USING SNOW WATER EQUIVALENT RECONSTRUCTION FOR OPERATIONAL USE: TWO CASE STUDIES

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EXTENDED ABSTRACT

In the snow water equivalent (SWE) reconstruction method, the snowpack is built up in reverse from downscaled energy balance forcings and satellite-based estimates of fractional snow covered area (f_{SCA}). For melt modeling, we have developed a full energy balance model called ParBal that relies on satellite-based measurements and does not need ground-based inputs. Using ParBal to compute the melt, SWE reconstruction has been shown to be accurate when compared with a variety of validation sources, most recently by comparison with Airborne Snow Observatory (ASO, Painter et al., 2016) measurements in the Upper Tuolumne Basin, CA USA (Bair et al., 2015; Bair et al., in review). The major disadvantage is that reconstructed SWE estimates are only available retrospectively. While this limitation cannot be overcome, we present two case studies where reconstructed SWE can be used in an operational context. 1) We run ParBal as a melt only model, examining seasonal and daily melt without reconstructing the snowpack. Although we cannot reconstruct snow on the ground in this manner, we can potentially make near real-time estimates of snowmelt if these daily melt estimates are then fed through a routing model and compared with streamflow measurements. ParBal can be driven by: a) Global Data Assimilation System (GDAS, Kleist et al., 2009) meteorological forcings, now available at 1/9° spatial resolution and at 3 hr intervals with almost no latency; and b) Moderate Resolution Imaging Spectrometer Snow Covered Area and Grain Size (MODSCAG, Painter et al., 2009) snow cover data, available daily with one or two day latency. 2) We use machine learning techniques to build statistical relationships between remotely-sensed products, such as the ones mentioned in 1), and reconstructed SWE in Afghanistan. This approach allows real-time SWE prediction in remote areas that previously had little or no baseline for comparison.

Case Study 1: ParBal as a Melt Model

An alternative to SWE reconstruction is to use ParBal to produce annual snowmelt estimates. If combined with rainfall and estimates of other water balance parameters, these annual melt estimates can be compared to streamflow. Using ParBal to estimate annual melt eliminates many of the constraints of SWE reconstruction. Namely, running ParBal as a melt model provides estimates of all snow and glacial melt year-round. Given the zero bias and high accuracy of reconstructed SWE calculated with ParBal (Bair et al., in review), we suggest that its daily snowmelt estimates are accurate also. In fact, in 2013 and 2014 the reconstructed SWE was comparable to the ASO estimated SWE as a predictor (R^2=0.97-0.99) of inflows into Hetch Hetchy Reservoir (Figure 1). In 2015, it was a better predictor (R^2=0.94 vs. 0.63).

The basic water balance equation is:

$$R = P - E - \Delta S$$

where R is measured runoff, P is precipitation, E is evapotranspiration, and $\Delta S \approx 0$ is the annual change in storage. Using downscaled forcings from ParBal E can be modeled (Henn et al., 2015), and the water balance can be solved for P. Such a calculation has been called "doing hydrology backward" (Kirchner, 2009). Given accurate estimates of the snowmelt portion of precipitation from ParBal, basin wide rainfall can be estimated. This approach offers an independent method to produce basin wide rainfall estimates, which are usually based on interpolation of sparse rainfall gauge measurements.

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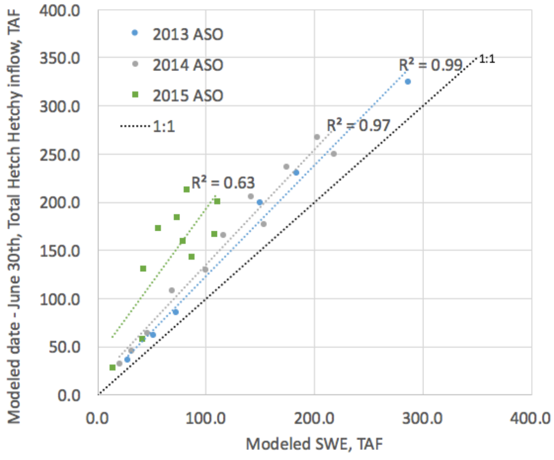

Figure 1. Modeled SWE vs. unimpaired total inflow into Hetch Hetchy Reservoir from ASO and reconstruction. Comparisons with ASO data are in the left figure, comparisons with reconstruction in the right.

Daily Runoff

For shorter timescales, a routing model must be used to account for the water transit from the snowpack to the reservoir. Figure 2 shows promising results from tests in the Upper Tuolumne using the Hydrologic Modeling System (HMS), getting the magnitude and timing of daily inflows into the Hetch Hetchy Reservoir correct. In this manner, ParBal could be run as an operational model, driven with operational forcings (i.e. GDAS with forcings available every 3 hr) and near real-time f_{SCA}, such as the near real time MODSCAG product, available with ~1 day lag.

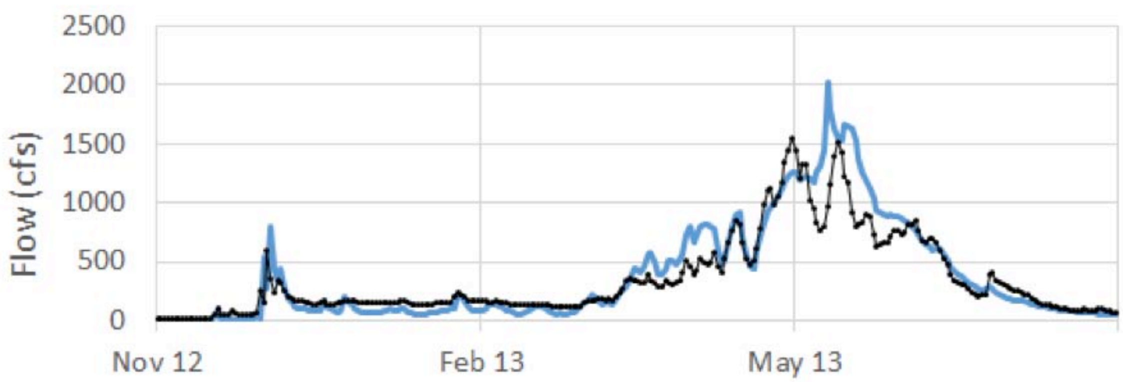

Figure 2. Modeled and observed streamflow on Tuolumne River above California's Hetch Hetchy Reservoir, using ParBal plus North American Land Data Assimilation System (Xia et al., 2012) precipitation as input. Modeled values are in blue, observed in black.

Case Study 2: Machine Learning

Another application of reconstructed SWE from ParBal is as training data in machine learning techniques that can be used to forecast seasonal runoff before the snow has melted. We use snow measurements that are available daily from optical- and micro-wavelength sensors aboard satellites as predictors. Machine learning allows for flexible utilization of these predictors since it is known that microwave sensors are more effective in certain geographic areas and during certain times of the year (Vuyovich et al., 2014). In this manner, we generate models that can be used for near real-time SWE prediction, with the lags (i.e. a day or two) coming only from processing time and satellite data availability. Initial results are encouraging, showing R^2 values around 0.85 and a bias error of only 10 mm.

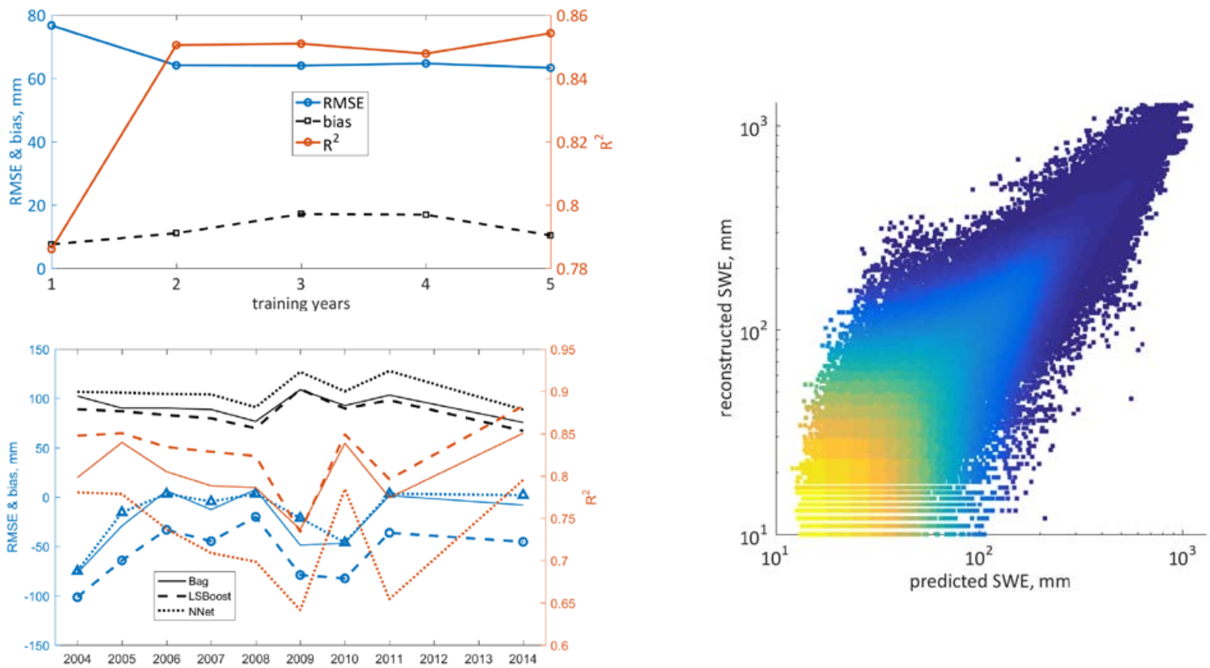

Figure 3. Real-time SWE prediction using machine learning. Top left: Training statistics for year 2008 for the Hindu Kush in Afghanistan using bagged decision trees, with the x-axis showing the number of training years (1=just 2007, 2=2007 & 2006, … 5=2003 through 2007). Right: Scatter diagram of predicted SWE for 2008 based on all training years. Colors indicate density of points with yellow showing the highest density. Bottom left: Training statistics for all years, trained on just the previous year, by three methods. The black lines indicate RMSE, blue lines bias, and red lines R^2.

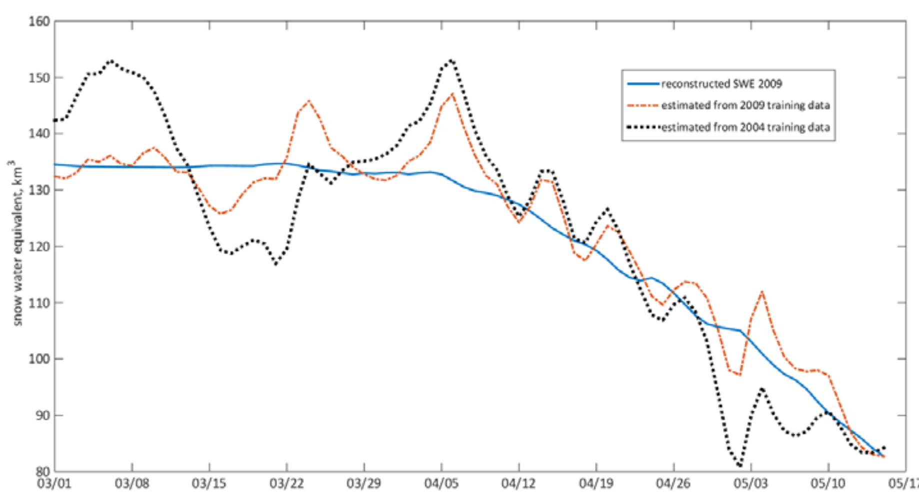

Figure 4. Modeled SWE from Reconstruction compared to estimates from machine learning for all Hindu Kush basins

SWE reconstruction offers accurate estimates of snow on the ground in remote regions, but with drawbacks, notably that is only available retrospectively. To address these drawbacks, we presented two uses of

SWE reconstruction that aid in near-real time snowpack estimates which could be used operationally.
(KEYWORDS: SWE reconstruction, Hindu Kush, Sierra Nevada, ParBal)

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