Fusion of high spatial and high temporal snow surface properties from satellite observations for estimating snow water equivalent

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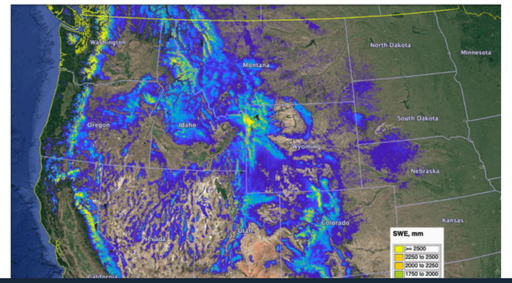
Introduction

Snow surface properties including snow cover fraction, snow grain size, snow albedo, and the impact of light absorbing particles on snow albedo measured by satellite can be used to validate or calibrate models of snow water equivalent (SWE) or be assimilated into these models directly. The tradeoff between spatial and temporal resolution of available satellite data for estimating these snow surface properties remains a challenge. Observations from satellites are available daily from MODIS at 500 m and VIIRS at 1 km, but snow surface properties vary at a much finer scale. Satellites such as Landsat 5, 7, and 8 and Sentinel 2a and 2b provide higher spatial resolution information but even when combined do not observe the Earth's surface daily. We explore combing information from different spatial and temporal resolutions in the Western United States and High Mountain Asia to fuse snow cover, snow albedo, and grain size.

Snow water equivalent

To estimate snow water equivalent (SWE) we use the Parallel Energy Balance model *(ParBal, Rittger et al, 2016; Bair et al 2016)*. In addtion to reanalysis data we rely on snow cover and snow albedo observations from MODIS *(Rittger et al 2019; Bair et al 2019)*. The higher spatial resolution of harmonized Landsat 8 and Sentinel 2ab combined with daily MODIS data will allow us to more accurately estimate the spatial variability of SWE.



Spectral mixture analysis

Snow mapping at multiple spatial resolutions

We compared 30 snow maps from Landsat 8 to MODIS and VIIRS in the Pamir region of High Mountain Asia. We found small biases of -0.005 and -0.013 and RMSE values of 0.133 and 0.125 *(Rittger et al, submitted)*. The small errors between observations at multiple spatial resolutions makes them ideal cadidates for fusion.

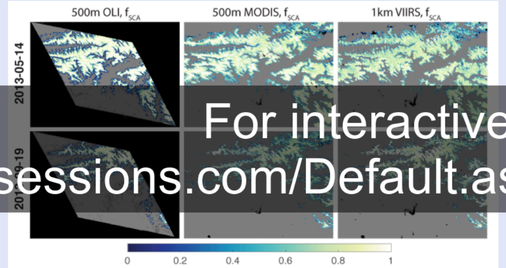
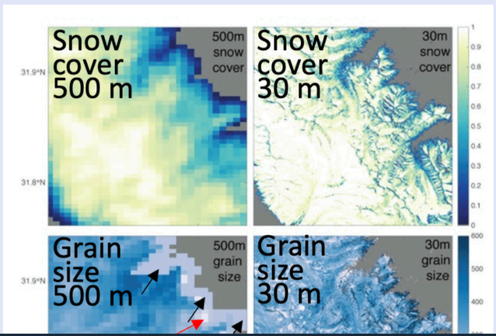


Figure 2: Landsat 8, MODIS, and VIIRS snow cover fraction

Snow cover & snow albedo for mixed pixels

Despite close agreement, elevated SWIR reflectances from mixed pixels lead to biases in grain sizes at low snow fractions. Figure 3 shows these examples. Errors from both spectral unmixing (white in 500 m grain sizes) and gap filling (northeast and southwest edge pixels) are evident.



Fusion of snow cover using random forest approach

Approach

We used a two-staged random forest algorithm with a suite of predictor variables to fuse MODIS and Landsat data. We trained the model on 170 Landsat snow cover maps and used 1 to 5 % of the data for training. Cross-validation with the remaining data showed mean differences of less than 1% and were consisent over all months of the year.

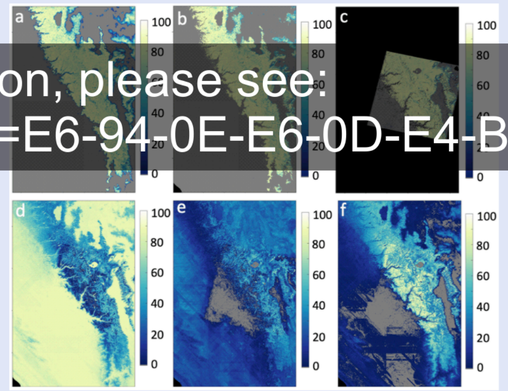
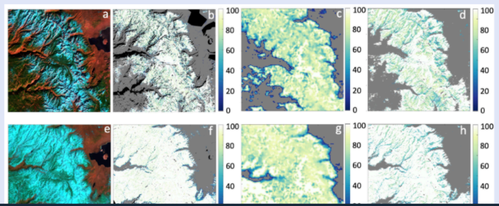


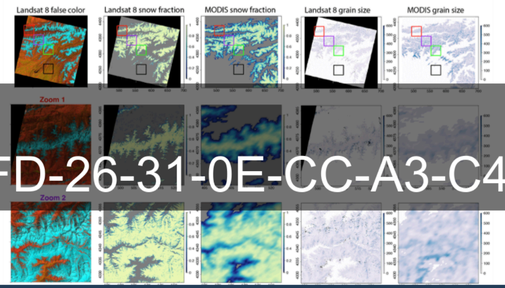
Figure 4: Downscaling uncertainty for February 16, 2008. The top row contains (a) MODIS fSCA at 500 m, (b) the spatially downscaled MODIS fSCA at 30 m and (c) Landsat fSCA for this day. The bottom row contains probabilities of (d) 0% fSCA, (e) a value between (0,100)% fSCA and (f) 100% fSCA, respectively.



Fusion of snow grain size using random forest approach

Initial approach

We use a random forest aprproach to fuse grain sizes from MODIS and Landsat in the Pamir region of High Mountain Asia. Slope, aspect, and rock fraction were of higher relative importance in predicting snow grain size the MODIS data.



Next steps

Spectral mixture analysis

- Expand the number of high spatial resolution images for training
- Generalize to use harmonized Landsat 8 and Sentinel 2 data

Data fusion

- Exclude interpolated data from training
- Add VIIRS data as a predictor for snow cover and grain size
- Incorporate MODDRFS and OLIDRFS to account for darkening from light absorbing particles

SWE

- Rerun ParBal to estimate SWE at 30 m
- Compare to previous 500 m SWE estimates

For interactive version, please see:
agu2020fallmeeting-agu.ipostersessions.com/Default.aspx?s=E6-94-0E-E6-0D-E4-B1-45-FD-26-31-0E-CC-A3-C4-E1