Streamflow estimation from hydrologic model updates of remotely sensed snow information in snowmelt dominated basins

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Abstract

The USGS Precipitation Runoff Modeling System (PRMS) hydrologic model was used to evaluate experimental, gridded, 1-km² snow covered area (SCA) and snow water equivalent (SWE) products for simulating snowmelt runoff from 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-km² pixel covered by snow and was derived from NOAA Advanced Very High Resolution Radiometer imagery. The SWE product was developed by combining the SCA product with SWE estimates interpolated from National Resources Conservation Service Snow Telemetry (SNOTEL) point measurements for a six-year period (1995-2000). Streamflow was modeled with and without assimilation of the SCA and SWE products. In the assimilation SCA and SWE values estimated by PRMS were replaced with measured SCA and SWE values each time step the products were available. The largest differences between modeled versus measured SCA and SWE occurred in the forested areas of the heterogeneous, mid-elevation (2750 m – 3500 m) terrain in the Rio Grande. Measured SCA and SWE improved model streamflow magnitude estimates in the relatively homogeneous Black basin. A canopy correction improved SCA and SWE estimates at all elevations in the Rio Grande and Black basins, but not enough to improve upon the base model estimates of streamflow in the Rio Grande. Streamflow estimation was improved by updating only to peak accumulation in the Rio Grande, which avoids mass balance losses from the lower estimates of measured SCA and SWE during the ablation period.

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 regarding 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 that 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 examines the extent to which assimilation of experimental fractional SCA and snow water equivalent (SWE) products can improve model estimates of streamflow in snowmelt-dominated mountain basins. To accomplish this we used PRMS (Leavesley et al., 1983) due to its minimal forcing data requirements and previous use of measured spatial snow information.

2. Data and Methods

Study Area

The Black River headwaters 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, an average of 3225 m (Figure 1). Both basins are heavily forested and precipitation is dominated by snow, but the Rio 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 Rio Grande and Black basins are located in different regions (Black, Arizona/New Mexico region; Rio 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 Rio 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 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 unlikely to be the same temperature
as SCA. 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. Rio 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 Rio 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 > 3 inches of snow fell and daily maximum temperatures after that precipitation did not exceed 0°C, the ground should be snow covered and therefore a value of 99% SCA, the highest classification value for the RESAC SCA product. 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 estimated 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-km$^2$ 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 five were selected for the Rio Grande. Data at sites included in a 500-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. If no data were available in any given pixel, the model values were carried forward to the next time step. We compared spatial SCA and SWE statistics for remotely-derived products and a base model case to evaluate the spatial distribution of RESAC estimates. Streamflow is then compared for five simulations using model updates from satellite-derived SCA and SWE and a model base case to illustrate the influence of spatial snow information in hydrologic modeling. Streamflow 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-km² low-pass averaging filter; veg correct, updated from the canopy corrected SCA and SWE estimates. These simulations are repeated for the Rio Grande using measurement updates through April 1 each year, for a total of 116 updates.

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

Water balance was good across the simulations in the Black basin (Table 2). The remote and filter simulations improved upon the base simulation, by increasing the Nash-Sutcliffe correlation, or hydrograph fit (correlation to volume and timing of the hydrograph), and by achieving better water balance in reducing the base case over-prediction to 3% vs. 5% for the base case, summed over the six-year period. The remote SWE simulation did worse than the remote by removing the measured SCA signature and using the larger modeled SCA estimate. Increasing the measured SCA by applying an average canopy correction factor of 3.33 (Figure 2) led to a runoff over-prediction of 12%, while filtering the measured SCA added less snow by smoothing lower values. Low Nash-Sutcliffe values were due to difficulty in estimating both runoff volume and timing, a common problem in semi-arid basins for which streamflow is low (Figure 3).
Simulations with an update generally over-predicted streamflow during wetter years (WY 1995, WY 1997, and WY 1998) due to the influence of higher biased 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 (Figure 4). Measured SCA underestimated model SCA and the differences decreased with elevation, with an average difference of 15% for the remote SCA, 15% for the filtered SCA, and only 10% for the canopy corrected SCA, averaged over all elevation bands over the period (Figure 5). Measured SWE is heavily influenced by measured SCA and follows the SCA changes with elevation (Figure 6).

Water balance was poor across the simulations in the Rio Grande basin (Table 2). Nash-Sutcliffe was good for the base case but poor for the updated simulations. All simulations underestimated runoff except for the base case, with the base, remote, remote SWE, filtered, and veg correct simulations estimating 102%, 44%, 49%, 43%, and 45% that of observed runoff. The Remote SWE simulation improved upon remote by removing the influence of the lower RESAC SCA and increasing snow by using the relatively higher model SCA estimates. The average canopy correction factor of 2.3 (Figure 2) further improved both the runoff estimation and the hydrograph fit for the RESAC SCA by adding snow at all elevations (Figure 5), while the filtered estimate of measured SCA decreased snow and runoff. All simulations had an earlier onset of melt and a lower magnitude than observed flow at the gauge (Figure 3) due to overall lower measured SCA (Figure 5) and SWE (Figure 6) estimates at mid-to-high elevations. Using updates up to April 1 improved the water balance and Nash-Sutcliffe for all updated simulations, but did not improve upon the base case. Improvements were
evident in both the magnitude and timing of streamflow for the updated simulations (Figure 3, Figure 4).

Differences between measured SCA and model SCA explain the trends in the hydrographs. There was a strong increasing trend with elevation (Figure 5). The greatest difference of 63% occurred at 3000 – 3250 m in the Rio Grande. A canopy correction improved upon the satellite estimate at all elevations, and the greatest impact occurred in the mid-elevations of 2750 – 3500 m where most forest and complex terrain is present. Lower measured snow at higher elevation led to a lower magnitude spring melt and earlier melt-out. Measured SWE followed the same general trend with greater variability (Figure 6).

4. Discussion

Model SCA estimates, generated from temperature and precipitation, were greater than measured SCA for both basins (Figure 5). Differences ranged from a maximum of 63% in the 3000 m – 3250 m elevation region of the Rio Grande to a minimum of 10% in the 2500 m – 2750 m region to near zero in the Black in the 3250 m – 3500 m region. Highest underestimates in the Rio Grande were primarily due to heterogeneous terrain and ubiquitous forest within the mid-elevation zone (2750 m – 3500 m). The relatively low spatial resolution (1 km²) and spectral resolution (5 bands) of AVHRR SCA, as compared to the Moderate Resolution Imaging Spectrometer (MODIS) (500 m and 36 bands, respectively), introduces a mixed pixel issue at all elevations. Mixed pixels are most evident in the complex terrain which has 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 is 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) does better than NOHRSC (1-km) in the more heavily forested complex terrain of the Columbia basin than in the minimally forested, less topographically complex Missouri basin.

Measured SCA estimates detected less snow than the xyz model method in the topographically complex and forested higher elevations of the Rio Grande (Figure 5), which led to lower runoff estimates and earlier melt-out to base flow in the spring (Figure 3). A canopy correction improved the SCA product at elevations above 2500 m in the Rio 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. Remotely-based SWE is produced from 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, increasing with elevation (Figure 6). The canopy corrected SWE was an improvement upon the original remotely derived estimate and the smoothed, filtered estimate in both basins, reducing the average pixel difference over the dataset by more than 50% for the Rio Grande.

April 1 is the approximate date of peak SWE in the Colorado region, for which the Rio Grande is a part (Serreze et al., 1999). When using updates only through April 1,
the magnitude and timing of streamflow improved. 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, as water losses were incurred through
measured updates but were not distributed among mass and energy states.

The PRMS model requires reliable, distributed estimates of climate variables, CV,
(daily precipitation and temperature values) at each HRU to drive the model and simulate
a snowpack. Many geographic factors (e.g. elevation) affect that 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 CVs (dependent variables). This monthly relationship may not
hold true throughout the month as extreme storm conditions are likely to occur in the Rio
Grande during the relatively windy month of March, for example. Remotely sensed
snow and ground-based SWE can serve as a ground truth approximation to precipitation
inputs and model melt-rate formulations in some years for the Rio Grande basin. To
further improve SCA in complex mountainous areas, higher spatial resolution satellite
estimates must be used (e.g. MODIS) to better resolve mixed signatures such as forest
and snow in complex terrain. Differences between modeled and measured SCA and
SWE estimates may be a mixture of both the canopy influence on satellite SCA
determination and the model algorithm used to distribute climate data for calculation of a
snowpack.
Conclusions
Experimental fractional SCA from AVHRR and ground-based snow water equivalent (SWE) improved model estimates of streamflow magnitude in the relatively homogeneous Black basin. Improvements to measured SCA and SWE were made by correcting for canopy cover influences on the SCA signature, adding snow most effectively in forested, complex terrain. Higher resolution than the 1-km measured estimates are needed to discriminate mixed signatures of snow and terrain such as forest and bare ground. The simple replacement technique for updating snowpack state was sufficient for streamflow evaluation in the Black basin due to small differences between modeled and measured estimates of SCA and SWE. When using this technique, updates must either be truncated at peak accumulation to avoid water losses (lead to earlier and lower magnitude spring melt regimes) or model and measured estimate differences must be reconciled in mass and energy states.

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References


Tables

Table 1. Processed AVHRR SCA scenes for model updates.

Table 1. Processed AVHRR SCA scenes for model updates.

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<td>3020</td>
<td>38.5</td>
<td>1507</td>
<td>1670</td>
<td>0.69</td>
</tr>
</tbody>
</table>
Figures

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

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

Figure 3. Simulated streamflow for a) Black, b) Rio Grande (updates for all 229 dates), and c) Rio Grande (January 1 - April 1 updates, 116 dates). Simulations were based on manually calibrated parameters and xyz distribution of climate forcing data. Observed was measured at the USGS streamflow 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-km² averaging filter, and veg correct used the canopy corrected RESAC SCA and SWE.

Figure 4. Cumulative simulated streamflow (1995-2000) for a) Black, b) Rio Grande (updates for all 229 dates), and c) Rio Grande (January 1 - April 1 updates, 116 dates). Simulations as per Figure 3.

Figure 5. Average normalized SCA differences for the Black and Rio Grande basins. Values were calculated by subtracting the measured value from the xyz model value for each time step an update is available over the dataset (229 instances), expressed as the average value per 1-km² pixel within each 250 m elevation zone. Simulations are as per Figure 3.
Figure 6. Average SWE differences for the Black and Rio Grande basins. Values were calculated by subtracting the measured value from the xyz model value for each time step an update is available over the dataset (229 instances), expressed as the average value per 1-km² pixel within each 250 m elevation zone. Simulations are as per Figure 3.
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