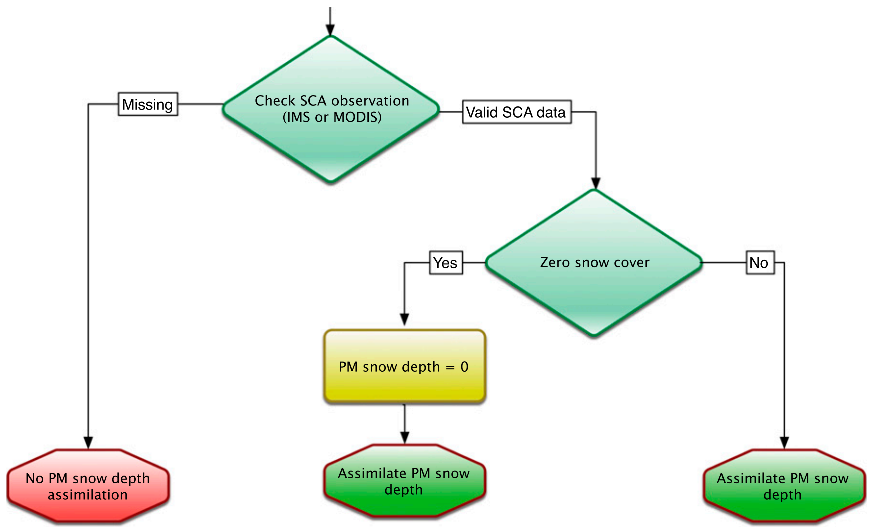

FIG. 1. A flowchart of the SCA databased constraints used in the assimilation of PM snow depth data.

spatial resolution daily. In this study we use the MOD10C1 product, which is an aggregated product on the 0.05° Climate Modeling Grid (CMG). SCA data from the MODIS product are considered valid if the associated cloud cover is less than 10% and the observation of snow cover fraction is greater than 25%.

The experimental setup includes four model integrations: 1) open loop (OL), the model integration without data assimilation (DA); 2) DA1, where only PM data are assimilated; 3) DA2, where PM data are assimilated but constrained by IMS snow cover (from 1997 to 2011); and 4) DA3, where PM data assimilation is constrained by IMS (from 1997 to 2000) and MODIS (from 2000 to 2011) snow cover data. DA2 and DA3 not only capture the impact of introducing the SCA-based constraint, but they also quantify the relative impact of IMS and MODIS SCA data.

The results of the model integrations are evaluated against a number of independent datasets. To evaluate the modeled snow fields, the spatially distributed snow depth estimates from the Canadian Meteorological Centre (CMC) daily snow depth analysis (Brown and Brasnett 2010; available at approximately 25-km spatial resolution globally) is used. The downstream impacts on simulated streamflow are evaluated using the daily streamflow data obtained from the U.S. Geological Survey (USGS; http://nwis.waterdata.usgs.gov/nwis) over 572 small, unregulated basins. These basins range in size from 625 up to 10 000 km^2 and had no visible signs of reservoir operations. In the results shown below, evaluations of the modeled snow depth and streamflow fields are conducted for a common time period 2000–11.

3. Results

We first examine the influence of data assimilation on improving snow depth estimates. Figure 2 shows the average seasonal cycle of spatial means of daily RMSE and bias for the OL and the three DA integrations compared against the CMC product. Generally, the OL RMSE is improved by the DA integrations. The inclusion of IMS data has a smaller impact, whereas the addition of MODIS data helps in systematically reducing RMSE, especially in the peak snow months (approximately 6% aggregate improvement in RMSE over the DA1 integration is obtained in the peak winter months). The bias errors are large in the open loop estimates and are significantly reduced in the data assimilation integrations, especially in the peak winter months of December–February. Note that the biases of all PM snow depth assimilation integrations increase during early spring, relative to the OL bias estimate. One possible reason for this degradation could be that the PM radiance observations are noisy for wet snow, leading to increased errors in the snow depth retrievals during such conditions (Slaymaker and Kelly 2007). The introduction of MODIS (DA3) leads to increased biases in the snow evolution months, compared to DA1 and DA2. During the late snow peak and spring months, all DA integrations behave in a similar manner. To provide a measure of the spatial distribution of the mean RMSE, Fig. 2 also shows a comparison of the spatial standard deviation of the RMSE and bias estimates for each month. The spatial standard deviations of the errors are large, but they are also systematically improved in the DA integrations. DA3 shows the smallest spatial

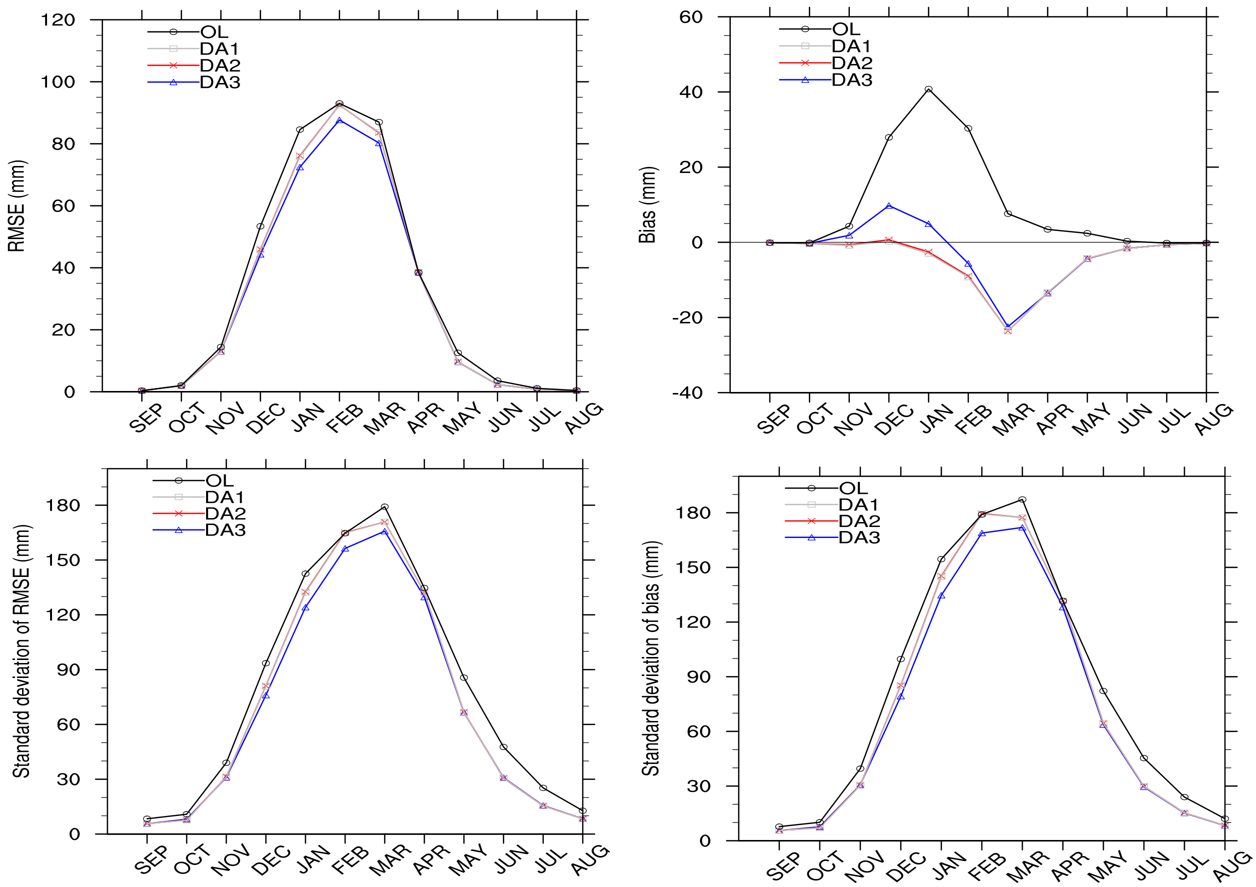

FIG. 2. Average seasonal cycle of spatial (top) mean and (bottom) std dev of daily (left) RMSE and (right) bias from the OL and various DA integrations compared to the CMC product, during the time period 2000–11.

standard deviations of RMSE, particularly in the peak winter months.

To capture the added impact of SCA data on snow depth estimates relative to the PM-only assimilation, RMSE difference maps (using CMC as the reference data) are generated by subtracting the RMSE of DA1 from the RMSE of both DA2 and DA3 integration and are shown in Fig. 3. Similar to the mean RMSE and bias seasonal cycles shown in Fig. 2, the use of IMS data has a minor effect and the areas of improvements are limited to a few locations over the western United States. Comparatively, the use of MODIS data is more impactful. DA3 simulation leads to improvements over several regions, including parts of the Colorado headwaters, Missouri River basin, and over the upper Northeast extending into Canada. Some degradations are also observed, especially over parts of the Rocky Mountains and the Midwest.

It was shown in Kumar et al. (2014) that though snow depth estimates were improved through the assimilation of PM data, the subsequent impact on streamflow estimates was marginal. The most notable degradations occurred in the western United States and over parts of the upper Mississippi and Missouri basins. Here, we examine the added impact of incorporating SCA products on streamflow simulations. Similar to Fig. 3, Fig. 4 shows a comparison of the differences in Nash–Sutcliffe efficiency (NSE) of DA2 or DA3 relative to DA1. The NSE is a common metric used to evaluate the goodness of fit of hydrological models and is defined as

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{t=T} (O_t - S_t)^2}{\sum_{t=1}^{t=T} (O_t - \overline{O})^2}, \tag{1}$$

where S_t and O_t are the simulated and observed streamflow, respectively, at time t and $\overline{O}$ is the time-averaged observed streamflow. An NSE value of one indicates a perfect match with observations, whereas an NSE of zero indicates that the model estimates are only as good as the mean observation. Negative NSE values indicate that the simulations are worse than the mean observation.

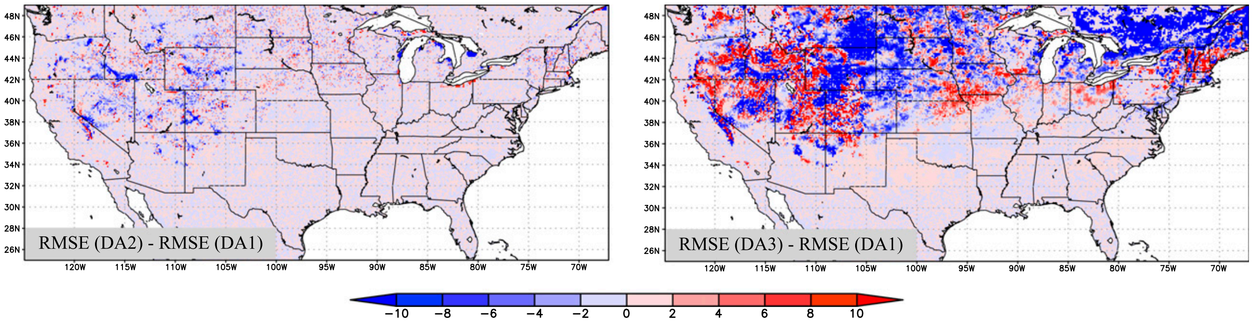

FIG. 3. RMSE differences (mm) of snow depth from DA3 (PM assimilation constrained by MODIS and IMS) and DA2 (PM assimilation constrained by IMS) integrations relative to the DA1 (PM assimilation only) integration for the time period 2000–11. Cool colors indicate areas of improvement and warm colors indicate areas of degradations.

Figure 4 indicates that the addition of both IMS and MODIS datasets generally improves streamflow simulations, though the magnitude of improvements is small. The SCA constraint through IMS helps in improving streamflow mostly in some western basins. In comparison, the incorporation of MODIS data has more positive impacts at several basins, including the western United States, the upper Missouri, and parts of the Northeast and the upper Mississippi River. The trends of improvements in the streamflow estimates are consistent with the spatial patterns in Fig. 3, which shows similar regions with improvements in snow depth estimates from the use of MODIS and IMS data. Note that approximately 5% added improvements in aggregate NSE are obtained from the use of MODIS data compared to the use of IMS.

4. Summary

Though passive microwave observations of snow states provide quantitative measurements, data assimilation studies employing them have only reported marginal or no improvements because of the large uncertainty associated with these products (Andreadis and Lettenmaier 2006; De Lannoy et al. 2012). The Kumar et al. (2014) study showed that the use of in situ measurements for bias correction of the PM retrievals is an effective strategy to improve the skill of these products for data assimilation. In this paper, we explore the introduction of the higher-resolution SCA data as a snow detection constraint for further improving passive microwave snow depth assimilation.

The modeling study is conducted over the continental United States in the NLDAS-2 domain configuration and using datasets with the Noah land surface model. The model simulations are conducted over the 32-yr time period 1979–2011, with a number of PM-based snow depth datasets assimilated into the model with a 1D EnKF algorithm. The IMS and MODIS datasets are used as additional constraints for snow detection during assimilation. The added impact of SCA datasets for improving modeled snow states and their subsequent contribution toward the estimation of streamflow are quantified.

The results indicate that the SCA-based constraint introduced in the assimilation of passive microwave retrievals is effective in improving estimates of snow depth, especially with the use of MODIS datasets. The

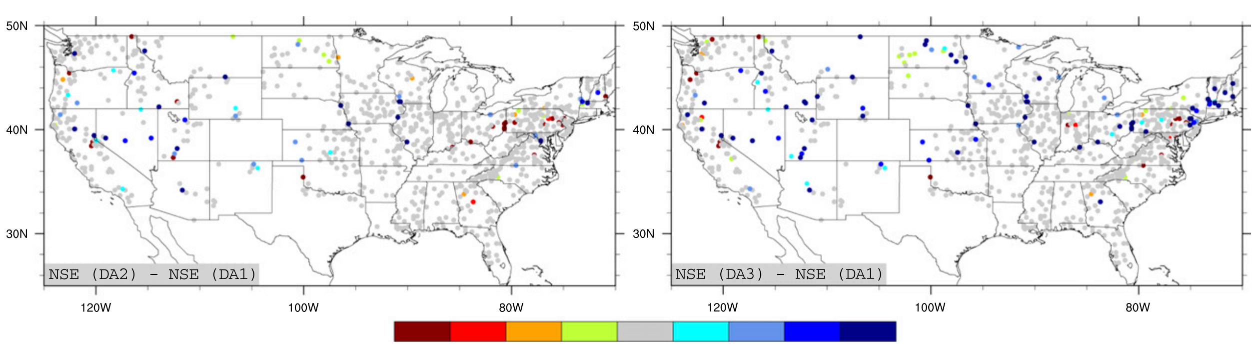

FIG. 4. NSE difference (unitless) of streamflow estimates from DA2 and DA3 integration relative to DA1 simulation for the time period 2000–11. Cool and warm colors show locations where incorporating SCA leads to improvements and degradations in NSE, respectively.

added impact of using IMS data was small, possibly because of the low spatial resolution of the IMS product and the fact that passive microwave snow data are already used for IMS data generation. Therefore, the use of IMS here does not provide sufficient enough independent information over the PM data. In comparison, MODIS snow cover data provide more independent information and a finer spatial resolution, both of which help to generate added improvements (approximately 6% in aggregate RMSE) relative to PM snow depth assimilation. Though the aggregate improvements are small, larger improvements are likely at finer temporal scales, which are important for applications such as water management and forecast model initialization.

The improvements in snow depth fields from the use of MODIS SCA are also found to translate to small yet systematic improvements in streamflow estimates over several basins, most notably in the western United States. Similar to the trends observed with the snow depth fields, the MODIS SCA-based constraint was more effective in improving streamflow estimates compared to the IMS-based constraint. At the domain-averaged scale, approximately 5% added improvements in NSE are obtained from the use of MODIS data compared to the use of IMS snow cover measurements.

Acknowledgments. Funding for this work was provided by the NASA Science Mission Directorate's Earth Science Division through the National Climate Assessment (NCA) project and NOAA's Climate Program Office MAPP program.

REFERENCES

Andreadis, K., and D. Lettenmaier, 2006: Assimilating remotely sensed snow observations into a macroscale hydrology model. *Adv. Water Resour.,* **29,** 872–886, doi:10.1016/j.advwatres.2005.08.004.

Arsenault, K., P. Houser, G. De Lannoy, and P. Dirmeyer, 2013: Impacts of snow cover fraction data assimilation on modeled energy and moisture budgets. *J. Geophys. Res. Atmos.,* **118,** 7489–7504, doi:10.1002/jgrd.50542.

Barlage, M., and Coauthors, 2010: Noah land surface model modifications to improve snowpack prediction in the Colorado Rocky Mountains. *J. Geophys. Res.,* **115,** D22101, doi:10.1029/2009JD013470.

Brown, R., and B. Brasnett, 2010: Canadian Meteorological Centre (CMC) daily snow depth analysis data (updated annually). National Snow and Ice Data Center, accessed January 2014, doi:10.5067/W9FOYWH0EQZ3.

De Lannoy, G., R. Reichle, K. Arsenault, P. Houser, S. Kumar, N. Verhoest, and V. Pauwels, 2012: Multiscale assimilation of Advanced Microwave Scanning Radiometer–EOS snow water equivalent and Moderate Resolution Imaging Spectroradiometer snow cover fraction observations in northern Colorado. *Water Resour. Res.,* **48,** W01522, doi:10.1029/2011WR010588.

Dong, J., J. Walker, and P. Houser, 2005: Factors affecting remotely sensed snow water equivalent uncertainty. *Remote Sens. Environ.,* **97,** 68–82, doi:10.1016/j.rse.2005.04.010.

Ek, M., K. Mitchell, L. Yin, P. Rogers, P. Grunmann, V. Koren, G. Gayno, and J. Tarpley, 2003: Implementation of Noah land surface model advances in the National Centers for Environmental Prediction operational mesoscale Eta mode. *J. Geophys. Res.,* **108,** 8851, doi:10.1029/2002JD003296.

Getirana, A., A. Boone, D. Yamazaki, B. Decharme, F. Papa, and N. Mognard, 2012: The Hydrological Modeling and Analysis Platform (HyMAP): Evaluation in the Amazon basin. *J. Hydrometeor.,* **13,** 1641–1665, doi:10.1175/JHM-D-12-021.1.

Hall, D., G. Riggs, V. Valomonson, N. DiGirolamo, and K. Bayr, 2002: MODIS snow-cover products. *Remote Sens. Environ.,* **83,** 181–194, doi:10.1016/S0034-4257(02)00095-0.

——, V. Salomonson, and G. Riggs, 2006: MODIS/*Terra* Snow Cover Daily L3 Global 0.05deg CMG, version 5. National Snow and Ice Data Center, accessed January 2014, doi:10.5067/EI5HGLM2NNHN.

Kumar, S., and Coauthors, 2014: Assimilation of remotely sensed soil moisture and snow depth retrievals for drought estimation. *J. Hydrometeor.,* **15,** 2446–2469, doi:10.1175/JHM-D-13-0132.1.

Liu, Y., C. Peters-Lidard, S. Kumar, J. Foster, M. Shaw, Y. Tian, and G. Fall, 2013: Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska. *Adv. Water Resour.,* **54,** 208–227, doi:10.1016/j.advwatres.2013.02.005.

Ramsay, B., 1998: The interactive multisensor snow and ice mapping system. *Hydrol. Processes,* **12,** 1537–1546, doi:10.1002/(SICI)1099-1085(199808/09)12:10/11<1537::AID-HYP679>3.0.CO;2-A.

Rodell, M., and P. Houser, 2004: Updating a land surface model with MODIS derived snow cover. *J. Hydrometeor.,* **5,** 1064–1075, doi:10.1175/JHM-395.1.

Salomonson, V., and I. Appel, 2004: Estimating fractional snow cover from MODIS using the normalized difference snow index. *Remote Sens. Environ.,* **89,** 351–360, doi:10.1016/j.rse.2003.10.016.

Slaymaker, O., and R. Kelly, 2007: *The Cryosphere and Global Environmental Change.* Blackwell Publishing, 261 pp.

Su, H., Z.-L. Yang, G.-Y. Niu, and R. Dickinson, 2008: Enhancing the estimation of continental-scale snow water equivalent by assimilating MODIS snow cover with the ensemble Kalman filter. *J. Geophys. Res.,* **113,** D08120, doi:10.1029/2007JD009232.

Xia, Y., and Coauthors, 2012: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *J. Geophys. Res.,* **117,** D03109, doi:10.1029/2011JD016048.