

Assimilation of multi-frequency, multi-polarization passive microwave brightness temperature observations in North America over snow-covered regions using support vector machines

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Snow matters and Snow risks

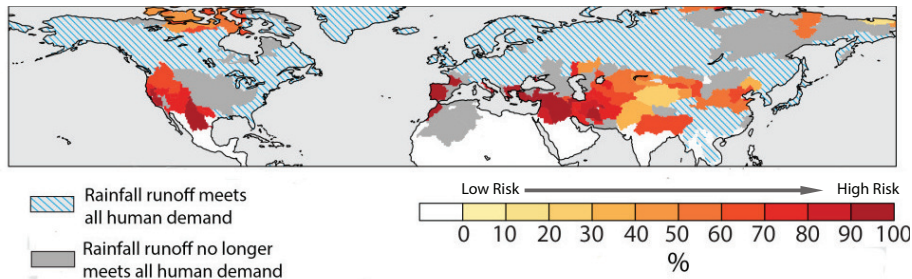


Figure: Projections of decreased potential for snowmelt water to supply human water demand by 2080. (Mankin et al., 2015 Environmental Research Letter)

Objective and Methodology

- Goal: Better characterize **snow water equivalent (SWE)** and **snow depth** across regional and continental scales.
- Study domain: North America
- Methodology: Data assimilation (DA) approach — Ensemble Kalman filter (EnKF) $\implies$ 1D-EnKF
- Merge observations **and** model estimates

DA Formulation

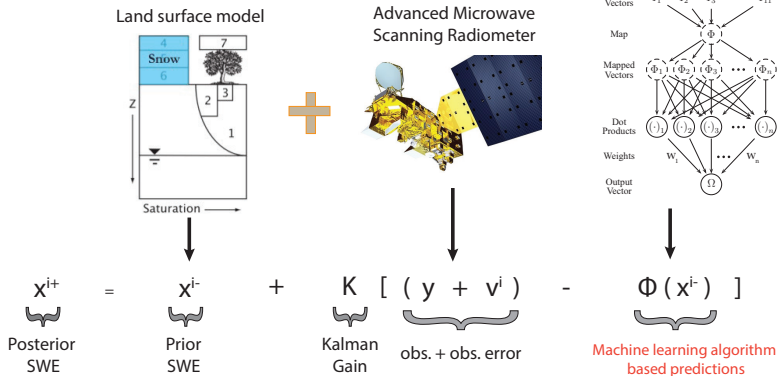
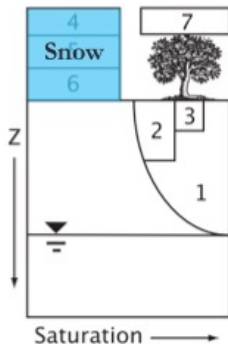


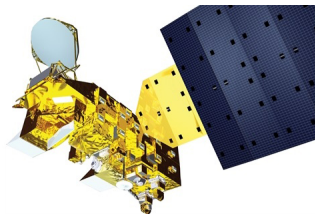
Figure: A conceptual representation of the update step in the EnKF, where the superscript i is the i^{th} replicate in the ensemble.

Forward model



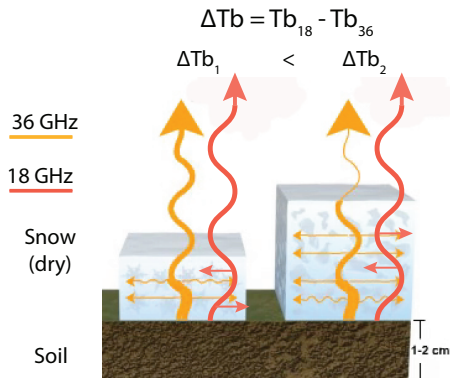
- NASA Catchment model, forced by Modern-Era Retrospective-Analysis for Research and Applications (MERRA)
- three-layer snow model
- 25-km Equal-Area Scalable Earth Grid (EASE-Grid)
- initialize when seasonal snow cover at minimum

Passive microwave observations



- Advanced Microwave Scanning Radiometer EOS (AMSR-E)
- measures passive microwave emissions (i.e., brightness temperatures (Tb))
- from 01 September 2002 to 01 July 2011
- multi-frequency (10 GHz, 18 GHz, and 36 GHz), multi-polarization (H pol., and V pol.) Tbs
- 25-km Equal-Area Scalable Earth Grid (EASE-Grid)

Relationship between SWE and ΔT_b



- **first-order approximation:** $\Delta T_b \uparrow$, SWE (or snow depth) $\uparrow$
- similar approximation for $\Delta T_b = T_{b_{10}} - T_{b_{36}}$
- longer wavelength, deeper snow information

Observation operator

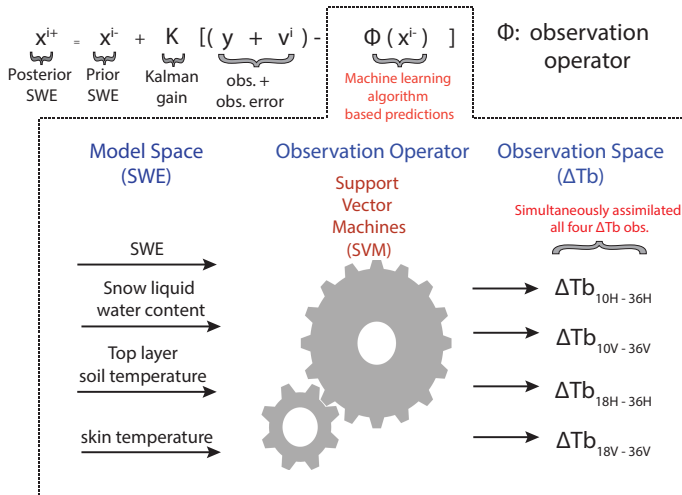


Figure: A conceptual representation of the machine learning algorithm based ΔT_b prediction framework.

Others Terms in the EnKF Formulation

- Ensemble size: 40
- Perturb precipitation, shortwave radiation, and longwave radiation
- ΔT_b observation error: $\sim \mathcal{N}(0, 3K) \implies$ same for all four channels
- SWE is the only state variable in the EnKF update
- Other snow-related modeled states were adjusted accordingly

- Model-derived results vs. ground-based stations
 - National Water and Climate Center Snow Telemetry (SNOTEL) SWE
 - SNOTEL snow depth
 - NOAA Global Summary of the Day (GSOD) snow depth
 - USGS daily and cumulative discharge
- Model-derived results vs. available snow products
 - Canadian Meteorological Centre (CMC) snow depth
 - AMSR-E SWE
 - European Space Agency (ESA) GlobSnow SWE

**Note: Model-derived results:

- (1) open-loop derived (OL; without assimilation) ensemble mean
- (2) data assimilation derived (DA; with assimilation) ensemble mean

Goodness-of-fit statistics

- e.g., **bias**, **unbiased root-mean-squared error (ubRMSE)**
- Normalized information contribution (NIC) (Kumar et al., 2009), including **NIC_{RMSE}** , and **NIC_{NSE}**
 - $NIC > 0$: DA outperforms OL
 - $NIC = 0$: DA is comparable to OL
 - $NIC < 0$: DA degrades OL

*RMSE: root-mean-squared error

*NSE: Nash-Sutcliffe model efficiency coefficient

Comparison against snow products and ground-based stations

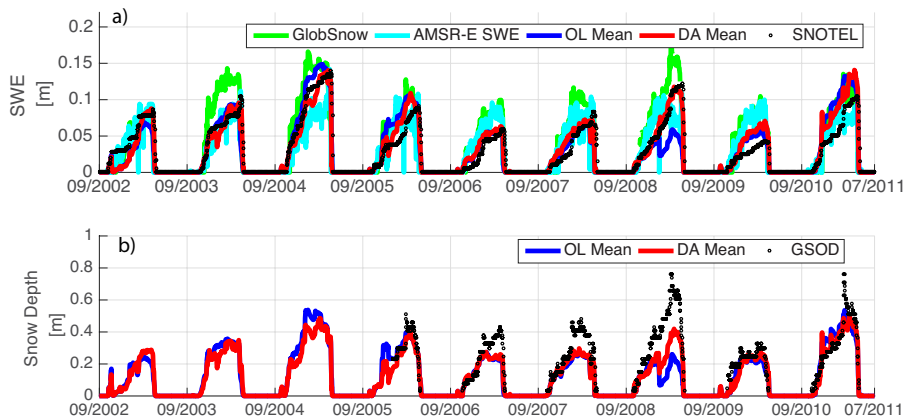
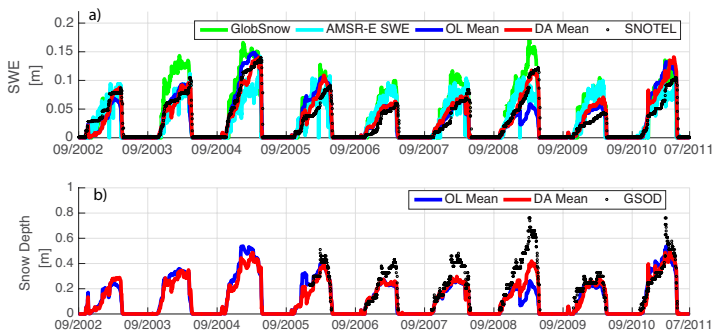


Figure: An example time series of SWE and snow depth for (64.78°N , 147.85°W) from 01 September 2002 to 01 July 2011. SNOTEL snow depth measurements are not available at this location.

Comparison against snow products and ground-based stations



- DA reduced the bias in snow depth estimates by 14% from OL (7.97cm) to DA (6.86cm)
- DA reduced the ubRMSE in snow depth estimates by 31% from OL (11.98cm) to DA (8.30cm)

Comparison against GSOD stations

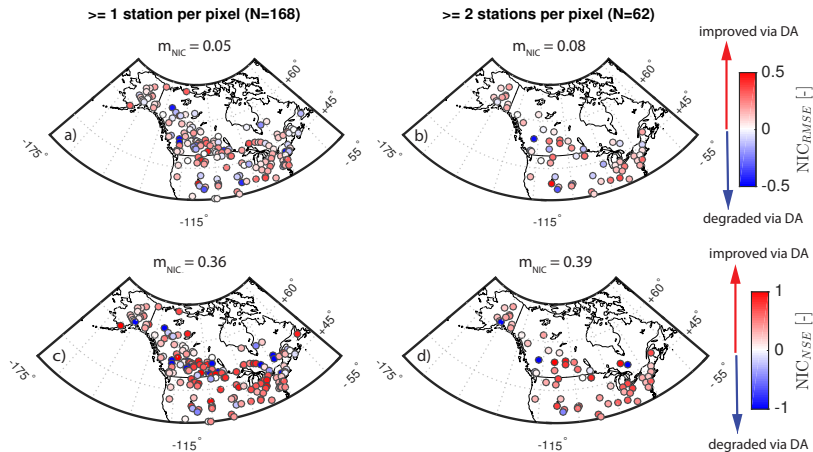
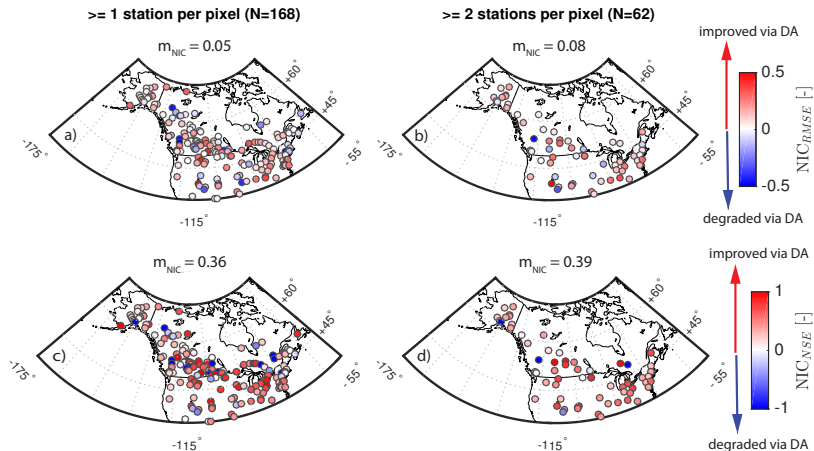


Figure: Spatial maps of NIC_{RMSE} (top row) and NIC_{NSE} (bottom row) during comparison against GSOD snow depth measurements from 2002 to 2011.

Comparison against GSOD stations



- DA agrees better with GSOD measurements than OL estimates in $\sim 82\%$ (56 out of 62) pixels that are colocated with at least two ground-based stations.

Comparison against USGS discharge

- 13 major USGS gauged basins in Alaska ($> 625 \text{ km}^2$, with at least two consecutive years of measurements record)

% of basins	NICs > 0	NICs < 0
vs. daily discharge	68.3%	31.7%
vs. cumulative discharge	84.7%	15.3%

- Relatively good snow estimates obtained from DA (relative to OL) also has the potential to translate into improved runoff estimates.

Filter sub-optimality assessment

- Normalized innovation (NI) sequence
- NI sequence approximates white noise $\implies$ “optimal” assimilation
- Violation of assumptions: nonlinear observation model operator + nonlinear model dynamics + non-Gaussian model errors

Domain-averaged	10H-36H	10V-36V	18H-36H	18V-36V
$\overline{NI}$ [-]	0.00	0.03	-0.04	-0.02
σ_{NI} [-]	1.56	1.46	1.16	1.14

- higher σ_{NI} : might underestimate observation errors and/or forecast errors

Conclusions and ongoing research

- SVM can serve as an efficient and effective observation model operator within a radiance assimilation system (Xue et al., under review, WRR).
- Investigate the effects of removing non-SWE related signals from the observations prior to integrating into the DA (Xue and Forman, IGARSS, July 2017)
- Conduct feasibility test of a multi-sensor assimilation framework for global snow (e.g., GRACE + AMSR-E) (Wang et al., AGU, Dec 2017)

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