Evaluation of gridded snow water equivalent and satellite snow cover products for mountain basins in a hydrologic model

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Abstract

The USGS Precipitation Runoff Modeling System (PRMS) hydrologic model was used to evaluate experimental, gridded, 1-km$^2$ snow covered area (SCA) and snow water equivalent (SWE) products for two headwater basins in the Rio Grande and Salt River drainages in the Southwestern United States. The SCA product was the fraction of each 1-km$^2$ pixel covered by snow and was derived from NOAA Advanced Very High Resolution Radiometer imagery. The SWE product was developed by multiplying the SCA product by SWE estimates interpolated from National Resources Conservation Service Snow Telemetry (SNOTEL) point measurements for a six-year period (1995-2000). Measured SCA and SWE estimates were consistently lower than values estimated from temperature and precipitation within PRMS. Differences between modeled and measured snow were different for the accumulation period vs. the ablation period and had an elevational signature. Greatest difference occurred in the relatively complex terrain of the Grande, as opposed to the Black where differences were small. Assimilating the measured snow fields into a version of PRMS calibrated to achieve water balance without assimilation reduced model performance, i.e. modeled streamflow, because this effectively removed water from the basins. Incorporating observed SCA and SWE will require either model recalibration, an averaging strategy for modeled versus observed quantities, or adjustments to water balance accounting at each time step assimilation occurs in order to maintain water balance across the snowmelt season.

KEYWORDS: assimilation, snow water equivalent, snow covered area, hydrologic modeling, PRMS
1. Introduction

Accurate snowpack and snowmelt estimates in cold regions are critical for operational flood control, water delay planning, and resource management in snowmelt-dominated basins. Snow-covered area (SCA) has been used as a driving hydrologic variable for streamflow prediction (e.g., Martinec, 1975; Rango and Martinec, 1979; Barrett et al., 2001). Observations of areal extent have been used in hydrologic model forecasts for decades (Maurer et al., 2003), and many studies have focused on using SCA to estimate snow water equivalent (SWE) through depletion curves (e.g., Anderson, 1973; Liston, 1999). Ground estimates of SWE are essential for physically based snowmelt runoff models, which include mass balance of water (Molotch et al., 2004a) and have been used for evaluation of energy-balance snow models (e.g. Cline et al., 1998). However, estimating snow cover properties at a basin scale, particularly SWE but also SCA, remains a challenge.

Hydrologic models generally involve time-invariant descriptions of basin characteristics through parameters (e.g., temperature-precipitation relationships) and variable states (e.g., flux, storage and residence time of snow) (Moradkhani et al., 2005). These models require accurate initial conditions to adequately simulate runoff (Day, 1985). Accurate snowmelt runoff estimation in hydrologic models is a challenge, especially in mountainous terrain where the signature of snow is large (Fontaine et al., 2002) and data are poor in spatial resolution (Davis and Marks, 1980). Cazorzi and Fontana (1996) improved data resolution by distributing temperature, a primary forcing variable in snowmelt (Zuzel and Cox, 1975), with distributed solar radiation and
adiabatic lapse rate. Both energy budget (e.g., Anderson, 1976) and temperature-index or degree-day (e.g., Martinec et al., 1983) snowmelt models are routinely used in hydrologic models. Temperature-index models are widely used because the data needed for energy budget approaches (Rango and Martinec, 1995; Cazorzi and Fontana, 1996; Walter et al., 2004) is often unavailable.

Operational forecasts of streamflow could benefit from updated estimates of distributed snow cover. Satellite remote sensing in the visible and near-infrared wavelengths has been used operationally for many years to map snow cover (e.g. Cline et al, 1999), however there has been little evaluation of the impact of assimilating those spatial snow products in mass and energy balance hydrologic models for streamflow estimation over a large spatial scale. The United States Geological Survey’s (USGS’s) precipitation-runoff modeling system (PRMS) is well-suited for such evaluation. PRMS is a modular, deterministic, distributed-parameter modeling system developed to evaluate the impacts of various combinations of precipitation, climate, and land use on streamflow, sediment yields, and general basin hydrology (Leavesley and Stannard, 1995). PRMS has performed well in simulating streamflow in mountain basins, e.g. the Upper Gunnison River, CO (Leavesley et al., 2002). In that study, remotely sensed estimates of binary SCA from the US National Weather Service National Operational Hydrologic Remote Sensing Center (NOHRSC, http://www.nohrsc.nws.gov) were similar to SCA simulated by PRMS over the period 1990-1999. This reasonable agreement independently validated the viability of the PRMS parameter estimation approach in mountainous terrain. Many techniques have evolved for updating models, including simple “replacement” or “updating” of state variables to more complex four
dimensional data assimilation used in meteorological applications (Stauffer and Seaman, 1990), and the potential model improvements depend on both the quality of the input data and accurate parameter estimation (Moradkhani et al., 2005).

This study is a comparative evaluation of SCA and SWE products (with and without a vegetation correction) based on blending satellite and ground-based measurements versus a modeled snowpack (estimated from temperature and precipitation) in two headwater basins. We used PRMS (Leavesley et al., 1983) in part because its minimal forcing data requirements were compatible with available data and also because of previous success in simulating snow packs in the study region. Differences between modeled and measured fields are evaluated in time and space and in the context of simulated discharge from those different fields.

2. Data and Methods

Study Area

The Black River headwaters of the Salt River near Phoenix, AZ is a 1441 km$^2$ basin with elevation ranging from 3334 m in the northeastern section of the basin to 1761 m at the stream gauge (USGS 09489500 near Point of Pines, AZ; operating since 1953), an average elevation of 2454 m (Figure 1). The Rio Grande headwaters, above the Del Norte, CO stream gauge, is a 3397 km$^2$ basin with elevation ranging from 2438 m at the gauge (USGS 0822000; operating since 1890) to 4084 m in the northwestern alpine portion of the basin, and an average of 3225 m (Figure 1). Both basins are heavily forested and precipitation is dominated by snow, but the Grande is higher elevation and more topographically complex than the Black. Average stream flows are 24.1 m$^3$/s and 5.8 m$^3$/s, respectively.
Serreze et al. (1999) report that the western United States can be divided into 8 regions that are topographically, climatologically, physically, and hydrologically different. Although within region differences are expected on the smaller scale, regional heterogeneities are expected to dampen that signature. The Grande and Black basins are located in different regions (Black, Arizona/New Mexico region; Grande, Colorado region), and therefore, enable evaluation of differences in satellite-based SCA, SWE, and runoff estimation over differing basin characteristics found in southwestern mountains.

**Snow Data**

SCA maps for the Grande and Colorado River basins of the Southwestern U.S. were developed for a six year period (1995-2000) from AVHRR scenes using a three-part cloud masking procedure and spectral un-mixing algorithm (Bales et al, in preparation). Level 1b AVHRR scenes were acquired through the University of California-Santa Barbara and New Mexico State University. Processing occurred in three steps. First, images were converted from digital counts to radiances for all 5 bands, then to surface reflectance for bands 1 (0.58-0.68 µm), 2 (0.725-1.10 µm), and 3 (3.55-3.93 µm), and to brightness temperature for bands 3 (3.55-3.93 µm), 4 (10.3-11.3 µm), and 5 (11.5-12.5 µm). Atmospheric corrections were made on the reflectance bands (1-3). These 3 bands were then introduced into a decision-tree algorithm, which is based on training against a set of 532 cases of mixtures of 23 theoretical spectra of snow, vegetation, and snow types (Rosenthal and Dozier, 1996). The decision-tree algorithm returns fractional SCA for each pixel likely to be covered by snow, in 16 discrete increments: 0.0, 0.1, 0.18, 0.21, 0.3, 0.32, 0.38, 0.45, 0.47, 0.56, 0.58, 0.66, 0.74, 0.82, 0.89, and 0.99. The result is a mixed product of snow, clouds, and highly reflective surfaces, which must be corrected to
give just the snow-covered pixels. Secondly, a supervised cloud mask was constructed. An additional aperiodic “no data” mask was generated to account for pixels within the study area, but outside the AVHRR swath during overpass. Thirdly, a temperature mask was generated to eliminate highly reflective surface features that are unlikely to be snow. Many highly reflective surfaces (light colored desert sand, dry lake beds, water) are warmer than snow. Pixels were identified using a supervised classification of brightness temperatures for band 4.

Fractional SCA in each pixel was estimated, scenes georegistered, orthorectified, and gridded to 1-km$^2$. Since some clouds were present in most scenes, all scenes with at least one major headwater basin (e.g. Grande) cloud free were processed. In doing so, 229 days were processed for January 1 – June 30 during the 1995 – 2000 period (Table 1). This fractional SCA product was developed by the Southwest Regional Earth Science Applications Center (Southwest RESAC) at the University of Arizona in Tucson, Arizona.

Spatially distributed SWE was estimated daily at a 1-km$^2$ resolution for the same area by interpolating point SWE measurements from SNOTEL stations (Fassnacht et al., 2003) operated by the National Resource Conservation Service (NRCS) (http://www.nrcs.usda.gov). For each grid cell in the basin, all SNOTEL sites within a 200-km radius, including those outside of the basin, were identified. A linear regression was computed between elevation and SWE for all of the SNOTEL sites within the search radius. This hypsometric relationship was used to estimate SWE for each grid cell using a 1-km digital elevation model (DEM). A residual was obtained at each grid block where an observing SNOTEL station was located by removing the observed value from the
analysis, i.e., jack-knifing, and subtracting the observed SWE from the computed SWE. Elevation dependent bias in the residuals was removed by regressing residuals to a datum of 5,000 meters above sea level using the dry adiabatic lapse rate. Once regressed to the common datum, the lapsed residuals were spatially distributed using inverse distance weighting with a power of 2. The gridded residual surface was regressed back to the basin surface using the same lapse rate and subtracted from the hypsometrically derived SWE grid in order to derive the final SWE surface. Daly et al. (2000) used a similar method, except one hypsometric relationship was computed for each sub-basin, instead of using a moving search radius to compute the hypsometric relationship at each pixel. Total basin SWE was then obtained by multiplying the interpolated SWE product with the fractional SCA product. In this way the interpolated SWE maps were adjusted on a pixel-by-pixel basis for the fraction of area determined as snow covered.

RESAC SCA and SWE were adjusted by applying a pixel-by-pixel canopy correction for all 229 product days. First, a day with maximum change in SWE from the previous few days and minimum clouds was selected for each basin. March 3, 1996 was selected for the Grande, for which a basin average of 104 mm of snow fell 9 days before; and March 2, 1997 was selected for the Black, for which a basin average of 213 mm of snow fell the day before. It was assumed that if > 75 mm of snow fell and daily maximum temperatures after that precipitation did not exceed 0°C, the ground should be completely snow covered. Second, pixels that contain any forest (from the gridded 1-km USFS vegetation type data set; USDA, 1992) and are above 2100 meters elevation (considered as the maximum snow extent for the dataset) were identified for correction. All other pixels and those mapped as clouds were assigned a canopy factor of 1, i.e. no
correction. Third, the pixel-by-pixel canopy factor was calculated by dividing 99% (maximum AVHRR SCA) by the mapped value in the pixel to get the pixel-specific canopy correction factor (Figure 2). Fourth, total SWE in each pixel on all remaining 229 days snow was multiplied by the pixel canopy correction factor.

**Hydrologic Model**

Catchment characteristics used in the model were defined using ArcInfo (ESRI, 1992) ARC macro language (AML) functions with digital databases to calculate distributed model parameters (e.g., elevation, slope, aspect, available water holding capacity of the soil, stream reach slope, vegetation cover density). Digital databases used for this study include: (1) USGS 30 m digital elevation model; (2) State Soils Geographic (STATSGO) 1-km gridded soils data (USDA, 1994); and (3) US Forest Service 1-km gridded vegetation type and canopy density data (USDA, 1992). PRMS hydrologic response units (HRUs) were defined as the same 1-km² grid as the AVHRR data. That is, each AVHRR 1-km SCA cell is an HRU.

An objective calibration procedure similar to the one in Leavesley et al. (2002) for other western USA basins was used. No changes were made to spatial parameters, and the calibration focused on water balance parameters affecting potential evapotranspiration (ET) and precipitation distribution and on the subsurface and groundwater parameters affecting streamflow volume and timing. Simulated potential ET was adjusted manually to match published values for the region and gauge catch corrections for snow were applied manually to minimize the difference between simulated and observed streamflow. This base parameter set was used for all model runs in order to maintain a base condition for comparison purposes. Adjusting parameters
differently in each model run would bias simulations to particular snowpack characteristics associated with each input dataset.

PRMS requires distributed estimates of temperature and precipitation as forcing variables. We used the xyz approach (Hay et al., 2000; Hay and McCabe, 2002; Hay et al., 2002) to distribute National Weather Service (NWS) cooperative climate observing station point values of precipitation, and maximum and minimum daily temperatures across the HRUs. Four climate stations were selected for the Black and twelve were selected for the Grande. Data at sites included in a 50-km buffer surrounding the study basins were extracted from the National Climatic Data Center (NCDC, 2004) Summary of the Day (TD3200) summarized by Eischeid et al. (2000) and obtained online at <http://www.ncdc.noaa.gov/oa/climateresearch.html>. Quality-control procedures of Reek et al. (1992) were applied. Records at most stations start in 1948 and continue through present.

Assimilation Approach

We used the simple replacement or update technique of Jastrow and Halem (1970), i.e. measured, gridded SCA and SWE replaced PRMS model SCA and SWE in each HRU at each time step data are available. This technique was used, as opposed to a more complex averaging or nudging technique, for the purpose of evaluating the measured SCA and SWE against a simulated estimate from temperature and precipitation data. If no data were available in any given pixel (i.e. cloud), the model values were carried forward to the next time step. We compared spatial SCA and SWE for remotely-derived products and a base model case to evaluate the spatial distribution of RESAC
estimates. Discharge was then compared for five simulations using model updates from satellite-derived SCA and SWE and a model base case.

Simulation runs were:

- “base” – PRMS model with no data assimilation
- “remote” – model updated with both SCA and SWE
- “remote SWE” – PRMS model using an update from SWE data, with SCA simulated within the model and not updated
- “filtered” – PRMS model updated with both SCA and SWE smoothed with a 9-km$^2$ low-pass averaging filter
- “veg correct” – updated from the canopy corrected SCA and SWE estimates.

These simulations were repeated for the Grande using measurement updates only through April 1 each year (peak SWE), for a total of 116 updates. These simulations with the April 1 cutoff date initialized the model snowpack state for the snowmelt period and were compared to simulations that update during the ablation period to evaluate potential water losses from updates of measured snow fields.

For pixel updates from remote sensing of SWE > 0, the internal dynamics of the snowpack were maintained consistent with the pre-existing pack by adjusting snowpack physical states of free water holding capacity, cold content, and depth. Energy balance equations may be referenced in Leavesley and Stannard (1995). The snow depletion curve was updated with SCA estimates, when available, and reset for every pixel in the basin, adjusting the threshold magnitude to maintain a consistent SCA/SWE relationship with the predefined depletion curve from Anderson (1973).
3. Results

Measured SCA and SWE were systematically lower than modeled SCA and SWE in the Black (Figure 3) and Grande (Figure 4) basins over the 1995-2000 period. Underestimation was generally greater for the Grande than for the Black for both SCA and SWE. In Figures 3 and 4, the representative average water year (WY) 1998 is shown to further illustrate the differences. Total SWE followed the pattern of SCA. However, in some cases for the Black, total measured SWE was greater than modeled SWE, while measured SCA was less than modeled SCA for the same day (e.g. February 10, 1998). This is an artifact of the ground-based SWE data. The vegetation correction decreased the difference by adding snow in forested areas. The average canopy factors of 3.3 for the Black and 2.3 for the Grande, however, did not increase SCA and SWE everywhere due to the presence of clouds for which no correction was applied.

Differences between modeled and measured SCA were dependent on elevation (Figure 5). On average, SCA and SWE were always higher for the model. During the accumulation period, differences generally decreased with elevation for both basins. The elevational trend in the ablation period differed from the accumulation period: it increased to a peak in the 3000-3500 m elevation range and then decreased above 3500 m. The greatest differences occurred in the Grande, with a maximum of 67% in the 3000 – 3250 m region. The canopy correction improved upon the satellite estimate at all elevations, with the greatest impact at mid-elevations (2750 – 3500 m) where most forest and complex terrain occurs. Differences in SWE followed the same general trends as differences in SCA for both basins (Figure 6), but with less variability. However, measured SWE was greater than modeled during the accumulation period for the Black.
Replacement of modeled SCA and SWE with measured updates reduced model performance as shown in the water balance (Table 2) and cumulative discharge (Figure 7). Overall low Nash-Sutcliffe values in the Black were due to inaccuracies in estimating both runoff volume (over and underestimates) and timing (earlier melt), common problems in semi-arid basins for which streamflow is low (Figure 7). Black basin simulations with updates generally over-predicted streamflow during wetter years (WY 1995 WY 1997, and WY 1998) due to the higher SWE estimates after interpolation, and under-predicted during drier years (WY 1999 and WY 2000) due to less consistent snowpack coverage, i.e. patchier snow, which can lead to a mixed snow and terrain signature. Grande simulations with updates systematically under-predicted relative to both the base simulation and observed cumulative discharge in all years.

In the Black, the updated simulations overestimated the modeled and observed discharge during the rising limb of the hydrograph due to the positive change in SWE volume when replacing model snow fields with measured snow fields (Figure 8). After March 1, the measured updates removed SWE when replacing modeled fields. This decreases the discharge for both updates simulations. In all update cases for the Grande, model performance was reduced as measured snow fields removed SWE from the basin (Figure 8). The negative impact progressively increased through peak discharge and melt-out to base flow conditions, because, as noted above, the measured fields were systematically lower than modeled (Figure 4). During WY 1998 in the Grande basin, the response to April snow events was lagged in the hydrograph with the remote case melting out earlier and a lower peak magnitude due to the replacement of modeled fields with lower measured SCA in the four May updates, an average of 73% less SCA. Because
snow is updated after the accumulation period, the lower estimates in the update removed snow that is not redistributed or added at a later date. An additional set of model runs were performed for the Grande with updates only through April 1 (Figure 9), as an ablation season initialization of snowpack. Because SWE was not removed during the ablation period by lower measured snow updates (Figure 4), simulated discharge was improved through better water balance and Nash-Sutcliffe values (Table 2).

4. Discussion

Measured SCA and SWE estimates were systematically less than the modeled estimates for both basins (Figures 3 and 4). Highest underestimates were in the Grande due to heterogeneous terrain and ubiquitous forest in the mid-elevation zone (2750 – 3500 m). Observed SWE was estimated by combining interpolated ground based SWE from SNOTEL and SCA from AVHRR. Therefore, the elevational trend of SWE differences (model – measured estimate) was similar to and heavily influenced by SCA (Figure 6). The canopy corrected SWE gave an improvement (relative to modeled fields) upon the original remotely derived estimate in both basins, reducing the average pixel difference over the dataset by more than 50% for the Grande during the accumulation period. However, corrections were limited by cloud cover.

The lower spatial resolution of AVHRR SCA (1-km²), as compared to the Moderate Resolution Imaging Spectrometer (MODIS) (500-m), potentially introduced more mixed pixel signatures. Mixed pixels were most evident in the complex terrain, which had a more heterogeneous distribution of vegetation, soil and snow, for example. Similar results were reported in Barrett et al. (2001) in which fewer successful matches of modeled and satellite-derived SCA were made in vegetated, heterogeneous terrain of the
East River basin, Colorado. Marsh et al. (1999) reported that both model and satellite estimates of SCA in topographically complex and forested areas were less accurate than in relatively homogeneous, non-forested areas. Additionally, Maurer et al. (2003) compared the SCA product of MODIS with the binary product of the National Operational Hydrologic Remote Sensing Center (NOHRSC). They concluded the higher resolution MODIS (500-m) has less mis-classification of snow than NOHRSC (1-km²) in the more heavily forested complex terrain of the Columbia basin, indicating an improvement in classifying snow in the presence of clouds. Geo-registration errors associated with measured SCA in the current dataset are known to be as much as 2 km in some cases, causing shifts in consecutive scene snowpacks (Bales et al, in preparation). This shift can cause snow distribution errors that influence the discharge timing and magnitude from ablation season melt.

Measured SCA estimates detected less snow than the xyz model method in the topographically complex and forested higher elevations of the Grande (Figure 4), which led to lower runoff estimates and earlier melt-out to base flow in the spring (Figure 8) when replacing model snow fields with measured snow fields. A canopy correction improved the SCA product at elevations above 2500 m in the Grande due to a large signature of forest (e.g. 88% forest in the 3000 – 3250 m elevation range) and to a lesser extent at the highest elevation (3750 m and above), for most of those pixels were above the tree line, and no correction was applied. The average canopy factors of 3.33 for the Black and 2.3 for the Grande did not increase SCA in every pixel due to clouds, which cannot be corrected. For example, all pixels for May 5, 1997 in the Grande and March 26, 1997 in the Black are classified as cloud.
April 1 is the approximate date of peak SWE in the Colorado region over the study period, for which the Grande headwaters is a part (Serreze et al., 1999). When using updates only through April 1 (considered an initialization of ablation period melt), the magnitude and timing of streamflow improved, because less water was removed from the catchment. The simple replacement technique used in PRMS did not account for mass losses (i.e. measured values of SCA and SWE are lower than the xyz model) in the ablation period, because water losses were incurred through measured updates (i.e. removed water from the basin), but those losses were not distributed among mass and energy states in this study.

The PRMS model requires reliable, distributed estimates of climate variables (daily precipitation and temperature values) at each HRU to drive the model and simulate a snowpack. Many geographic factors (e.g. elevation) affect this distribution. The xyz approach distributes precipitation and temperature first by determining if precipitation occurs (binary decision) in the basin and then interpolates the values using monthly multivariate regressions of the spatial relations between geographic variables (independent) and the climate variables (dependent variables). This monthly relationship may not hold true throughout the month because extreme storm conditions are likely to occur in the Grande during the relatively windy month of March, for example. Remotely sensed snow and ground based SWE can serve as estimates of precipitation inputs and model melt-rate formulations in these cases. To further improve SCA in complex mountainous areas, higher spatial resolution satellite estimates (e.g. MODIS) are indicated to better resolve mixed signatures such as forest and snow in complex terrain. The differences between modeled and measured SCA and SWE estimates may be a
mixture of the canopy influence on satellite SCA determination, variability in the SNOTEL SWE, and the model algorithm used to distribute climate data for calculation of a snowpack.

5. Conclusions

Experimental fractional SCA from AVHRR and ground-based SWE (with and without a vegetation correction) were evaluated against modeled snow fields in PRMS. The comparison was made under the assumption that modeled snow fields are reasonable because of PRMS’s previous success in simulating snowmelt runoff in the region. RESAC SCA and SWE were consistently low with respect to modeled SCA and SWE estimated from temperature and precipitation. The difference between the two fields depended on elevation and was different for the accumulation period versus the ablation period. An improvement to RESAC SCA and SWE (relative to modeled fields) was made by applying a canopy correction. When the RESAC snow fields were directly introduced into the model to replace modeled snow fields, they inevitably reduce model performance, and the negative impact progressively increases through the season. Since RESAC estimates were systematically low, water was discarded each time a substitution was made and there was an accumulating error in the water balance of the catchment. Although it was not possible to decisively determine which snowpack estimate was better in this study, if RESAC snow fields are to be used in a hydrologic model, it is clear that the model must be calibrated in way consistent with the measured input data.
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References


Table 1. Processed AVHRR SCA scenes for model updates.

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### Table 2. Water balance (mm) and hydrograph fit for model runs (1995-2000).

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Figures

Figure 1. Elevation (USGS 30 m DEM) and land cover (USDA, 1992) for the Grande (panels a and b) and Black basins (panels c and d).

Figure 2. Canopy correction for the Black and Grande. The canopy factor was calculated on 2 March 1997 for the Black and 3 March 1996 for the Grande. The canopy factor was then applied to all 229 SCA acquisition dates.

Figure 3. Modeled (base) vs. measured (remote and veg correct) SCA and SWE for the Black basin, calculated as an average per pixel over all update days annually (top) and for individual update days as shown for 1998 (bottom). “Base” was the model run with no updates, “remote” was RESAC SCA and SWE, and “veg correct” was the canopy corrected RESAC SCA and SWE.

Figure 4. Modeled (base) vs. measured (remote and veg correct) SCA and SWE for the Grande basin, calculated as an average per pixel over all update days annually (top) and for individual update days as shown for 1998 (bottom). Values are the same as Figure 3.

Figure 5. Average normalized SCA differences ± standard error for the Black before April 1 (a) and after April 1 (b); and for the Grande before April 1 (c) and after April 1 (d). Values were calculated by subtracting the measured value from the model (base) value for each time step an update is available, expressed as the average value per 1-km² pixel within each 250-m elevation zone.

Figure 6. Average SWE differences ± standard error for the Black before April 1 (a) and after April 1 (b); and for the Grande before April 1 (c) and after April 1 (d). Values were calculated by subtracting the measured value from the model (base) value for each time
step an update is available, expressed as the average value per 1-km$^2$ pixel within each 250-m elevation zone.

**Figure 7.** Cumulative simulated discharge (1995-2000) for Black (a), Grande (updates for all 229 dates) (b), and Grande (January 1 - April 1 updates, 116 dates) (c).

Simulations were based on manually calibrated parameters and xyz distribution of climate forcing data. “Observed” was measured at the USGS gauge, “base” was the model run with no updates, “remote” used RESAC SCA and SWE, “remote SWE” used RESAC SWE and the model SCA, “filter” used RESAC SCA and SWE processed with a low pass 9-km$^2$ averaging filter, and “veg correct” used the canopy corrected RESAC SCA and SWE.

**Figure 8.** Discharge for the Black and Grande during 1998. Simulations were the same as Figure 7. Cooperative stations used for calibration provided climate data.

Precipitation values represent events > 0.1 inches accumulation and updates shown had less than 50% cloud in the measured SCA AVHRR scene. SWE change was calculated as measured minus modeled so that negative values indicate a loss of SWE from the catchment.

**Figure 9.** Discharge for the Grande using updates only through April 1. Simulations were the same as Figure 7 and climate data were the same as Figure 8.
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