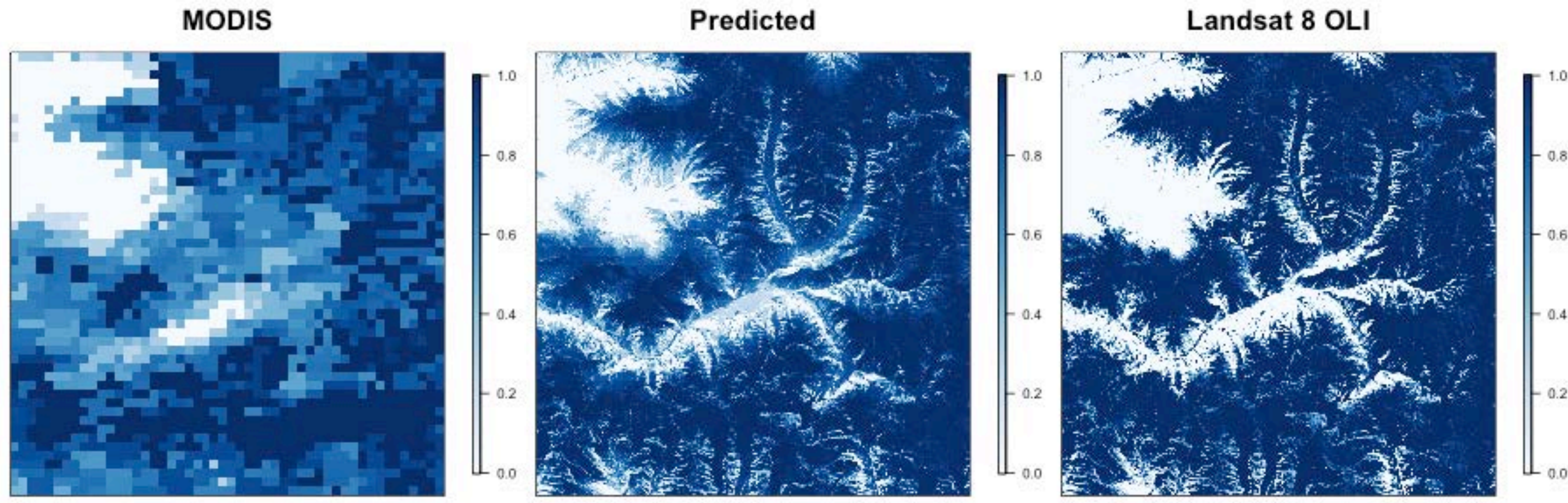
Fusion of MODIS, VIIRS, and Landsat snow cover data to create estimates of snow water equivalent



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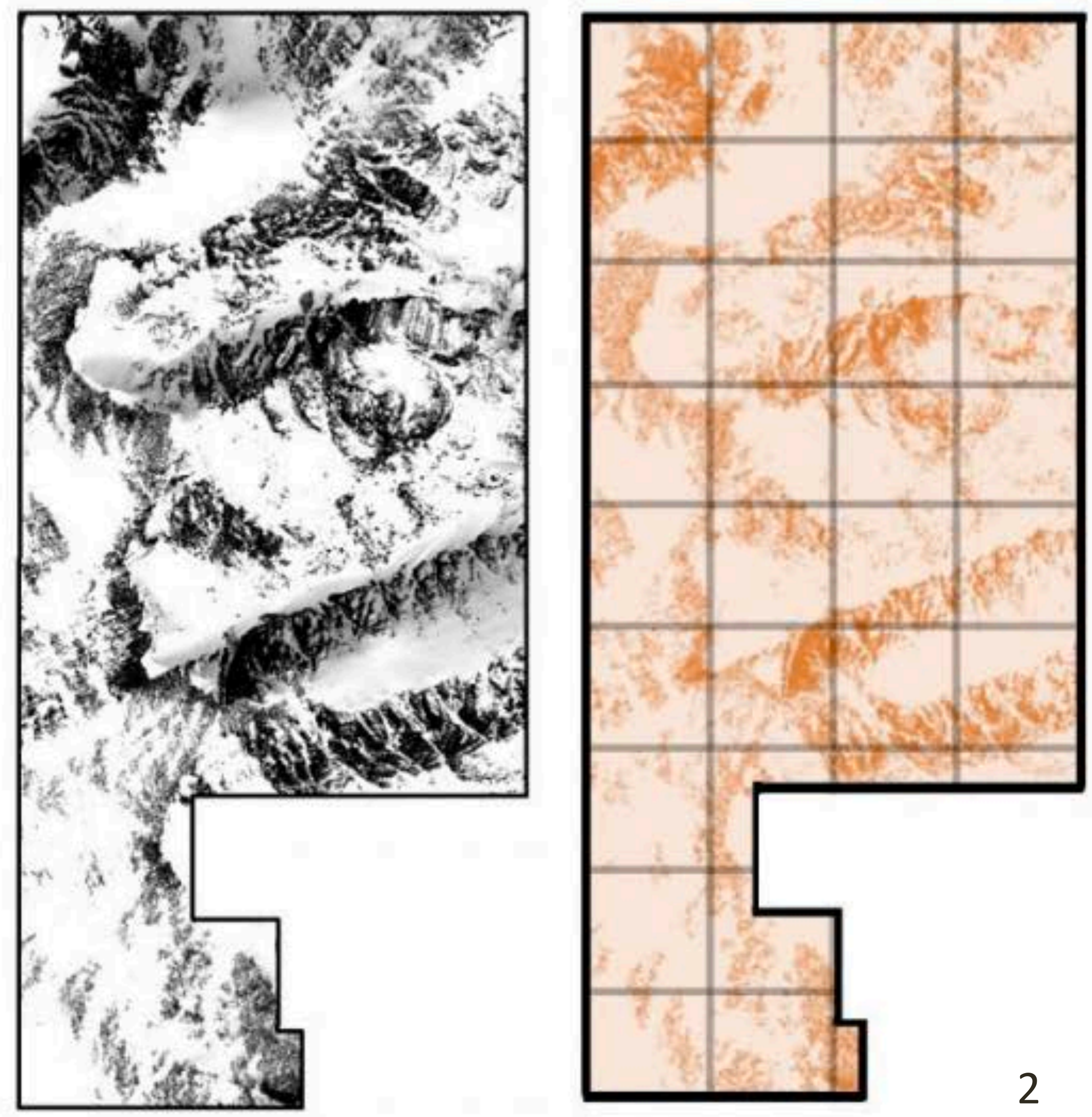
MODIS VIIRS Science Team Meeting, MODIS Land Science Analysis, Cypress Ballroom
10/17/18 10:10 am

Why do we need accurate snow cover estimates?

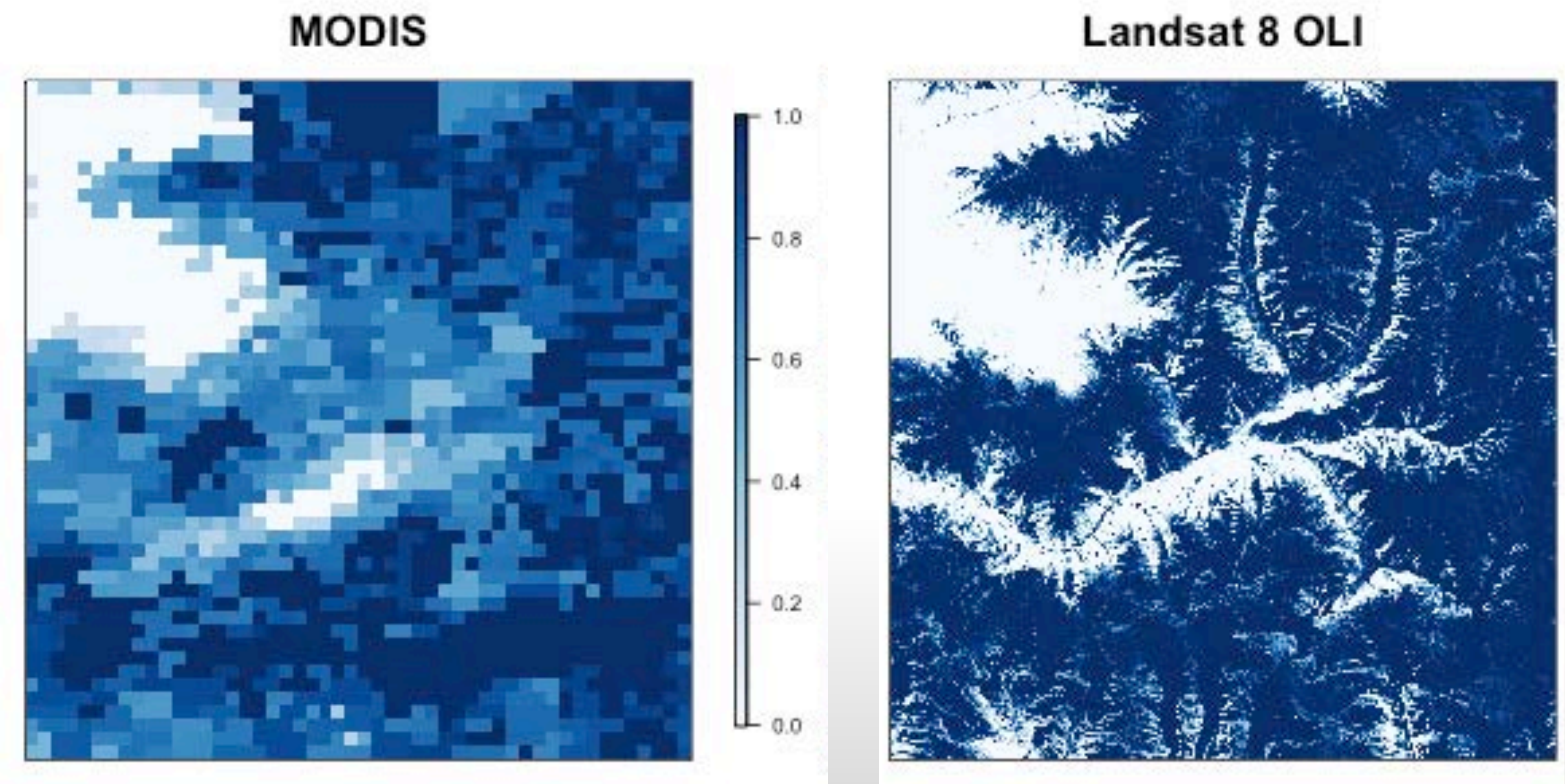
- A billion people worldwide depend on snow and ice melt for water (Barnett et al. 2005)
- Snow cover in the mountains varies dramatically, both spatially and temporally
- For water resources, that variability needs to be captured to accurately model basin-wide snow water equivalent (SWE)

Selkowitz et al. (2014)



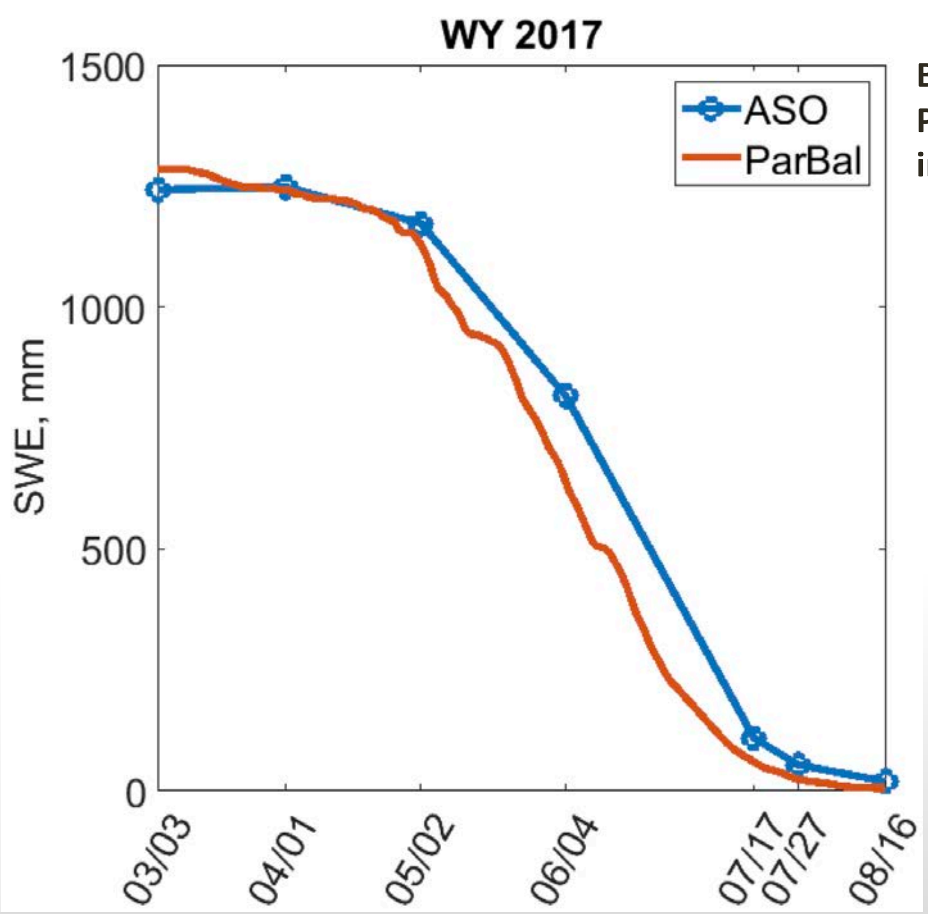
The general problem

- Satellite-borne sensors can have high temporal or high spatial resolution, but not both.
- For example, consider fractional snow-covered area (fSCA) from this imagery over the Himalaya. The left image is from daily MODIS Terra at 500 m while the right image is from LandSat 8 at 30 m, but is only available every 16 days.



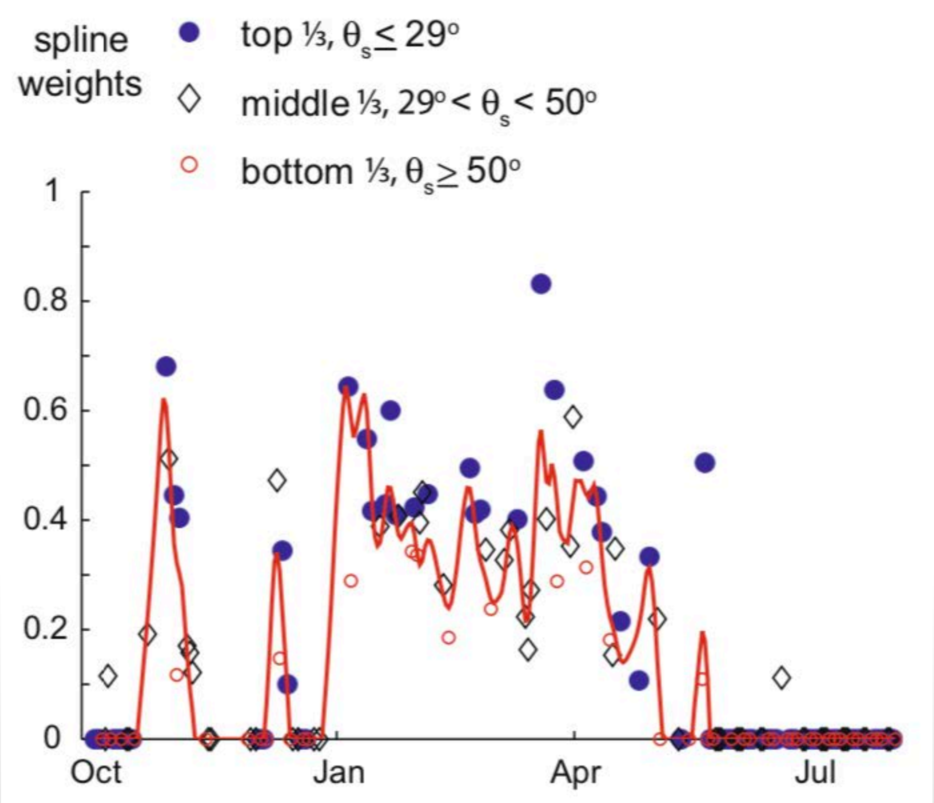
SWE reconstruction

- SWE is built up in reverse, from melt out to its peak
- Potential melt M_p is calculated using our Parallel Energy Balance model (ParBal)
- Potential melt is spread around a pixel and converted to melt M using: $M = f_{SCA} \times M_p$



Basin-wide SWE reconstructed with ParBal and measurements from ASO in the upper Tuolumne Basin, CA USA

A summary of our current approach for fSCA

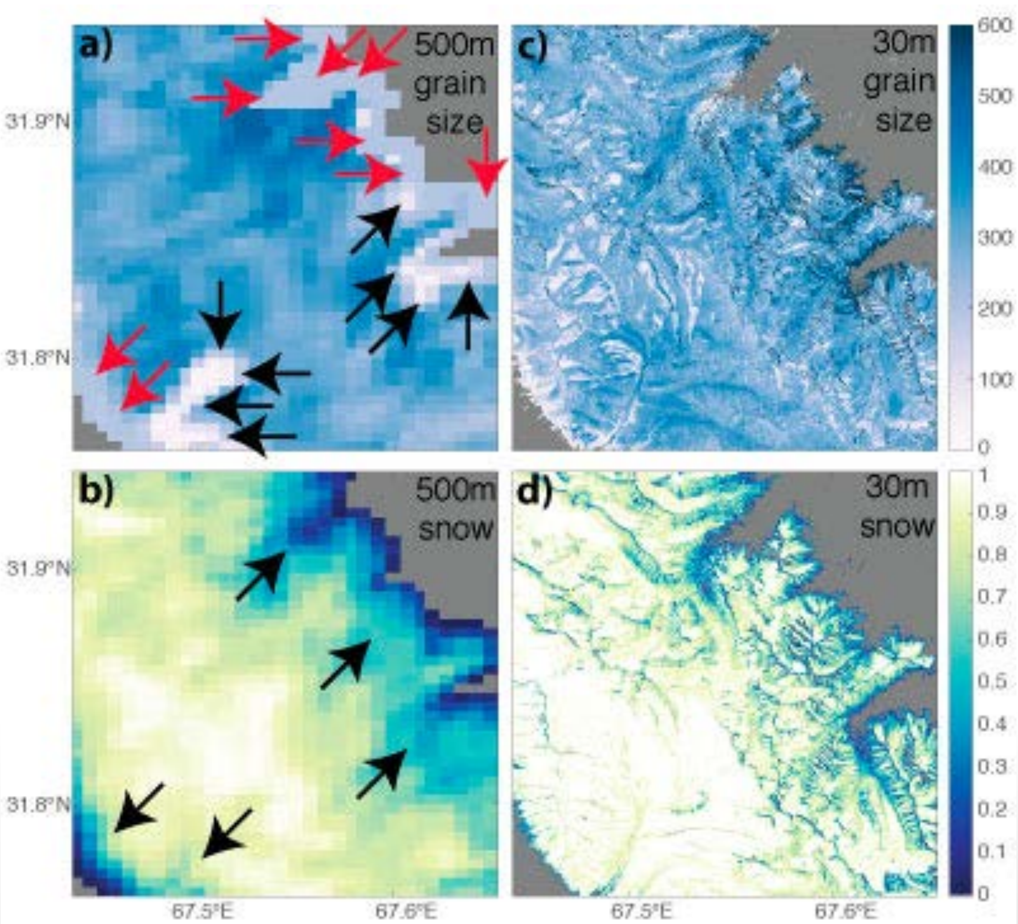


Dozier et al. 2008

1. We use spectral unmixing for fSCA and other snow surface properties, specifically MODIS Snow Covered Area and Grain Size (Painter et al. 2009) and VIIRSCAG (MODSCAG for VIIRS).
2. MODSCAG shows 9% vs. 23% RMSE when compared to a standard product fSCA (MOD10A1 v5), validated using LandSat 7 (Rittger et al. 2013).
3. We also smooth and gap-fill using weighted splines based on viewing geometry (Dozier et al. 2008).

Problems with our current approach that can be helped with improved spatial & temporal resolution

- Snow cloud discrimination remains an issue, see D. Hall et al. poster #127:
  - Optically thick clouds are brighter in all bands than snow, but thin clouds/snow can be spectrally inseparable from other non-snow mixtures, especially at 0.5-1 km resolution.
- MODSCAG grain sizes are too small at lower elevations (see image to the right)
- Snow albedo retrievals need work, and perform best on pure (unmixed) pixels
  - no snow albedo standard product for mixed pixels



MODIS and VIIRS both perform similarly at mapping fSCA, validation with LandSat 8

	Statistic	MODIS	VIIRS
Binary	Recall	0.900	0.889
	Precision	0.871	0.855
	Fstat	0.883	0.867
Fractional	Mean difference	-0.004	-0.013
	Median difference	-0.002	-0.005
	RMSE	0.133	0.125

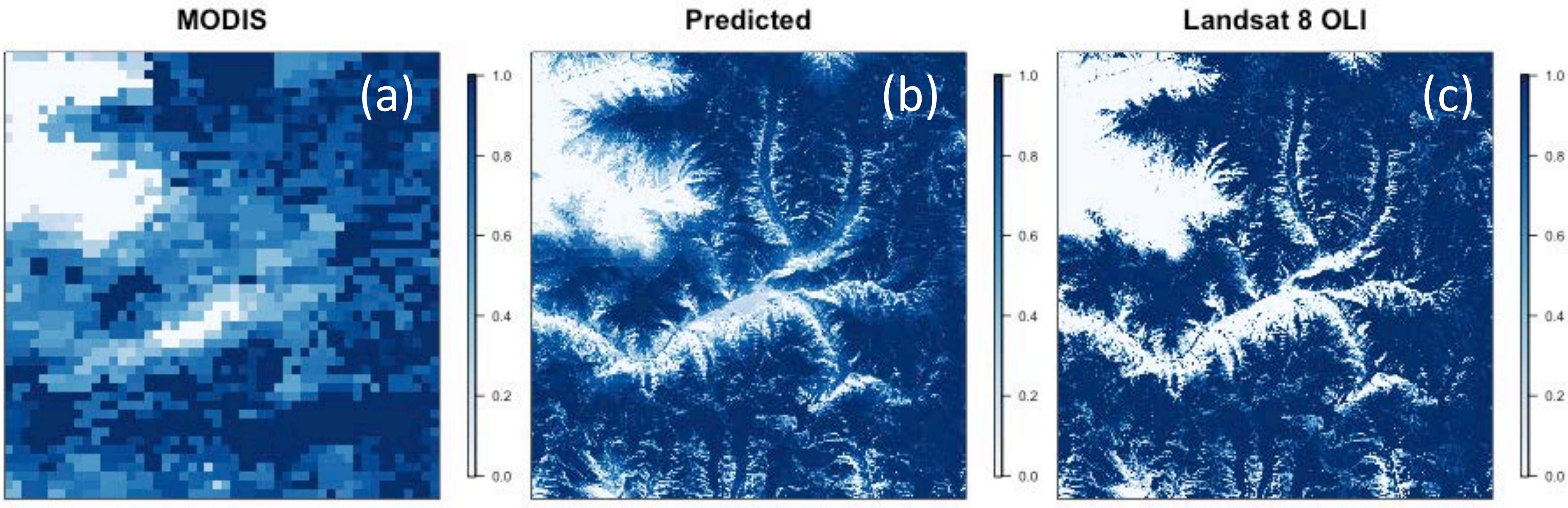
Our proposed approach: Bayesian fusion

$$\Phi^{-1}\big(Y(s,t)\big) = \mu(s,t) + f_1\big(X_1(s,t)\big) + \ f_2\big(X_2(s,t)\big) + \cdots$$
$$+ f_p\left(X_p(s,t)\right) + \varepsilon(s,t)$$

- Φ^{-1} - quantile function, transformation to real values with normal distributions
- $Y(s,t)$ - model realizations, with s as location and t as time
- $\mu(s,t)$ - mean function based on physiographic variables
- $f_1 \ldots f_{\mathrm{p}}$ - nonlinear transformations
- $X_1 \ldots X_{\mathrm{p}}$ - space-time features (e.g. Sobel filter, sharpening kernel)
- $\varepsilon(s,t)$ - space-time error

- Uncertainty is expressed through conditionally simulated ensembles
- Flexible in terms of number of features employed

Bayesian fusion example

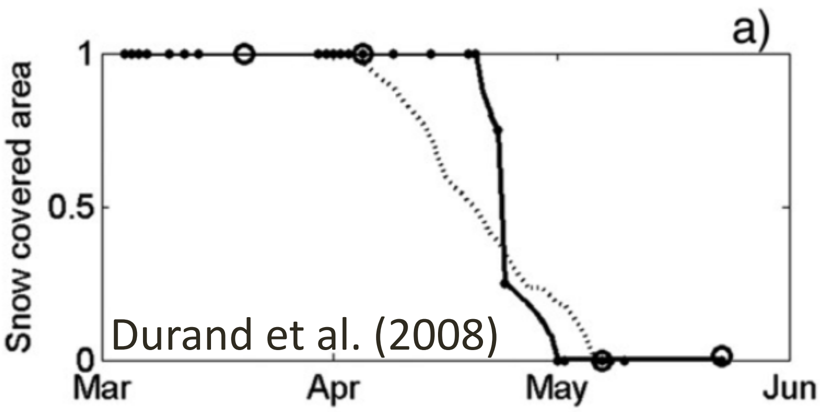


Example of downscaled MODIS imagery using Bayesian fusion:

- (a) Original, MODIS fSCA at 500 m spatial resolution; (b) Fused product, trained off data from other days; (c) Validation, LandSat 8 fSCA at 30 m spatial resolution.

Fused fSCA products have been tried before

- Durand et al. (2008) used a linear program approach to fuse MOD10A V.4 binary snow cover with fSCA from LandSat 7.
- Compared to using MODIS fSCA alone, they report a 51% reduction in Mean Absolute Error when run through a SWE reconstruction model (more on this later).
- This study showed promising results for fSCA fusion, but has several significant drawbacks:
  - Linear program is simple – constraints are linear and uncertainty is not addressed
  - Binary fSCA is inherently biased
  - LandSat 7 saturates issues in snow (8 bit vs 12 bit radiances)

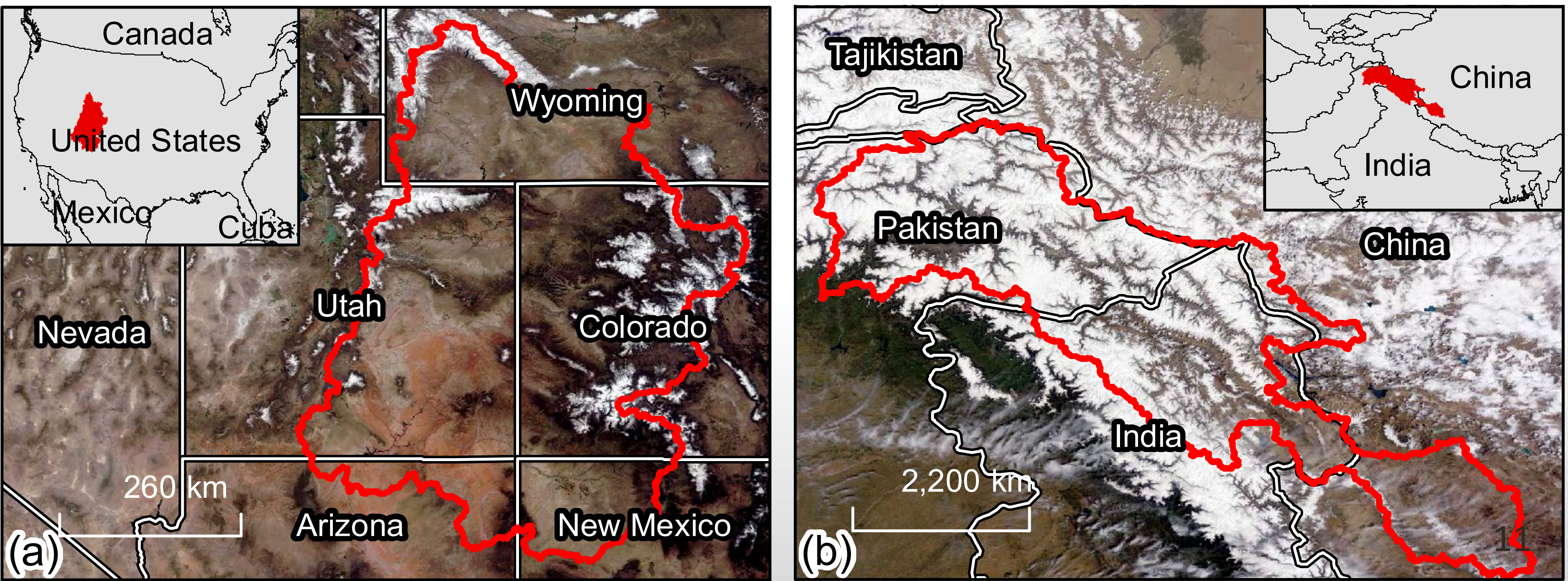


Small circles – MOD10A V.4
Large circles – LandSat 7
Dotted line – fused product

Study areas

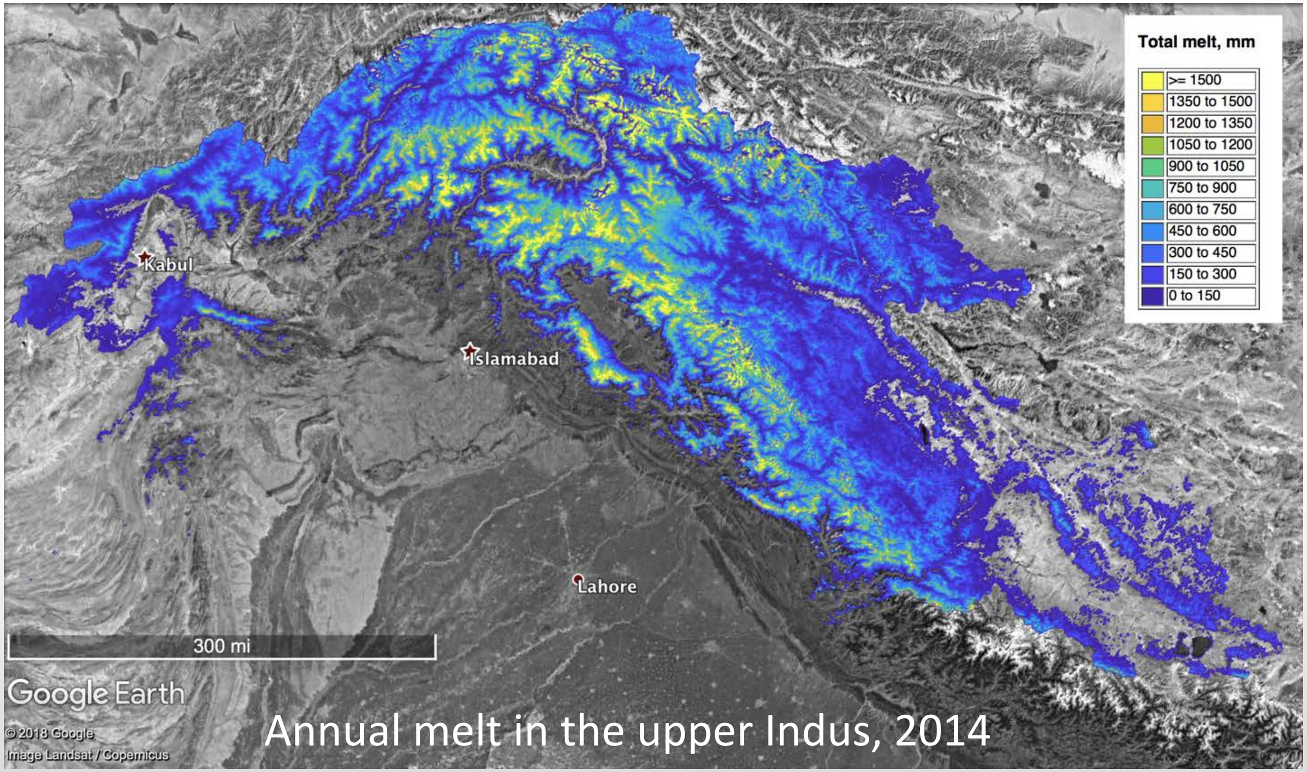
Snow covered MODIS imagery of study areas:

upper Colorado River Basin (a), upper Indus River Basin (b)



Five planned phases

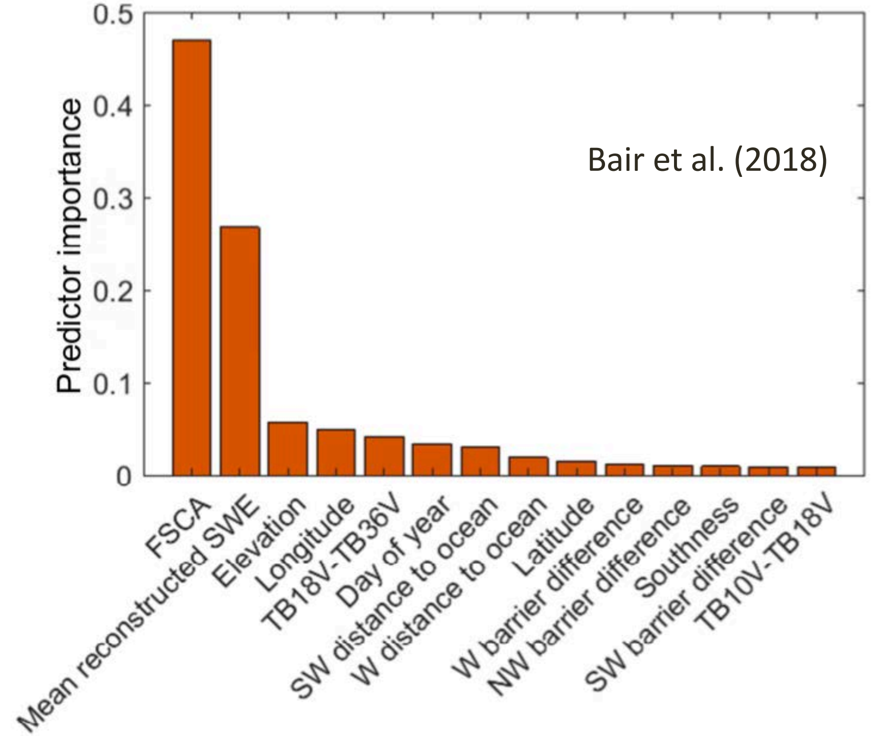
1. Fusion of MODIS and VIIRS: 500 m fSCA and albedo
2. Downscaling and fusion with LandSat: 30 m fSCA and albedo
3. Reconstructed SWE in both study areas
4. Leveraging other funded work: machine-learning based SWE estimates in both study areas
5. Leveraging other funded work: Model ready (HEC HMS) snow and ice estimates for upper Indus

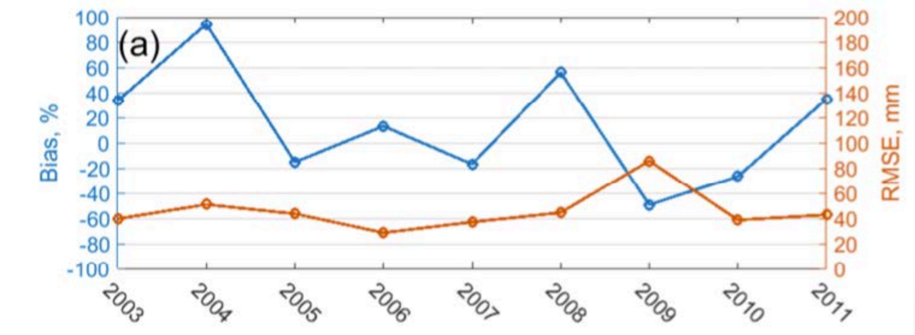


Annual melt in the upper Indus, 2014

Where does machine learning fit ? To predict today’s SWE

- Reconstruction is accurate but can only be done after all the snow melts
- Use reconstructed SWE to train machine learning models that use predictors available for today
- Specifically, bagged trees (random forests) and neural networks were used
- Those models were used to predict today’s 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 a mean forecast





Top: Bagged tree predictor importance
Bottom: Bagged tree bias and RMSE, validated using 20% hold out

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