Methods to robustly assess the snow water resource in remote mountains

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Reconstruction of snow water equivalent (SWE)

• Using remotely-sensed data on radiation and temperature, we build the snowpack in reverse with energy balance components to create historical maps of SWE

• Advantage: Can be done in areas with no ground-based measurements

• Limitation: Can only do this retrospectively after snow melts out
SWE Reconstruction works well in the Sierra

Snow measurements in Hindu Kush supported by Aga Khan Agency for Humanity

- It has been difficult to get recent snow measurements for validation in remote, inhospitable regions
- The Aga Khan Agency for Humanity (AKAH) provided daily snow measurement from 88 stations for model validation (Chabot and Kaba, 2016)

Bair et al. (2018)
SWE Reconstruction works well in Afghanistan (2017)

• Catch is that only snow depth is measured, so density had to be modeled based on snow climate (Sturm et al. 2011), yielding -12 to +26% uncertainty in SWE. Graphs above show the best-case given that uncertainty in density.
Problems with passive microwave snow assessment in mountains

- Aggregated over large basins in Afghanistan, our reconstructed SWE values agree well with passive microwave estimates on April 1 (Daly et al. 2012)
- But on April 1, many areas are snow-free or have shallow snow cover, which masks errors in volume
- Passive microwave, even at enhanced (3 km) resolution, fails to capture the correct magnitude or rank for deep snow areas, such as Salang Pass (left)
- It also saturates at about SWE=200 mm
SWE prediction in Afghanistan using machine learning

- Use reconstructed SWE to train machine learning models that use predictors available during the snow season
- Specifically, bagged trees (random forests) and neural networks were used
- Those models were used to predict seasonal SWE throughout Afghanistan
- 20% of training data (reconstructed SWE) was held out for validation
- Nash-Sutcliffe efficiency is 0.68 for all years, indicating substantial improvement over currently used forecasts from Air Force Weather
Ongoing work, supported by U.S. Army

- 4 year effort through September 2020, now in Year 2
- We are at ARL 6 (System/subsystem model or prototype demonstration in a relevant environment). From the DOD Defense Acquisition Guidebook, we fit the ARL 6 example of “testing the prototype in a simulated operational environment”

<table>
<thead>
<tr>
<th>Task Name</th>
<th>Description</th>
<th>Product/Deliverable</th>
<th>Dates</th>
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</thead>
<tbody>
<tr>
<td>1) Improvements to ParBal and Reconstruction</td>
<td>e.g. improve $f_{SCA}$, snow cloud discrimination, albedo, and radiative forcings</td>
<td>Code and peer reviewed publication on new spectral unmixing ($f_{SCA}$) approach</td>
<td>ParBal code on GitLab; publication in 2019; ongoing development</td>
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<td>2) Machine learning</td>
<td>SWE prediction using machine learning</td>
<td>Code and peer reviewed publication on machine learning</td>
<td>Publication just completed (Bair et al., 2018); code on GitLab</td>
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<td>3) Improvement to passive microwave retrievals</td>
<td>e.g. enhanced resolution passive microwave products</td>
<td>Use of enhanced resolution passive microwave as a predictor in machine learning</td>
<td>Used in machine learning publication (Bair et al. 2018); ongoing development</td>
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<td>4) Hydrologic modeling</td>
<td>Not pursuing due to funding constraints</td>
<td>N/A</td>
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References


• Chabot, D., and A. Kaba (2016), Avalanche forecasting in the central Asian countries of Afghanistan, Pakistan and Tajikistan, paper presented at 2016 International Snow Science Workshop, Breckenridge, CO.

