SNOW PILLOWS, LIDAR, AND STREAMGAUGES: INCORPORATING SNOW AND STREAMFLOW OBSERVATIONS IN THE BASIN WATER BALANCE

Brian Henn[1], Martyn P. Clark[2], Dmitri Kavetski[3], Bruce McGurk[4], Thomas H. Painter[5] and Jessica D. Lundquist[6]

ABSTRACT

Prior studies have suggested that point measurements of SWE may not be spatially representative of the basin snowpack. The development of remotely-sensed snow observations, such as the Airborne Snow Observatory (ASO) and MODIS-based snow cover estimates, allows for relating point and distributed estimates of snow. We examine how SWE at courses and pillows compares with distributed ASO SWE in water year 2014 in a high-elevation basin in Yosemite National Park. We find that peak basin-mean ASO SWE was less than that found by averaging regional snow pillows, but that it melted at a slower rate than pillow SWE during the ablation season. Based on this, we develop an approach for bias-correcting historical snow pillow indices of SWE to better represent the basin mean.

We then calibrate an ensemble of lumped hydrologic models to infer basin-mean precipitation from streamflow and SWE. Models calibrated to only streamflow observations have substantial uncertainty in inferred precipitation. Including appropriate SWE observations in the calibration is found to reduce this uncertainty. However, calibrating to fractional snow cover in addition to streamflow did not improve the consistency of the models. We suggest that this approach can improve understanding of water balance components in high-elevation, sparsely-measured basins. (KEYWORDS: hydrologic modeling, remote sensing, orographic precipitation, basin hydrology)

INTRODUCTION

Mountain snowpack functions as a distributed reservoir, retaining water built up during winter precipitation events and releasing it to become streamflow and evapotranspiration during the warm season (Bales et al., 2006). Thus, snowpack serves as a critical portion of the overall water balance for a hydrologic basin. Because conservation of mass underlies all applications of physical hydrology, in order to simulate, analyze and predict hydrologic variables of mountain basins, it is necessary to quantify the water stored in snowpack across the landscape.

For example, quantifying basin snowpack storage is necessary in order to calibrate hydrologic models of snow-dominated basins. These models simulate streamflow and are used in water supply forecasts, flood prediction or hydrologic process exploration, and are generally calibrated only against observations of streamflow. Calibration of models to both streamflow and snowpack, however, has been shown to improve process representation and robustness (e.g., Finger et al., 2015). Calibration to multiple types of observations can help avoid equifinality of model parameters (Beven and Binley, 1992), a problem which makes it difficult to evaluate model parameters and hinders prediction.

The spatially-distributed nature of mountain snowpack challenges our ability to quantify it. Measurement of snowpack at individual points in the mountains Western United States has a long and successful history, beginning with early snow surveys in the 1930s, and continuing through the current set of snow courses and the NRCS SNOTEL network of over 700 automated snow pillows (Serreze et al., 1999). Point measurements have allowed near real-time estimation of snowpack and improved skill in seasonal streamflow prediction.

Paper presented Western Snow Conference 2015

[1] Brian Henn, Civil and Environmental Engineering, University of Washington, Seattle, WA, bhenn@uw.edu

[2] Martyn P. Clark, National Center for Atmospheric Research, Boulder, CO, mclark@ucar.edu

[3] Dmitri Kavetski, Civil, Environmental and Mining Engineering, University of South Australia, Adelaide, SA, dmitri.kavetski@adelaide.edu.au

[4] Bruce McGurk, McGurk Hydrologic, Orinda, CA, brucemcgurk@comcast.net

[5] Thomas H. Painter, NASA/JPL, Pasadena, CA, thomas.painter@jpl.nasa.gov

[6] Jessica D. Lundquist, Civil and Environmental Engineering, University of Washington, Seattle, WA, jdlund@uw.edu

Nonetheless, point measurements of snowpack only begin to sample the spatial variability at a wide range of scales of snow water equivalent (SWE) across the mountain landscape. Due to spatial variability from topography, wind, precipitation, radiative forcing, vegetation and other factors, snow courses and pillows generally do not reflect the amount of SWE in areas around them, even at relatively small spatial scales (Molotch and Bales, 2005; Clark et al., 2011). These biases are not always positive or negative, nor do they remain constant between the accumulation and ablation seasons or across different water years (Meromy et al.. 2013; Molotch and Bales, 2005; Rice and Bales, 2010). Further, practical constraints prevent installation and maintenance of snow sensors in high-elevation areas which have some of the deepest and most persistent snowpack. Thus, our in situ networks tend to oversample mid-elevation SWE and melt earlier in the ablation season than higher-elevation areas (Rice et al., 2011). All of these factors make it challenging to directly estimate basin-mean SWE from point observations alone.

Given the unpredictable biases that point measurements give in estimating basin-mean snow water storage, much effort has been devoted to remotely sensing snow. Snow observations via satellite providing a spatially-distributed of fractional snow covered area (fSCA, e.g., MODSCAG, Painter et al., 2009). fSCA can provide a means of retrospectively estimating spatially-distributed SWE via a known snow disappearance date (e.g., Molotch, 2009).

Additionally, LiDAR provides an airborne means of measuring snow depth with high spatial resolution (~1 m) across relatively large domains (a few to thousands of km^2; e.g., Deems et al., 2008). The development of these approaches offer the opportunity to fully sample the spatial distributions of snowpack across the landscape. The Airborne Snow Observatory (ASO) currently employs LiDAR to regularly observe the snow depth over several basins in the Sierra Nevada of California and the Colorado Rockies during the snow ablation season. When combined with modeled snow density, a spatially-distributed snapshot of SWE is produced. Importantly, ASO allows for a comparison of traditional point estimates of snow (pillows and courses) to spatially-distributed observations, potentially allowing us to retrospectively assess the representativeness of point-derived estimates of basin-mean SWE.

Using the Tuolumne River basin draining to Hetch Hetchy Reservoir in the Sierra Nevada of California as a testbed, we investigate spatially-distributed snow observations, for two purposes. First, we compare ASO estimates of basin-mean SWE with estimates from snow pillows and courses from the 2014 water year. We do this to assess the relationship between point-based SWE indicators and spatially-distributed ones, hypothesizing that a robust relationship may exist between the two. We estimate a long-term time series of basin-mean SWE only using point observations that have been bias-corrected to reflect the point-to-basin relationships found in 2014.

Second, we use snow observations as an additional calibration target for a set of hydrologic models of the Hetch Hetchy basin. We use the bias-corrected point SWE time series, as well as a MODIS fSCA time series, as additional calibration targets. We compare the results of calibrating multiple model structures to both streamflow and snow observations, versus calibrating the same set of models to streamflow alone. In particular, we are interested in improving our ability to infer precipitation from streamflow with hydrologic models, by using additional calibration data as compared with to the earlier efforts of Henn et al. (2015). These experiments allow us to assess the degree to which hydrologic model consistency is improved via calibration to additional types of observations.

In the discussion, we evaluate the assumptions made in relating point and basin-scale observations of snow. We assess the uncertainty of these basin-mean observations, and the degree to which they improve our understanding the of the basin's water balance.

DATA AND METHODS

SWE Observations from Yosemite-Area Snow Pillows and Courses

For point-scale observations of SWE, we use a collection of observations from snow pillows and snow courses in the vicinity of Yosemite National Park in the Sierra Nevada of California. We use 28 pillows and 40 courses both within and outside of the Hetch Hetchy basin in our analysis. In addition to the upper Tuolumne basin, the sites are located in the Merced, San Joaquin, Walker, Stanislaus, Mono and Owens drainages (Figure 1a). Course and pillow SWE data are from the California Data Exchange Center (CDEC, http://cdec.water.ca.gov/). We use daily observations of SWE at snow pillows, and monthly observations of SWE at snow courses, spanning water years 2000-2014, a period chosen to correspond to the availability MODIS observations.

We use sites outside the basin because of the small number of sites within it: 4 pillows and 7 courses, with fewer generally available during any one year due to missing data. While measurements made outside the basin do not sample from its SWE distribution, they provide useful information because of the high degree of correlation between sites. For example, the average correlation R^2 of annual peak SWE between all pairs of pillows used in this analysis is 0.74.

We then take the daily mean (for pillows) or monthly mean (for courses) of all sites, to generate a robust indicator of the 2000-2014 temporal pattern of SWE over this region. For water year 2014, in which we compare the pillows and courses to ASO distributed measurements, we do this using a subset of the sites that had a least 60% of days available (for pillows) or at least 4 surveys (for courses) during the water year.

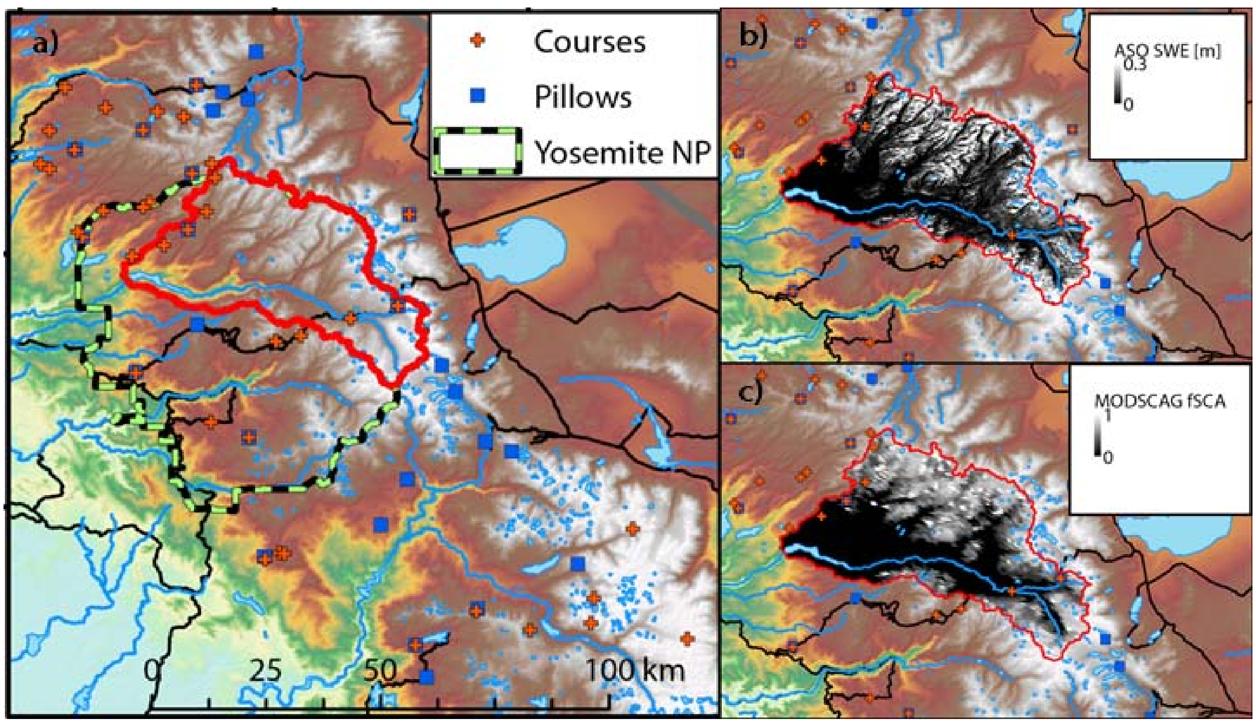

Figure 1. Different snow observations. a) Map of snow pillows and snow courses used to estimate time series of mean point observations of SWE. The Hetch Hetchy basins and Yosemite National Park borders are shown. b) Example of ASO LiDAR observations of SWE over the Hetch Hetchy basin, from the May 11, 2014 flight. The spatial resolution of the SWE grid is 50 m. c) Example of MODSCAG fSCA observations over the Hetch Hetchy basin, also from May 11, 2014, at 500 m spatial resolution.

Remotely-Sensed Snow Observations: ASO SWE and MODSCAG fSCA

We use LiDAR observations of snow collected on 11 ASO flights over the Hetch Hetchy basin in water year 2014 (http://aso.jpl.nasa.gov). While ASO began its flights over the basin in water year 2013, the data from that year and from 2015 are not yet available, so we are limited to one water year of observations. The 2014 flights began on March 23 and ended on June 5, and occurred at approximately weekly intervals.

For each flight, we use a 50 m SWE product that has been developed as follows by the ASO program. The high-resolution LiDAR snow depth data is first aggregated to 50 m resolution. Then a snow model is run over the basin in order to simulate snow density, using the LiDAR depth data as model forcing. The density and depth data are integrated to give a spatial map of SWE (e.g., Figure 1b).

For each flight, we average the SWE of the 50 m pixels within the basin to give a basin-mean value. We also average the SWE of pixels within each of 30 100 m elevation bands, to provide a vertical profile of the SWE distribution.

We use the sequence of basin-mean and elevation band-mean ASO SWE observations over the 2014 ablation season to compare against the time series of SWE from the pillows and courses. We note when the snow pillow and course indices of SWE exceed or are less than the ASO estimates of basin-mean SWE. We assume that the 2014 ASO is a much less biased indicator of basin-mean SWE than the point measurements, which may not be representative of the spatial mean SWE patterns. Thus, we develop a set of guidelines for "scaling" the time series of mean snow pillow SWE to better reflect the ASO-derived basin-mean SWE quantities (see Results section). Using these guidelines retrospectively, we develop a time series of basin-mean SWE that is derived from the mean pillow SWE, but is bias-corrected based on the ASO comparison. This time series spans water years 2000-2011.

MODSCAG fSCA (Painter et al., 2009) is used to provide an additional type of spatially-distributed observations of snow over the Hetch Hetchy basin. We downloaded the 500 resolution, daily maps of fSCA over the basin (e.g., Figure 1c). The mean fSCA over the cloud-free portion of the basin and over each elevation band are calculated for each day in which MODSCAG is available, beginning with water year 2000. We screen out days when cloud cover exceeded 50% of pixels in the basin, or about 16% of all days.

Hetch Hetchy Hydrologic Model Calibrations Using FUSE and BATEA

To examine the value of estimates of spatially-distributed SWE and snow coverage across the basin, we incorporate them into calibrations of hydrologic models of the Hetch Hetchy basin. We use a set of lumped, conceptual models which simulate snowpack, soil moisture, evapotranspiration (ET) and runoff. The hydrologic modeling is conducted with the goal of inferring basin-mean precipitation; this study builds on earlier precipitation inference work by Henn et al. (2015).

In this approach we use a precipitation multiplier parameter, which scales the entire forcing time series of precipitation. We use this construction because Hetch Hetchy basin-mean precipitation is uncertain; by calibrating the multiplier parameter using streamflow and other observational data, we can infer the "true" basin-mean precipitation.

We use FUSE (Framework for Understanding Structural Errors; Clark et al., 2008) hydrologic model structures. FUSE allows simulating an ensemble of models, with different architecture and flux parameterizations. Here we use six model structures which reflect different conceptualizations of ET, baseflow and percolation.

A degree-day snow model is used to simulate SWE in all FUSE model structures. SWE is independently tracked in each 100 m elevation band (Figure 2), using a partition temperature to separate rain from snow, and melt factors which linearly estimate snowmelt from air temperature. From the snow model and the fraction of basin area within each band, we derive simulated basin-mean SWE and basin-mean fSCA.

We simulate the Hetch Hetchy basin using the same forcing and calibration data for each FUSE model structure. Model forcing comprises daily air temperature, precipitation and potential ET (PET) time series. The forcing data is generated from three meteorological stations located in the foothills below the basin and at its outlet: Cherry Valley, Buck Meadows and Hetch Hetchy (Figure 2).

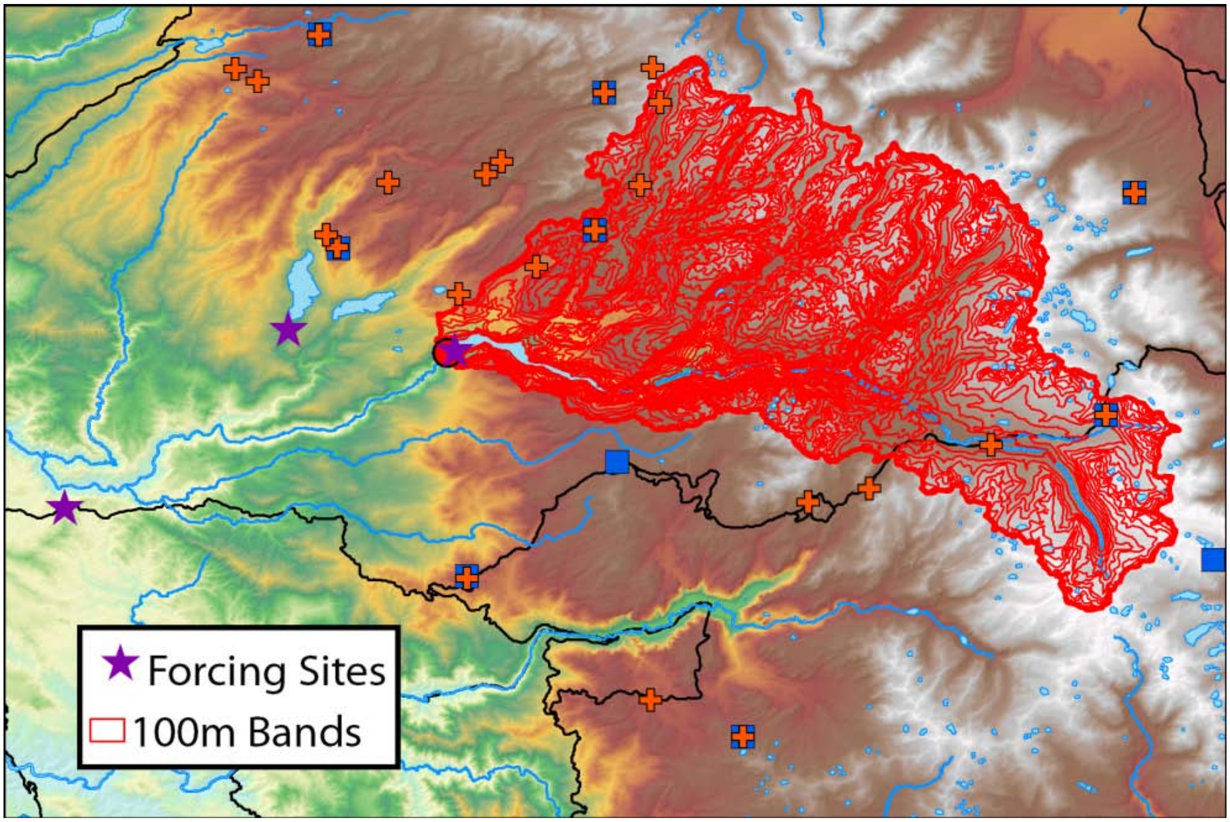

Figure 2. Map of the meteorological stations, basin outlet and 100 m elevation bands for the Hetch Hetchy model calibration experiments using FUSE and BATEA.

The model calibrations are performed using Bayesian parameter inference as implemented in BATEA (Bayesian Total Error Analysis, Kavetski et al., 2006). Parameters are estimated based on the combination of model fit to calibration data and prior distributions. In these calibrations we use uniform parameter prior distributions, and so the calibrated parameters essentially reflect the fit to the data. BATEA samples the posterior distribution of the calibrated model parameters, including the precipitation multiplier. From these samples the probability distribution of the inferred basin-mean precipitation can be computed.

The model is calibrated against reconstructed full natural flows at the outlet of Hetch Hetchy Reservoir. We use additional calibration targets, the time series of bias-corrected pillow SWE and the MODSCAG fSCA series. We run several sets of calibrations to assess the impacts of using snow observations in addition to streamflow for calibration. As a control, we calibrate the set of six FUSE model structures to only the time series of streamflow. Then, we perform two additional calibrations in which we calibrate the six models to match both streamflow and snow observation series: in one, the bias-corrected snow pillow basin-mean SWE series, and in another, the MODSCAG basin-mean fSCA series.

From each calibration, we assess the consistency of the calibrated parameters across the set of six FUSE model structures. The robustness of the calibrations can be determined from how consistent model parameters are between the structures. For example, we compare the inferred basin-mean precipitation values across the calibrated model structures, under each of the calibration scenarios. The extent to which the inferred precipitation agree (or disagree) indicates the robustness of the model calibrations and the certainty to which we can infer the water balance terms of the Hetch Hetchy basin using this approach.

We hypothesize that the addition of snow information to the calibration will improve the inference of the basin-mean precipitation, which is not well constrained when calibrated to streamflow alone (e.g., see Henn et al., 2015).

RESULTS

Comparison of Point and ASO SWE

We first compare SWE observations from point estimates against spatially-distributed ASO SWE. Fig. 3a shows the time series of the mean of the snow pillow SWE measurements and the mean of the snow course measurements. In water year 2014, the pillows and courses indicate that some snow fell early in December and was followed by an exceedingly dry period through early February. Pillow and course SWE then increased until early April, after which they declined steeply, reaching near zero by the end of May.

The Hetch Hetchy basin-mean SWE from the 11 ASO flights are also shown in Figure 3a. They show a relatively consistent decline in SWE from early April, reaching near zero by the last flight on June 5. In comparison with the pillow and course SWE, peak ASO SWE occurs at the same time (first week of April), but is less (just under 200 mm in comparison to just under 300 mm for the courses and pillows). In addition, the melt rate during the ablation season is less in the ASO observations: the ASO melt rate was 2.3 mm/day, whereas for the pillows it was 5.2 mm/day. The differences between the two types of observations likely reflect the different spatial samples, with ASO seeing a much greater elevation range than the point observations.

We hypothesize that the differences between ASO and pillow indices of SWE may be robust in that they repeat each year. One justification for this hypothesis is the observed strong elevation dependence of SWE (e.g., Rice et al., 2011); if the difference between ASO and the pillows is driven largely by their different (but temporally consistent) sampling of the basin's elevation profile, then the ratios between them should repeat each year. If that is the case, then a set of scaling factors could be used to translate the point indices of SWE into basin-mean quantities, as described by ASO.

For the 2014 comparison, we develop these factors (f, Figure 3b): first, peak SWE is 65% of the pillow peak SWE ($f = 0.65$). Then, the scaling factors are assumed to linearly vary between the peak SWE date and two points in time where $f = 1$, one at the beginning and one at the end of the observed snowpack. We define these points to be the dates when the pillow SWE index equals 50 and 125 mm, respectively. After the latter date, SWE is assumed to decline at a slope determined by the observed ASO ablation rate.

While this procedure may be ad hoc in that its parameters are likely basin-dependent, it does provide one way to bias-correct the historical time series of pillow SWE for years prior to the ASO flights. In other words, it estimates a time series of Hetch Hetchy basin-mean SWE based only on the mean SWE of the set of pillows, whose record extends back to the 1980s. We do this for years 2000-2011, in order to provide an estimate of basin-mean SWE against which our hydrologic model can be calibrated.

Comparison of Model Calibrations using Streamflow and Snow Observations

We now describe the results of using snow observations, in addition to streamflow observations, to calibrate hydrologic models of the Hetch Hetchy basin over water years 2000-2011. As a baseline, we first calibrate the set of six FUSE model structures using only streamflow observations, and compare simulated SWE and streamflow in of the six model structures. Fig. 4a shows time series of modeled snowpack for all structures in 2006; the SWE from the calibration to streamflow only is shown in solid blue lines. Large variance exists between the different models' SWE, and all of the models simulate more SWE than was observed (solid black line). However, all of these models simulate streamflow well (dashed blue lines; mean streamflow Nash-Sutcliffe coefficient of 0.80). This indicates that calibration to streamflow is not a guarantee of a robust calibration of other model states.

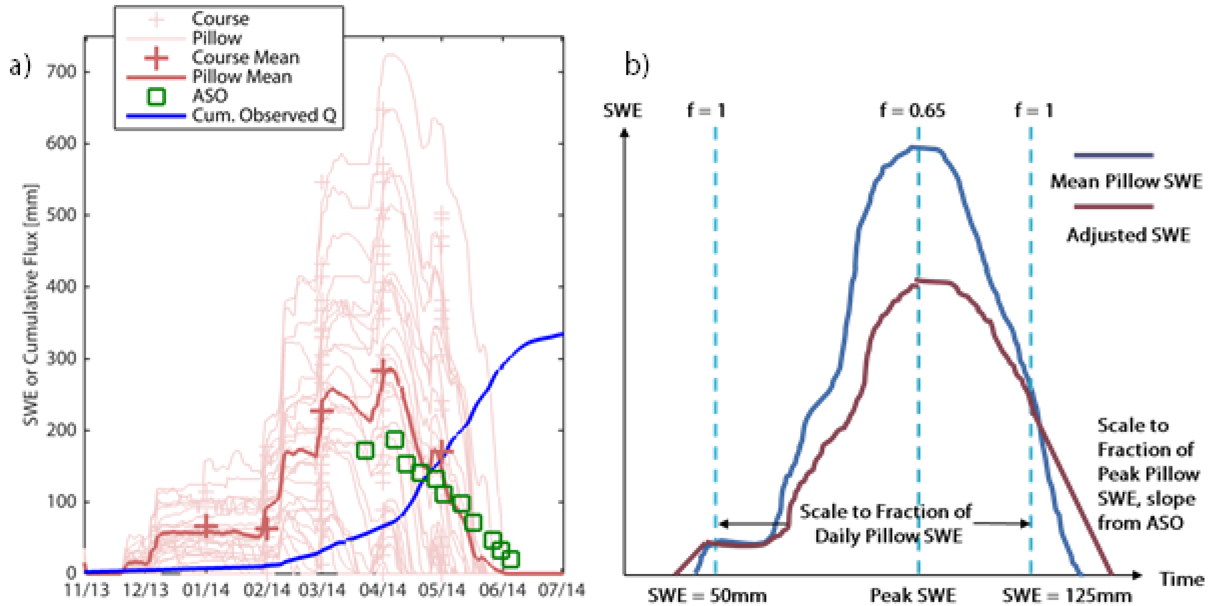

Figure 3. Comparison of point and distributed observations of SWE. a) 2014 water year comparison of mean pillow SWE, mean course SWE, and the Hetch Hetchy basin-mean ASO SWE for each flight. Individual pillows and courses are shown as the pale traces and crosses. b) Schematic of pillow index SWE and ASO basin-mean SWE time series, and of the scaling factors which relate them, for a hypothetical water year.

Next, the calibration of the models to both streamflow and the bias-corrected SWE series is considered (Fig. 4a, turquoise lines). SWE among the six model structures now converges relative to the streamflow-only case, and is much closer to the SWE observation time series. This result is not surprising given that the SWE series were calibrated to match observations. However, simulated streamflow continues to match observations well (mean streamflow Nash-Sutcliffe coefficient of 0.84). This suggests that calibration to both types of observations results in a Pareto improvement, in that the simulation of snowpack is substantially improved without a degradation of the streamflow simulation.

We then consider the impact of the calibration procedure on model parameter consistency, specifically the inferred precipitation, described in terms of mean annual precipitation over the study period. Fig. 4b shows bar charts of inferred precipitation for the streamflow-only calibration (dark blue) and the streamflow-and-SWE calibration (turquoise). The streamflow-only calibration has a range between model structures of 1,010 mm in inferred precipitation, relative to a mean of 1,315 mm. This indicates high uncertainty in the magnitudes of the basin water balance components. When the models are calibrated to both streamflow and SWE, the range of inferred precipitation decreases significantly, to 249 mm; the mean of the model structures' inferred precipitation is then 949 mm. Thus, this additional calibration increases model consistency and reduces uncertainty in the inference of the basin water balance.

Finally, we consider the results of calibrating to streamflow and fSCA. The SWE time series (yellow lines, Figure 4a) show similar or larger variance to that of the streamflow-only calibration. Modeled SWE is much greater than in the other two calibration routines. The match to streamflow also appears to be worse than in the other routines, with model overestimation of cumulative streamflow evident. The inferred precipitation when calibrating to both streamflow and fSCA (Figure 4b, bottom row) is much less consistent than in the other calibrations, with a range of 1,083 mm, and a higher mean (1,686 mm). Thus it appeared that calibrating to streamflow and fSCA resulted in greater inferred SWE and precipitation, but did not improve model consistency of these terms.

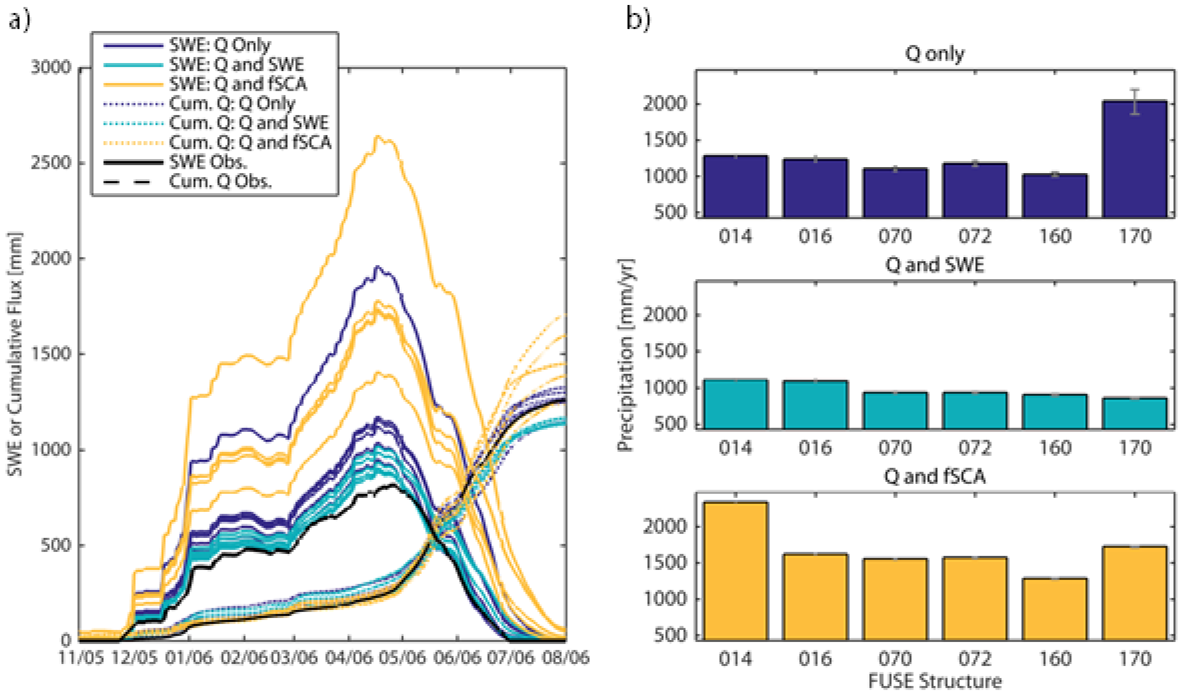

Figure 4. Effect of calibration data on model consistency. a) 2006 time series of modeled SWE and cumulative streamflow, for the streamflow-only calibration (blue), the streamflow and SWE calibration (turquoise) and the streamflow and fSCA calibration (yellow). Bias-corrected pillow SWE is shown with the solid black line, and observed cumulative streamflow is shown with the dashed black line. b) Inferred precipitation across six model structures for the three calibration routines, with colors the same as in a).

DISCUSSION AND CONCLUSIONS

Using the Hetch Hetchy basin as a test case, we compare indices of snow based on point observations (courses and pillows), with spatially-distributed snow observations from an airborne LiDAR platform (ASO). The comparison of the two types of data (Fig. 3a) is consistent with the idea that the current point observation network tends to oversample snowy, mid-elevation locations: the indices have greater peak SWE than ASO but melt out more rapidly. This conceptualization of the relationship between the two is the basis of our bias-correction approach.

It is important to recognize that this approach is based on one melt season of data. 2014 is unlikely to be representative of the long-term climate of the Yosemite area, because it was an anomalously warm and dry winter. Compared to the 1981-2014 period at the three sites used for model forcing, water year 2014 was both the warmest (1.9°C above average), and second-driest (54% of average precipitation). As a result, its snowpack was far below normal, and so relationships drawn from it may be different from those in the long term. The inclusion of other years of ASO data (currently, 2013 and 2015) will help alleviate this problem by allowing for a traditional split-sample, calibration-validation approach between multiple years. However, all years in the current ASO observing period have fallen during a prolonged drought in California, making it challenging to draw more general conclusions.

When we use SWE along with streamflow to calibrate the hydrologic models, model consistency is improved. This is similar to the findings of Finger et al. (2015), and suggests a general rule that the inclusion of additional types of data in calibrations will improve the robustness of the models. Thus, we caution against using only streamflow to calibrate hydrologic models when other data may be available.

We also note that the calibration of the models to both streamflow and fSCA does not result in improved model consistency in this case. We suggest two possible reasons for this. First, fSCA may not be sufficient to constrain the water balance, at least under the relatively simple model formulations used here. Snow-covered areas can have a wide range of SWE, and so requiring a model match to fSCA may still allow for variability in SWE. Second, the MODSCAG fSCA time series may underestimate snow-covered area in some parts of the basin (compare Figs. 1b and 1c), due to variable satellite view angle, steep terrain and forest canopy. Biased calibration data can propagate error into the calibrated parameters in unpredictable ways.

Despite these limitations, we suggest that the inclusion of multiple types of hydrologic observations is necessary to constrain the water balance of high-elevation, sparsely measured basins such as that of the Tuolumne above Hetch Hetchy. Because precipitation gauges are few, difficult to maintain during the winter, and suffer from undercatch of snow, it is difficult to directly estimate basin-mean precipitation in this basin. Incorporating multiple other types of observations (i.e., streamflow and SWE) is likely necessary to correctly estimate this component of the basin's water balance.

REFERENCES

Bales, R. C., N. P. Molotch, T. H. Painter, M. D. Dettinger, R. Rice, and J. Dozier. 2006. Mountain hydrology of the western United States. *Water Resour. Res.*, **42**, W08432, doi:10.1029/2005WR004387.

Beven, K., and A. Binley. 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Process.*, **6**, 279–298, doi:10.1002/hyp.3360060305.

Clark, M. P., A. G. Slater, D. E. Rupp, R. a. Woods, J. a. Vrugt, H. V. Gupta, T. Wagener, and L. E. Hay. 2008. Framework for Understanding Structural Errors (FUSE): A modular framework to diagnose differences between hydrological models. *Water Resour. Res.*, **44**, W00B02, doi:10.1029/2007WR006735.

--, and Coauthors. 2011. Representing spatial variability of snow water equivalent in hydrologic and land-surface models: A review. *Water Resour. Res.*, **47**, doi:10.1029/2011WR010745.

Deems, J. S., S. R. Fassnacht, and K. J. Elder. 2008. Interannual Consistency in Fractal Snow Depth Patterns at Two Colorado Mountain Sites. *J. Hydrometeorol.*, **9**, 977–988, doi:10.1175/2008JHM901.1.

Finger, D., M. Vis, M. Huss, and J. Seibert. 2015. The value of data availability versus model complexity for estimating snow , glacier and rain contribution to runoff in mountain streams. *Water Resour. Res.*, **51**, 1–20, doi:10.1002/2014WR015712.

Henn, B., M. P. Clark, D. Kavetski, and J. D. Lundquist. 2015. Estimating Mountain Basin-Mean Precipitation from Streamflow Using Bayesian Inference. *Water Resour. Res.*, **In Review**.

Kavetski, D., G. Kuczera, and S. W. Franks. 2006. Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory. *Water Resour. Res.*, **42**, 1–9, doi:10.1029/2005WR004368.

Meromy, L., N. P. Molotch, T. E. Link, S. R. Fassnacht, and R. Rice. 2013. Subgrid variability of snow water equivalent at operational snow stations in the western USA. *Hydrol. Process.*, **27**, 2383–2400, doi:10.1002/hyp.9355.

Molotch, N. P. 2009. Reconstructing snow water equivalent in the Rio Grande headwaters using remotely sensed snow cover data and a spatially distributed snowmelt model. *Hydrol. Process.*, **23**, 1076–1089, doi:10.1002/hyp.7206.

--, and R. C. Bales. 2005. Scaling snow observations from the point to the grid element: Implications for observation network design. *Water Resour. Res.*, **41**, 1–16, doi:10.1029/2005WR004229.

Painter, T. H., K. Rittger, C. McKenzie, P. Slaughter, R. E. Davis, and J. Dozier. 2009. Retrieval of subpixel snow covered area, grain size, and albedo from MODIS. *Remote Sens. Environ.*, **113**, 868–879, doi:10.1016/j.rse.2009.01.001.

Rice, R., and R. C. Bales. 2010. Embedded-sensor network design for snow cover measurements around snow pillow and snow course sites in the Sierra Nevada of California. *Water Resour. Res.*, **46**, 1–13, doi:10.1029/2008WR007318.

--, --, T. H. Painter, and J. Dozier. 2011. Snow water equivalent along elevation gradients in the Merced and Tuolumne River basins of the Sierra Nevada. *Water Resour. Res.*, **47**, 1–11, doi:10.1029/2010WR009278.

Serreze, M. C., M. P. Clark, R. L. Armstrong, D. A. McGinnis, and R. S. Pulwarty. 1999. Characteristics of the western United States snowpack from snowpack telemetry (SNOTEL) data. *Water Resour. Res.*, **35**, 2145–2160, doi:10.1029/1999WR900090.