USING MACHINE LEARNING AND SNOW WATER EQUIVALENT RECONSTRUCTION TO PREDICT TODAY'S SWE AND AVALANCHE CONDITIONS IN AFGHANISTAN

Edward H. Bair[a], Karl Rittger[b], and Jeff Dozier[c]

[a] *Earth Research Institute, University of California, Santa Barbara, USA*
[b] *National Snow and Ice Data Center, University of Colorado, Boulder, USA*
[c] *Bren School of Environmental Science and Management, University of California, Santa Barbara, USA*

ABSRACT: In Afghanistan, in situ snow measurements have been nonexistent. Thus, operational snowpack estimates use satellite sensors, with limitations. An accurate approach, reconstructs spatially distributed snow water equivalent (SWE) by calculating snowmelt backwards from a remotely sensed date of disappearance. However, reconstructed SWE estimates are available only retrospectively; they do not provide a forecast. Since we find our reconstructed SWE estimates to be the most accurate snowpack information available over large areas in austere regions, we use them as targets to train machine learning models, which in turn can be used to predict today's SWE. Results have been encouraging, but validation is a problem given the absence of ground-based snow measurements. Recently, we were provided with daily manual snow depth measurements from northern Afghanistan's watersheds by the Aga Khan Agency for Habitat (AKAH). These measurements as part of an avalanche forecasting program and comprise the first ground-based snow measurements available in Afghanistan in nearly 40 years. We have used these snow measurements to validate our modeled SWE. Two drawbacks are that they: 1) only contain snow depth, thus bulk density must be modeled to convert to SWE; and 2) they contain no stratigraphic information. To address the first drawback, we use a simple snow climate model and a more complex model driven by downscaled energy balance forcings to estimate bulk density. For the second drawback, we use snow profiles produced by the more complex model to better understand the avalanche conditions and stability in these remote mountain villages.

KEYWORDS: Afghanistan, Machine Learning, SWE, remote sensing

1 INTRODUCTION

There are many parts of the world where we know little about the snowpack. This lack of knowledge presents a challenge for water managers and for avalanche forecasters. The watersheds of Afghanistan are particularly austere, as there have been no snow measurements available since the early 1980s. To improve our knowledge about the snowpack in these areas, we have developed an approach that requires no in situ measurements. Using satellite-based estimates of the fractional snow-covered area (fSCA) and downscaled forcings in an energy balance model, we build up the snowpack in reverse, from melt out to its peak, using a technique called snow water equivalent (SWE) reconstruction (Martinec and Rango, 1981). This technique has been shown to accurately estimate SWE in mountain ranges across the world, including: the Sierra Nevada USA (Bair et al., 2016; Rittger et al., 2016); the Rocky Mountains USA (Molotch, 2009; Jepsen et al., 2012); and the Andes of South America (Cornwell et al., 2016). Unfortunately, reconstruction requires the snowpack to disappear before it can be used, so it is not useful for predicting today's snowpack. To address this challenge, we use machine learning models created with dynamic predictors that are available in real-time (e.g. fSCA and passive microwave SWE) and static predictors (e.g. physiographic variables and SWE climatology). These predictors are then trained on our reconstructed SWE estimates. The results are trained models that can be used to predict today's SWE. In Afghanistan's watersheds, our machine learning techniques have produced promising results. For instance, two machine learning techniques—bagged regression trees and feed-forward neural networks—produced similar mean results, with 0–14% bias and 46–48 mm RMSE on average (Bair et al., 2018a). Nash-Sutcliffe efficiencies averaged 0.68, indicating substantial improvement over a mean forecast.

However, the validation data was the reconstructed SWE using a technique called holdout, where the year being predicting was

* *Corresponding author address:*
Edward Bair, Earth Research Institute, University of California, Santa Barbara, CA USA

email: nbair@eri.ucsb.edu

not included as training data, but was instead held out for validation. For a more robust validation, a more independent validation source is needed.

In 2017, we received daily manual snow depth and other meteorological measurements from nearly 100 stations in an operational avalanche network (Chabot and Kaba, 2016). These stations are funded by the Aga Khan Agency for Habitat (AKAH) and are the first snowpack measurements available, at least that we know of, in Afghanistan in nearly 40 years. To validate our SWE estimates, however, we needed to transform these snow depth measurements into SWE using a density model. Our first approach was to use a simple density model based on snow climatology and day of year (Sturm et al., 2010). The density model itself has -12 to 26% bias in predicting SWE. When taking into account geolocational uncertainty of our SWE estimates and uncertainty in the density model, taking an ideal error estimate showed low errors on the order of 11-13% Mean Absolute Error (MAE) and -2 to 4% bias, depending on the date. Again, the uncertainty in the density model itself is not ideal, so we used a more sophisticated approach.

2 METHODS

From recent work (Bair et al., 2018b), we have shown that the SLF SNOWPACK model (Bartelt and Lehning, 2002; Lehning et al., 2002a; Lehning et al., 2002b) is capable of accurate SWE prediction when supplied only with snow depth for precipitation, as well as the other requisite forcings (i.e. radiation, temperatures, and wind speed). Thus, we modeled daily SWE at the AKAH stations during the 2017 water year using the manually measured snow depth combined with our downscaled energy balance parameters (for downscaling methodology see Bair et al., 2016; Rittger et al., 2016; Bair et al., 2018a). Recently, we have devoted considerable effort to improving our remotely-sensed snow albedo and radiation estimates, which together drive the snowmelt process in the Sierra Nevada USA (Marks and Dozier, 1992), which shares a similar dry and sunny melt season with Afghanistan.

In addition to predicting SWE, the SNOWPACK model also predicts stratigraphic parameters useful for avalanche prediction, thereby giving us an idea of the layering and stability in these remote mountain villages, albeit on flat study plots.

3 RESULTS

Preliminary results are encouraging. For 2017-3-1 (around peak SWE for most of the stations), the median bias error is 7 mm (3 %) for our reconstructed SWE estimates, using the modeled SNOWPACK SWE at 63 AKAH stations for validation (Figure 1). Note, this only includes stations with snow on the ground on 2017-3-1; we don't underestimate our errors by including stations without snow on the ground. The 25th percentile bias error is -3 mm (-1%), the 75th percentile error is 51 mm (18%). The mean absolute error is higher at 41 mm (15%), skewed because of some high-biased outliers.

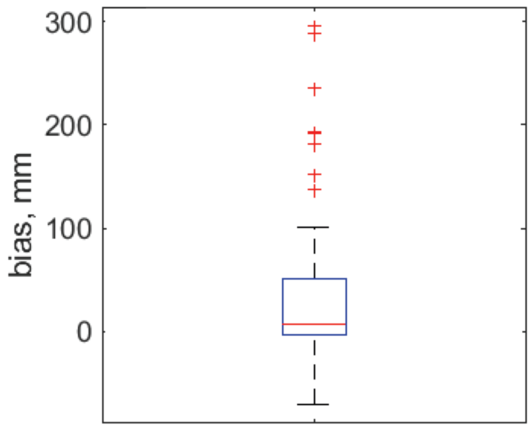

Figure 1: Bias error box plot of reconstructed SWE for 2017-3-1, using modeled SNOWPACK SWE at 63 AKAH stations.

We also examined how our reconstructed SWE estimates compared over the melt season for selected AKAH stations. Figure 2a-i can be compared with Figure 6a-i in Bair et al. (2018a) to see the how the SNOWPACK modeled SWE values differ from the modeled SWE values using the Sturm et al. (2010) method. Also, note that the reconstructed SWE values differ from Figure 6 in Bair et al. (2018a) because the values that most closely match the modeled SNOWPACK values in a 9-pixel neighborhood were chosen. As mentioned earlier, there have also been changes to the albedo scheme since that publication.

Looking throught the modeled profiles, we were surprised to find rather warm snowpacks, composed mostly of rounding forms, with fewer facetted layers than expected, given the continental locations, high elevations, and low snowfall amounts for most of these stations.

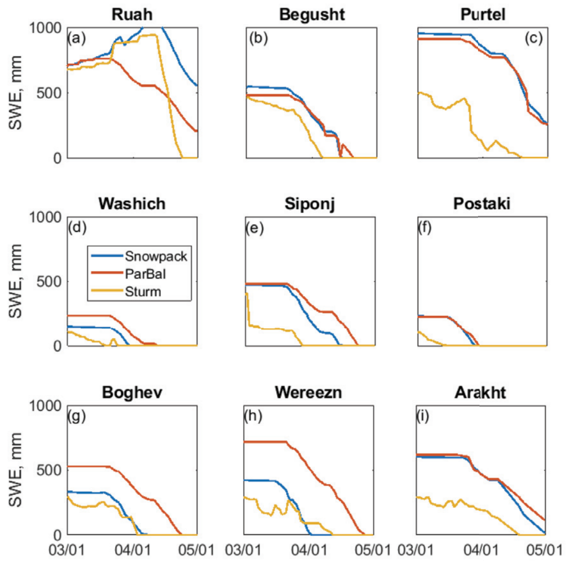

Figure 2: Time series of SWE at selected AKAH stations for 2017 using modeled values from SNOWPACK, ParBal, and the Sturm et al. (2010) density model.

4 CONCLUSION

We augmented previous work with additional validation data. We modeled SWE in remote villages of Afghanistan's watersheds using the SNOWPACK model, driven with manual snow measurements and downscaled forcings. We find good agreement overall between the modeled SWE values from the AKAH stations using the SNOWPACK model and our reconstructed SWE estimates with close to zero median bias. The outliers were biased high, maybe because of false positive identification of clouds as snow. This is a problem we are aware of and are working on.

Snow profiles showed relatively warm snowpacks with rounded grains, contrary to the more continental type of profiles expected. These findings are all preliminary and need to be explored further.

ACKNOWLEDGEMENTS

We are grateful to the Doug Chabot and the Aga Khan Agency for Habitat for supplying the first snow measurements in Afghanistan's watersheds since the 1980s.

REFERENCES

Bair, E.H., Abreu Calfa, A., Rittger, K. and Dozier, J., 2018a. Using machine learning for real-time estimates of snow water equivalent in the watersheds of Afghanistan. The Cryosphere, 12(5): 1579-1594.

Bair, E.H., Davis, R.E. and Dozier, J., 2018b. Hourly mass and snow energy balance measurements from Mammoth Mountain, CA USA, 2011–2017. Earth Syst. Sci. Data, 10(1): 549-563.

Bair, E.H., Rittger, K., Davis, R.E., Painter, T.H. and Dozier, J., 2016. Validating reconstruction of snow water equivalent in California's Sierra Nevada using measurements from the NASA Airborne Snow Observatory. Water Resources Research, 52: 8437-8460.

Bartelt, P. and Lehning, M., 2002. A physical SNOWPACK model for the Swiss avalanche warning: Part I: numerical model. Cold Regions Science and Technology, 35(3): 123-145.

Chabot, D. and Kaba, A., 2016. Avalanche forecasting in the central Asian countries of Afghanistan, Pakistan and Tajikistan, Proc. 2016 Intl. Snow Sci. Wksp., Breckenridge, CO, pp. 480-483.

Cornwell, E., Molotch, N.P. and McPhee, J., 2016. Spatio-temporal variability of snow water equivalent in the extra-tropical Andes Cordillera from distributed energy balance modeling and remotely sensed snow cover. Hydrol. Earth Syst. Sci., 20(1): 411-430.

Jepsen, S.M., Molotch, N.P., Williams, M.W., Rittger, K.E. and Sickman, J.O., 2012. Interannual variability of snowmelt in the Sierra Nevada and Rocky Mountains, United States: Examples from two alpine watersheds. Water Resources Research, 48(2): W02529.

Lehning, M., Bartelt, P., Brown, B. and Fierz, C., 2002a. A physical SNOWPACK model for the Swiss avalanche warning: Part III: meteorological forcing, thin layer formation and evaluation. Cold Regions Science and Technology, 35(3): 169-184.

Lehning, M., Bartelt, P., Brown, B., Fierz, C. and Satyawali, P., 2002b. A physical SNOWPACK model for the Swiss avalanche warning, Part II: Snow microstructure. Cold Regions Science and Technology, 35(3): 147-167, doi: 10.1016/S0165-232X(02)00073-3.

Marks, D. and Dozier, J., 1992. Climate and energy exchange at the snow surface in the alpine region of the Sierra Nevada, 2, Snow cover energy balance. Water Resources Research, 28(11): 3043-3054.

Martinec, J. and Rango, A., 1981. Areal distribution of snow water equivalent evaluated by snow cover monitoring. Water Resources Research, 17(5): 1480-1488.

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. Hydrological Processes, 23(7): 1076-1089.

Rittger, K., Bair, E.H., Kahl, A. and Dozier, J., 2016. Spatial estimates of snow water equivalent from reconstruction. Advances in Water Resources, 94: 345-363.

Sturm, M., Taras, B., Liston, G.E., Derksen, C., Jonas, T. and Lea, J., 2010. Estimating snow water equivalent using snow depth data and climate classes. Journal of Hydrometeorology, 11(6): 1380-1394.