Towards Multisensor Snow Assimilation: A Simultaneous Radiometric and Gravimetric Framework

Bart Forman

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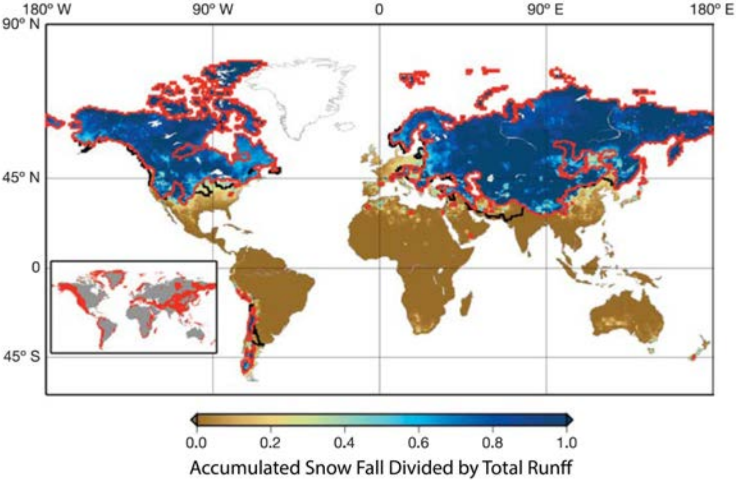
Department of Civil and Environmental Engineering

September 8^{th}, 2014

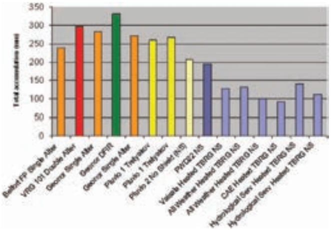
Significance of Snow



Barnett et al., 2005, *Nature*

Remote Sensing of Falling Snow

- Difficult to measure
  - ground-based observations can differ by $\gtrsim$100%
- Snowflakes not all alike (non-spherical, dendritic)
- NEXRAD radar $\Longrightarrow$ beam blocking in mountainous regions
- Satellite-based $\Longrightarrow$ issues with pixel-scale variability
- Forward model results contain significant error / uncertainty
  - Motivates hydrologic modeling with snow assimilation



Rasmussen et al., 2012, *BAMS*

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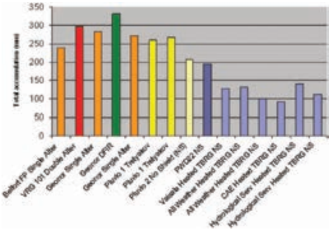

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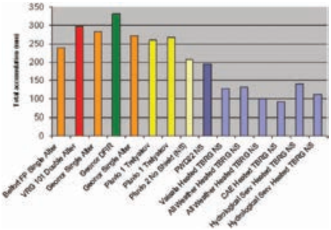

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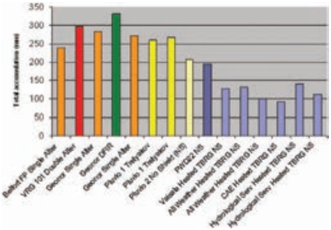

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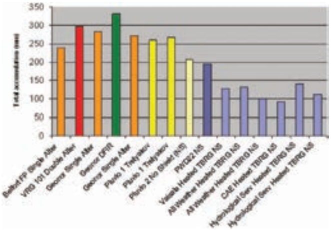

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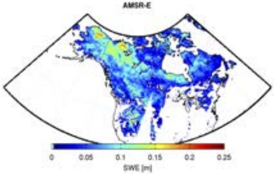
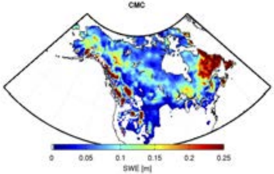
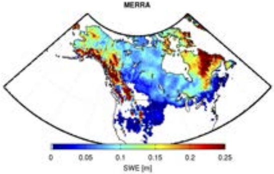
AMSR-E SWE Retrieval on March 1, 2004



AMSR-E SWE Retrieval

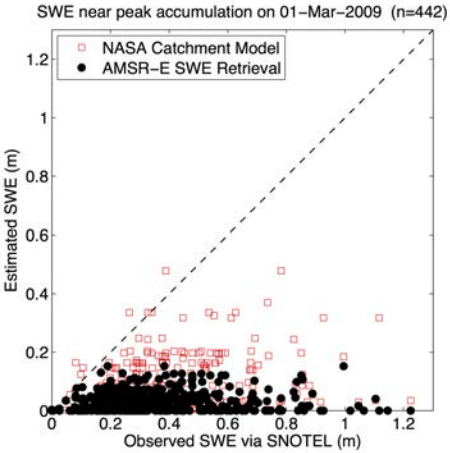


Canadian Meteorological Centre Daily Snow Analysis ⇒ "truth"



NASA Catchment model with NASA MERRA forcing

Snow Models are Good . . . But Not Great



Research Motivation

- Snow is a significant contributor to terrestrial freshwater supply
  - Vital resource for ~billion people worldwide
- Not exactly sure how much snow is out there
  - Significant uncertainty
- Global warming ⇒ rising snow line ⇒ reduced virtual reservoir
- Existing satellite-based snow retrievals have limitations
  - MODIS Visible ⇒ primarily measures snow extent
  - AMSR-E Microwave ⇒ deep snow, wet snow, ice layers, forest attenuation, etc.
  - GRACE Gravimetry ⇒ large spatial resolution, post-glacial rebound
- Need for computationally efficient measurement model operator
- Goal is to improve SWE at regional and continental scales

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California and Water

"Water. It's about water."

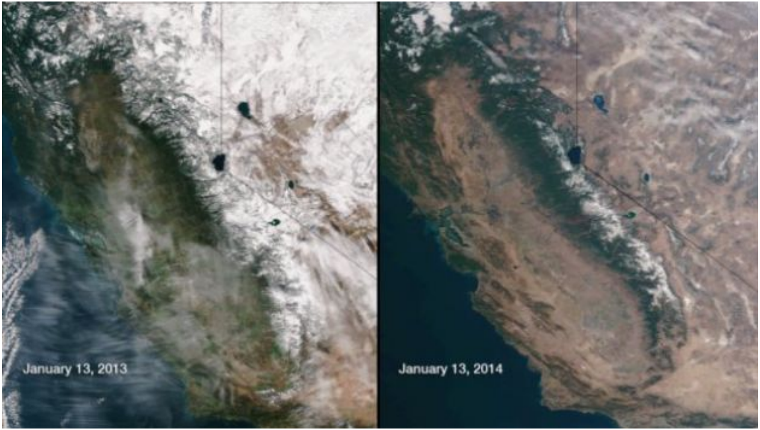
– Wallace Stegner

(response when asked by a journalist
"What is California about?")

California Drought and the Role of Snow

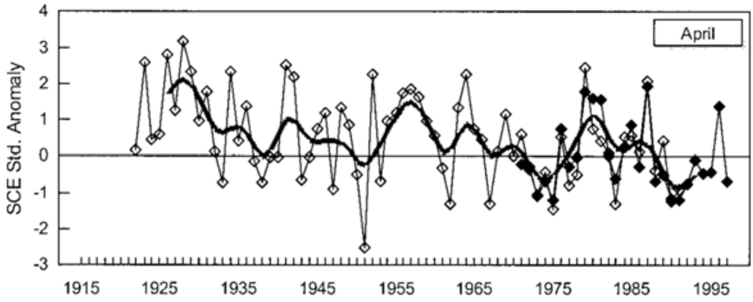
Lake storage and river runoff $\Longrightarrow$ majority fed by snow melt

Interannual Snow Variability



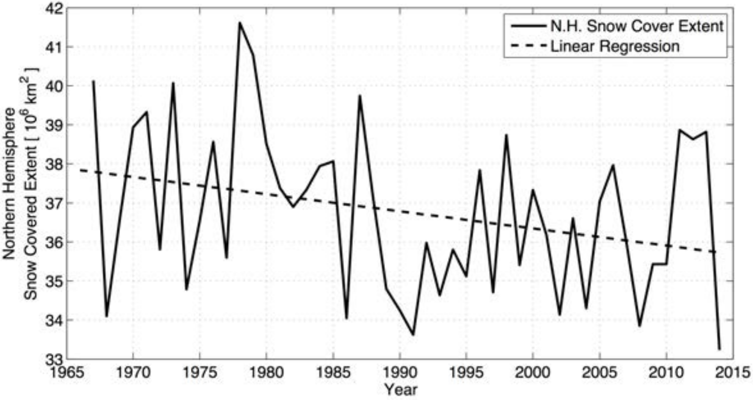
MODIS "true color" image showing snow covered area
(Figure courtesy of NASA)

Declining Spring Snow Cover



Brown, 2000, *Journal of Climate*

Declining Snow near Peak Accumulation

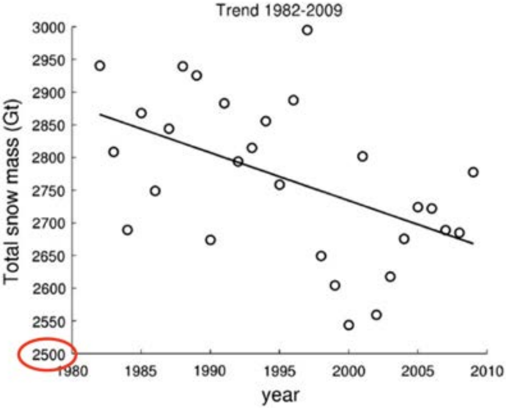


Analysis based on Rutgers Weekly Snow Cover Extent Product

Traditional Point-Scale SWE Measurements

http://nationalatlas.gov/articles/climate/a_snow.html

Declining Snow Mass via Satellite Retrieval?



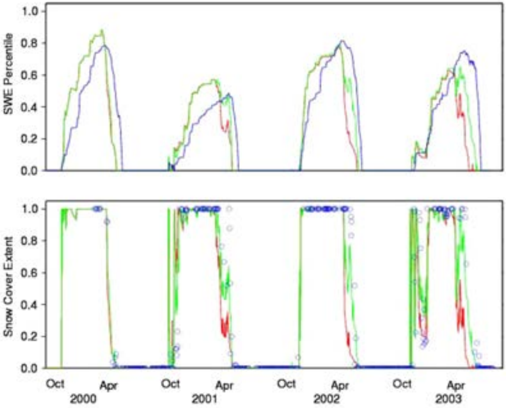
NOTE: Snow mass estimates ***exclude*** mountainous terrain

Takala et al., 2011, *Rem. Sens. Environ.*

Snow Cover Extent Assimilation

Andreadis and Lettenmaier, 2006, *Adv. in Water Resour.*

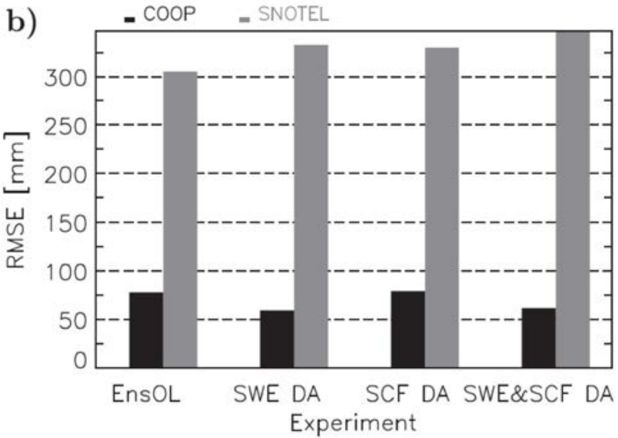
SNOTEL Open Loop EnKF



Added value via assimilation limited to ablation (melt) season

PMW SWE Retrieval Assimilation

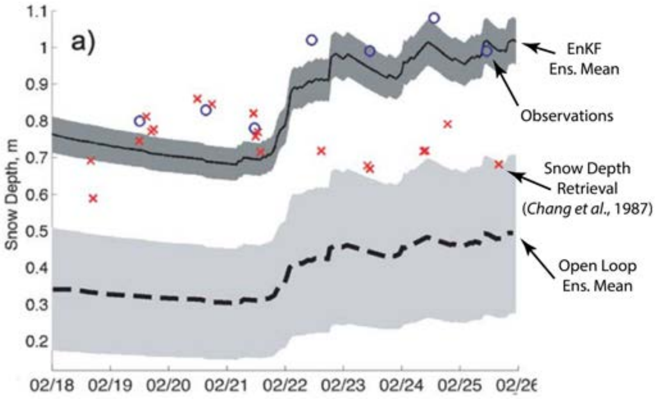
De Lannoy et al., 2012, *Water Resour. Res.*



Conditioned estimate degraded via SWE retrieval assimilation

PMW T_b Assimilation

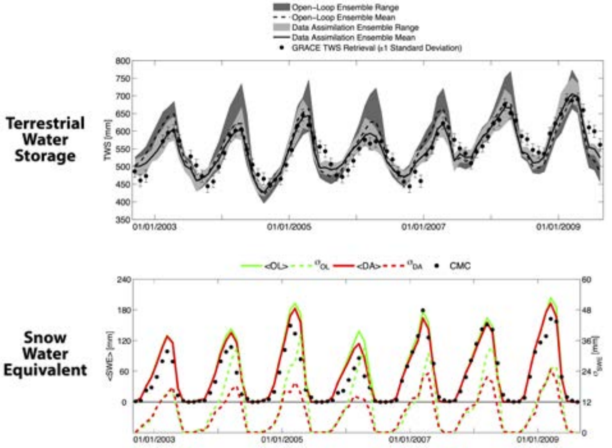
Durand et al., 2009, *Geophys. Res. Letters*



Conducted using snow pit (~1 meter scale) observations

GRACE Assimilation

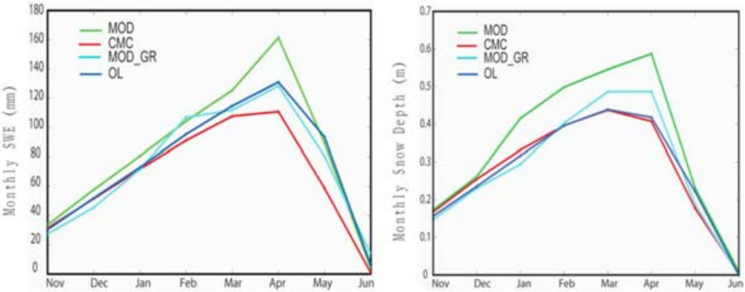
Forman et al., 2012, *Water Resour. Res.*



Improvement in SWE estimate (and runoff), but limited by large spatial resolution and post-glacial rebound

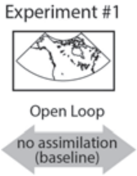
GRACE + Snow Cover Extent Assimilation

Su et al., 2010, *J. Geophys. Res.*



Multisensor (visible+gravimetric) framework improved SWE estimates

Multisensor Assimilation Framework



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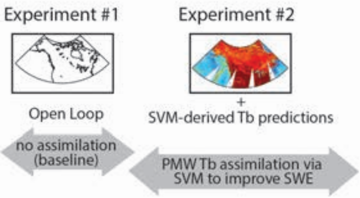

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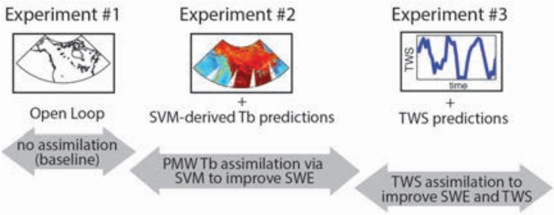

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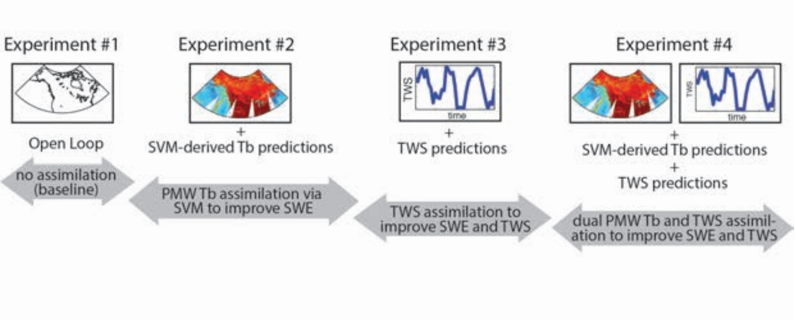

Multisensor Assimilation Framework

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Austin, TX
Sept. 8, 2014

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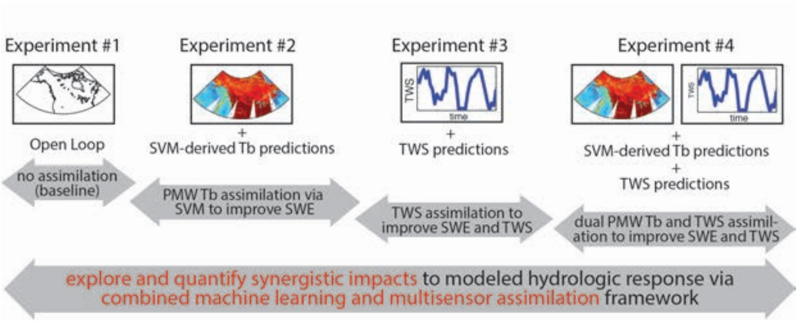
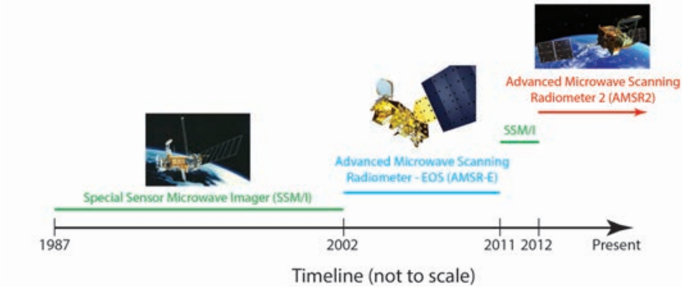


Vision for PMW T_b Assimilation



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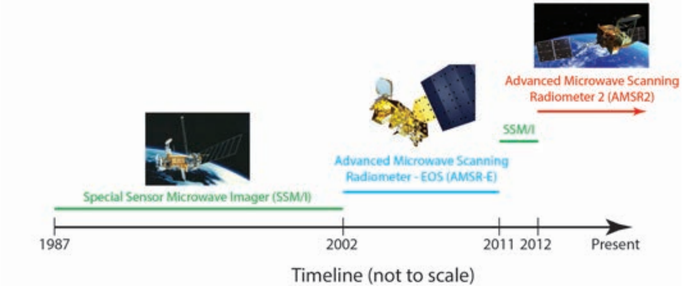
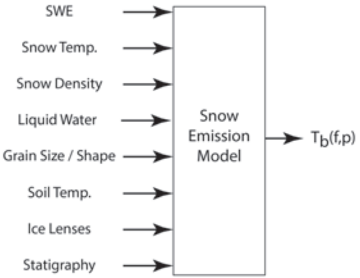


$$\underbrace{\mathbf{y}_i^+}_{\text{posterior SWE}} = \underbrace{\mathbf{y}_i^-}_{\text{prior SWE}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{Z_{T_b}}_{\text{PMW } T_b} - \underbrace{h(\mathbf{y}_i^-)}_{\text{machine learning}} \right]$$

Snow Emission Model vs. Machine Learning



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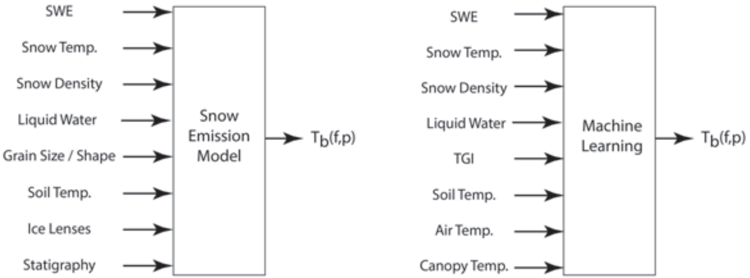

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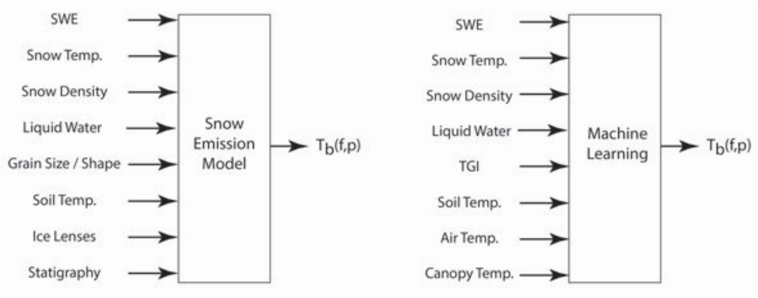


Global land surface models lack the fidelity required by snow emission model

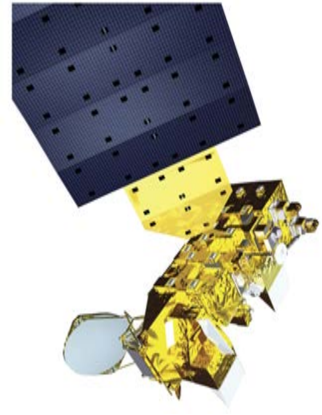
Best Summed Up by Anonymous Reviewer

''[At the continental scale,] the strategy of using machine learning to perform forward T_b estimation is a good choice short of the **computationally-frightening** idea of using a physically-based forward T_b model.''

– Anonymous Reviewer

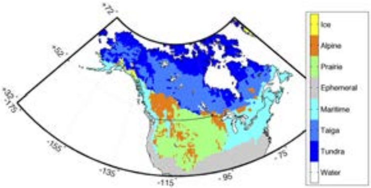
AMSR-E Background

- Advanced Microwave Scanning Radiometer EOS (AMSR-E)
- Onboard the Aqua satellite
- Measures passive microwave radiation
- Dual-polarized measurements at multiple frequencies
- Twice daily estimates (utilize nighttime only)
- Utilize ~25 km EASE grid product
- Data record from 1 Sep 2002 to 1 Sep 2011 (9 years)



http://aqua.nasa.gov/reference/publications.php

Experimental Setup: North America



Snow classification map [*Sturm et al.*, 1995].

Domain

- North America (north of 32°)
- 1 Sept. 2002 – 1 Sept. 2011

Model

- GEOS-5 Catchment model
- MERRA forcing

SVM Training Targets

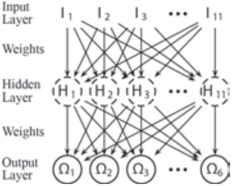
- AMSR-E nighttime overpass
  - 10.65, 18.7, and 36.5 GHz
  - V- and H-polarization

Validation Approach

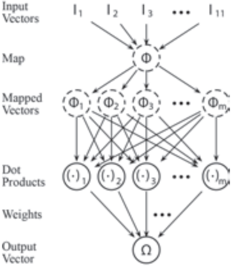
- AMSR-E "Jackknife approach" (i.e., data *not* used during training)

Machine Learning Background

ANN Schematic



SVM Schematic



ANN Architecture (*Forman et al.*, 2013)

- Single-layer, feed-forward perceptron
- Levenberg-Marquardt optimization

SVM Architecture (*Forman and Reichle*, 2014)

- Radial basis function using split-sample training/validation
- LibSVM library courtesy of NTU

ANN / SVM Inputs

- Snow water equivalent; snow liquid water content; temperature gradient index (proxy for snow grain size); snow temperature and density at multiple depths; near-surface soil, vegetative canopy, and near-surface air temperatures
- Catchment snow coincident with NOAA IMS Snow Cover product

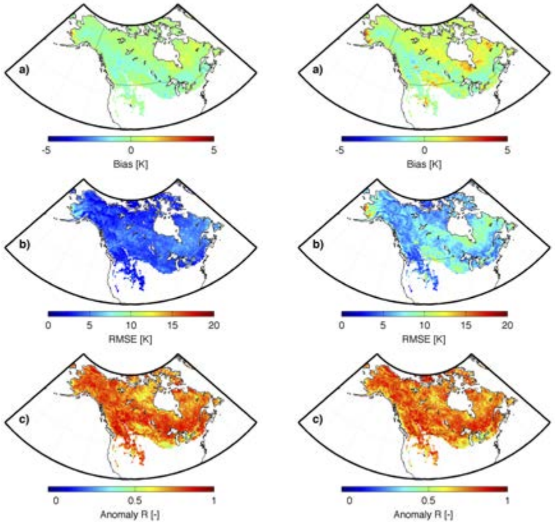
ANN / SVM Outputs

- T_b at 10H, 10V, 18H, 18V, 36H, and 36V

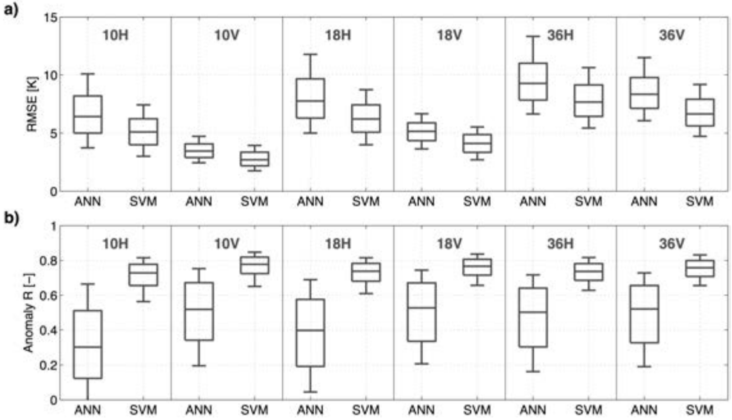
AMSR-E Comparison (9-year Study Period)

18.7 GHz, V-pol

36.5 GHz, V-pol



Comparisons for All Frequencies/Polarizations

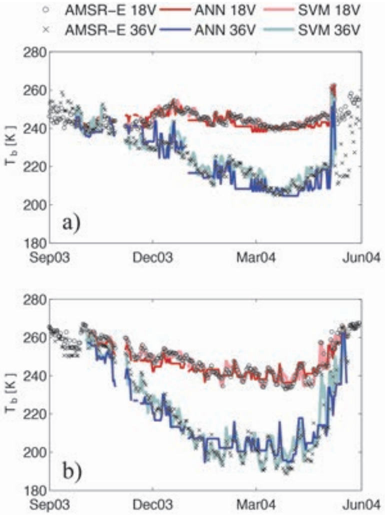


T_b predictions effectively unbiased at all frequencies/polarizations

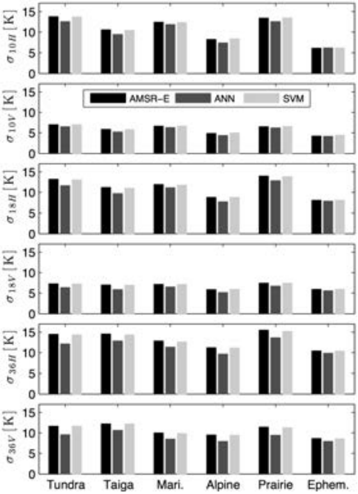
AMSR-E Comparison (2003-2004 Season)

Relatively shallow snow (max. SWE = 0.07 cm) and limited forest cover (forest fraction = 0.01)

Relatively deep snow (max. SWE = 0.22 cm) and thick forest cover (forest fraction = 0.42)



Predictive Variability



- Variability computed as spatial standard deviation for each day, then averaged over 9-years
- Snow classification derived from *Sturm et al.*, 1995

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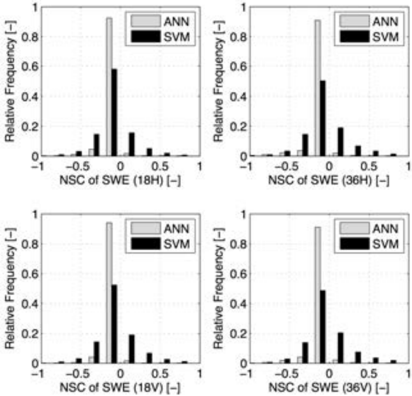
Sensitivity Analysis of AMSR-E T_b Predictions

$$NSC_{T_b,\,SWE} = \left(\frac{\partial T_b}{\partial SWE}\right)\left(\frac{SWE_0}{T_{b,0}}\right) \approx \left(\frac{T_{b,i} - T_{b,0}}{\Delta SWE}\right)\left(\frac{SWE_0}{T_{b,0}}\right)$$



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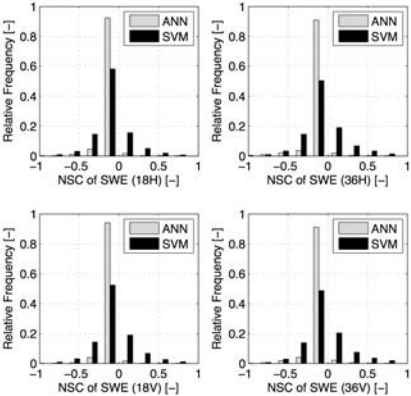
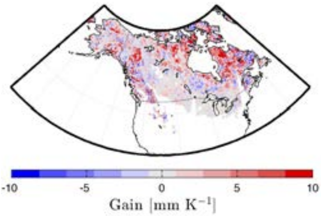


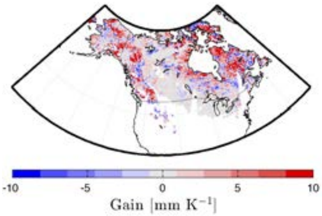
Increasing SWE $\longrightarrow$ decreasing T_b $\longrightarrow$ adheres to first-order physics

Gain Matrix Example

via SVM



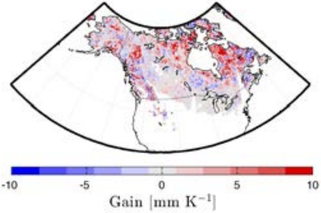
via ANN



- $\underbrace{\mathbf{y}_i^+}_{\text{posterior}} = \underbrace{\mathbf{y}_i^-}_{\text{prior}} + \underbrace{\mathbf{K}}_{\text{Kalman gain}} \left[\underbrace{Z_{T_b}}_{\text{AMSR-E}} - \underbrace{h(\mathbf{y}_i^-)}_{\text{via machine learning}} \right]$
- Computed gain on 6 February 2003 between modeled SWE and SVM-derived ΔT_b=18V-36V
- For $\mathbf{K} \approx 10$, if $Z^m - Z_i^p \approx 1$ K $\Longrightarrow y_i^+ - y_i^- \approx 1$ cm
- Non-zero error covariance structure exists!

Gain Matrix Example

via SVM



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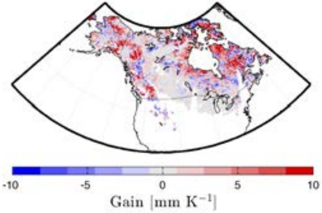

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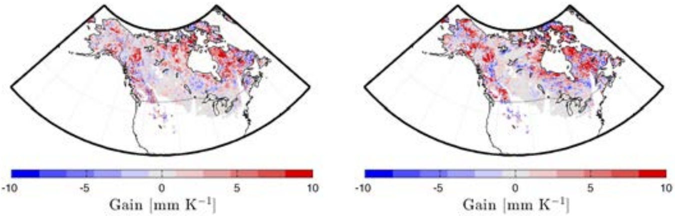
- Computed gain on 6 February 2003 between modeled SWE and SVM-derived ΔT_b=18V-36V
- For $\mathbf{K} \approx 10$, if $Z^m - Z_i^p \approx 1$ K $\Longrightarrow y_i^+ - y_i^- \approx 1$ cm
- Non-zero error covariance structure exists!

Gain Matrix Example

via SVM | via ANN



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Potential Sources of Error

- Sub-grid scale lakes?
- Sub-grid scale sea ice (coastal regions only)?
- Vegetation effects?
- Soil moisture effects?
- Depth hoar evolution?
- Internal ice layer(s) and/or ice crust(s)?

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- LSM predictions possess skill due to improved forcings
- SVM predictions are relatively unbiased at all frequencies/H or V
- Domain-averaged $RMSE \lesssim 8$ K at all frequencies/H or V
- Significant skill at predicting inter-annual variability
- Predictive capability during accumulation (dry snow) and ablation (wet snow) phases
- Issues with ice layer(s) and sub-grid scale lake ice
- Computationally efficient
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CAHMDA-VI
Austin, TX
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Bart Forman

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Thank You.

Questions and/or Comments?

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