Towards Multisensor Snow Assimilation: A Simultaneous Radiometric and Gravimetric Framework

Bart Forman

Assistant Professor, University of Maryland
Department of Civil and Environmental Engineering

September 8th, 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 $\rightarrow$ beam blocking in mountainous regions
- Satellite-based $\rightarrow$ issues with pixel-scale variability
- Forward model results contain significant error / uncertainty
  - Motivates hydrologic modeling with snow assimilation

Rasmussen et al., 2012, *BAMS*
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 $\Rightarrow$ beam blocking in mountainous regions
- Satellite-based $\Rightarrow$ issues with pixel-scale variability
- Forward model results contain **significant error / uncertainty**
  - Motivates **hydrologic modeling with snow assimilation**

Rasmussen et al., 2012, *BAMS*
Remote Sensing of Falling Snow

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

Rasmussen et al., 2012, *BAMS*
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 $\rightarrow$ beam blocking in mountainous regions
- Satellite-based $\rightarrow$ issues with pixel-scale variability
- Forward model results contain significant error / uncertainty
  - Motivates hydrologic modeling with snow assimilation

Rasmussen et al., 2012, *BAMS*
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 $\rightarrow$ beam blocking in mountainous regions
- Satellite-based $\rightarrow$ issues with pixel-scale variability
- Forward model results contain significant error / uncertainty
  - Motivates hydrologic modeling with snow assimilation

Rasmussen et al., 2012, *BAMS*
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
• Snow is a **significant** contributor to terrestrial **freshwater supply**
  
  ▶ Vital resource for ~1 billion people worldwide

• Not exactly sure how much snow is out there
  
  ▶ Significant **uncertainty**

• Global warming $\Rightarrow$ rising snow line $\Rightarrow$ reduced **virtual reservoir**

• Existing satellite-based snow retrievals have limitations
  
  ▶ MODIS **Visible** $\Rightarrow$ primarily measures snow extent
  
  ▶ AMSR-E **Microwave** $\Rightarrow$ deep snow, wet snow, ice layers, forest attenuation, etc.
  
  ▶ GRACE **Gravimetry** $\Rightarrow$ large spatial resolution, post-glacial rebound

• Need for **computationally efficient** measurement model operator

• Goal is to **improve SWE at regional and continental scales**
Research Motivation

- **Snow is a significant contributor to terrestrial freshwater supply**
  - Vital resource for ~1 billion people worldwide
- **Not exactly sure how much snow is out there**
  - Significant uncertainty
- **Global warming \(\Rightarrow\) rising snow line \(\Rightarrow\) reduced virtual reservoir**
- **Existing satellite-based snow retrievals have limitations**
  - MODIS Visible \(\Rightarrow\) primarily measures snow extent
  - AMSR-E Microwave \(\Rightarrow\) deep snow, wet snow, ice layers, forest attenuation, etc.
  - GRACE Gravimetry \(\Rightarrow\) large spatial resolution, post-glacial rebound
- **Need for computationally efficient measurement model operator**
- **Goal is to improve SWE at regional and continental scales**
• Snow is a **significant** contributor to terrestrial **freshwater supply**
  ▶ Vital resource for ~bi-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**
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 $\Rightarrow$ rising snow line $\Rightarrow$ **reduced virtual reservoir**
- Existing satellite-based snow retrievals have limitations
  - MODIS Visible $\Rightarrow$ primarily measures snow extent
  - AMSR-E Microwave $\Rightarrow$ deep snow, wet snow, ice layers, forest attenuation, etc.
  - GRACE Gravimetry $\Rightarrow$ large spatial resolution, post-glacial rebound
- Need for computationally efficient measurement model operator
- Goal is to **improve** SWE at regional and continental scales
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**
Research Motivation

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

“Water. It’s about water.”

– Wallace Stegner

(response when asked by a journalist “What is California about?”)
Lake storage and river runoff → 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?


**Added value via assimilation limited to ablation (melt) season**
PMW SWE Retrieval Assimilation


Conditioned estimate degraded via SWE retrieval assimilation
Durand et al., 2009, *Geophys. Res. Letters*

Conducted using snow pit (~1 meter scale) observations
GRACE Assimilation


Improvement in SWE estimate (and runoff), but limited by large spatial resolution and post-glacial rebound
Su et al., 2010, *J. Geophys. Res.*

Multisensor *(visible+gravimetric)* framework improved SWE estimates
Multisensor Assimilation Framework

Bart Forman

Background
Importance
Motivation
Existing Snow DA Studies
DA Framework
AMSR-E
Experimental Setup
Domain
Machine Learning
Results
AMSR-E Comparison
Time Series
Variability
Sensitivity
Gain Matrix
Remaining Issues
Conclusions
Multisensor Assimilation Framework
Multisensor Assimilation Framework

Background
Importance
Motivation
Existing Snow DA Studies
DA Framework
AMSR-E
Experimental Setup
Domain
Machine Learning
Results
AMSR-E Comparison
Time Series
Variability
Sensitivity
Gain Matrix
Remaining Issues
Conclusions
Multisensor Assimilation Framework

Background
Importance
Motivation
Existing Snow DA Studies

DA Framework
AMSR-E

Experimental Setup
Domain
Machine Learning

Results
AMSR-E Comparison
Time Series
Variability
Sensitivity
Gain Matrix

Remaining Issues

Conclusions
Multisensor Assimilation Framework

Experiment #1
- Open Loop
- no assimilation (baseline)

Experiment #2
- SVM-derived Tb predictions

Experiment #3
- TWS predictions
- TWS assimilation to improve SWE and TWS

Experiment #4
- SVM-derived Tb predictions
- TWS predictions
- dual PMW Tb and TWS assimilation to improve SWE and TWS

Explore and quantify synergistic impacts to modeled hydrologic response via combined machine learning and multisensor assimilation framework
Vision for PMW $T_b$ Assimilation

Background
Importance
Motivation
Existing Snow DA Studies
DA Framework
AMSR-E
Experimental Setup
Domain
Machine Learning
Results
AMSR-E Comparison
Time Series
Variability
Sensitivity
Gain Matrix
Remaining Issues
Conclusions
Vision for PMW $T_b$ Assimilation

\[
\begin{align*}
\mathbf{y}_i^+ &= \mathbf{y}_i^- + \mathbf{K} \left[ Z_{T_b} - h(\mathbf{y}_i^-) \right] \\
\text{posterior SWE} & \quad \text{prior SWE} & \quad \text{Kalman gain} & \quad \text{PMW } T_b & \quad \text{machine learning}
\end{align*}
\]
Snow Emission Model vs. Machine Learning
Snow Emission Model vs. Machine Learning

Background
Importance
Motivation
Existing Snow DA Studies
DA Framework
AMSR-E
Experimental Setup
Domain
Machine Learning
Results
AMSR-E Comparison
Time Series
Variability
Sensitivity
Gain Matrix
Remaining Issues
Conclusions
Global land surface models lack the fidelity required by snow emission model.
‘‘[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

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)

Snow classification map [Sturm et al., 1995].
Machine Learning Background

**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
AMSRE E Comparison (9-year Study Period)

18.7 GHz, V-pol

36.5 GHz, V-pol
$T_b$ predictions effectively unbiased at all frequencies/polarizations
AMSRE 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
Sensitivity Analysis of AMSR-E $T_b$ Predictions

$$NSC_{T_b, SWE} = \left( \frac{\partial T_b}{\partial SWE} \right) \left( \frac{SWE_0}{T_{b,0}} \right) \approx \left( \frac{T_{b,i} - T_{b,0}}{\Delta SWE} \right) \left( \frac{SWE_0}{T_{b,0}} \right)$$
Sensitivity Analysis of AMSR-E $T_b$ Predictions

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

Increasing SWE $\rightarrow$ decreasing $T_b$ $\rightarrow$ adheres to first-order physics
Gain Matrix Example

\[
\begin{align*}
\begin{aligned}
\text{via SVM} & \quad \text{via ANN} \\
\end{aligned}
\end{align*}
\]

\[
\begin{align*}
\mathbf{y}_i^+ &= \mathbf{y}_i^- + \mathbf{K} \left [ Z_{T_b} - h(\mathbf{y}_i^-) \right ], \\
\text{posterior} & \quad \text{prior} & \quad \text{Kalman gain} & \quad \text{AMSRE-E} & \quad \text{via machine learning}
\end{align*}
\]

- Computed gain on 6 February 2003 between modeled SWE and SVM-derived $\Delta T_b=18V-36V$
  - For $\mathbf{K} \approx 10$, if $Z^m - Z^p_i \approx 1$ K $\implies \mathbf{y}_i^+ - \mathbf{y}_i^- \approx 1$ cm
  - Non-zero error covariance structure exists!
Gain Matrix Example

\[ y_i^+ = y_i^- + K \begin{bmatrix} Z_{Tb} - h(y_i^-) \end{bmatrix} \]

• Computed gain on 6 February 2003 between modeled SWE and SVM-derived \( \Delta T_b = 18V-36V \)

• For \( K \approx 10 \), if \( Z^m - Z_i^p \approx 1 \) \( K \Rightarrow y_i^+ - y_i^- \approx 1 \text{ cm} \)

• Non-zero error covariance structure exists!
Gain Matrix Example

\[
\begin{align*}
\text{via SVM} & \quad \text{via ANN} \\
\begin{array}{c}
\text{Gain [mm K}^{-1}] \\
\text{Domain}
\end{array}
\end{align*}
\]

\[
\begin{align*}
\mathbf{y}_i^+ &= \mathbf{y}_i^- + \mathbf{K} \begin{bmatrix} Z_{T_b} - h(\mathbf{y}_i^-) \end{bmatrix} \\
\text{posterior} & \quad \text{prior} & \quad \text{Kalman gain} & \quad \text{AMSR-E} & \quad \text{via machine learning}
\end{align*}
\]

- Computed gain on 6 February 2003 between modeled SWE and SVM-derived \( \Delta T_{b} = 18V-36V \)
- For \( \mathbf{K} \approx 10 \), if \( Z^m - Z^p_i \approx 1 \) \( \mathbf{K} \Rightarrow y_i^+ - y_i^- \approx 1 \) cm
- Non-zero error covariance structure exists!
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)?
• **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
  • Bridge spatial / temporal scales between PWM $T_b$ and GRACE
  • Effectively add vertical resolution to GRACE TWS
  • Multiple frequencies/polarizations allow for flexibility in DA framework
  • Transferable methodology to SSM/I and AMSR2
• 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**
• Bridge spatial / temporal scales between PWM $T_b$ and GRACE
• Effectively add vertical resolution to GRACE TWS
• Multiple frequencies/polarizations allow for flexibility in DA framework
  ▶ Transferable methodology to SSM/I and AMSR2
Research Summary

- 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**
  - Bridge spatial / temporal scales between PWM $T_b$ and GRACE
  - Effectively add vertical resolution to GRACE TWS
  - Multiple frequencies/polarizations allow for flexibility in DA framework
    - **Transferable methodology to SSM/I and AMSR2**
Research Summary

- LSM predictions possess **skill due to improved forcings**
- SVM predictions are relatively **unbiased** at all frequencies/H or V
- **Domain-averaged** $RMSE \lesssim 8\ \text{K}$ 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**
- Bridge spatial / temporal scales between PWM $T_b$ and GRACE
- Effectively add vertical resolution to GRACE TWS
- Multiple frequencies/polarizations allow for flexibility in DA framework
  - Transferable methodology to SSM/I and AMSR2
LSM predictions possess **skill due to improved forcings**

SVM predictions are relatively **unbiased** at all frequencies/H or V

**Domain-averaged** \(RMSE \leq 8 \text{ K}\) 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**
- **Bridge spatial / temporal scales** between PWM \(T_b\) and GRACE
- Effectively **add vertical resolution** to GRACE TWS
- **Multiple frequencies/polarizations** allow for flexibility in DA framework
  - Transferable methodology to SSM/I and AMSR2
Research Summary

- 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**
- Bridge spatial / temporal scales between PWM $T_b$ and GRACE
- **Effectively add vertical resolution** to GRACE TWS
- **Multiple frequencies/polarizations** allow for flexibility in DA framework
  - Transferable methodology to SSM/I and AMSR2
Research Summary

- 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
  - Bridge spatial / temporal scales between PWM $T_b$ and GRACE
  - Effectively add vertical resolution to GRACE TWS
  - Multiple frequencies/polarizations allow for flexibility in DA framework
    - Transferable methodology to SSM/I and AMSR2
Research Summary

- 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**
- **Bridge spatial / temporal scales** between PWM $T_b$ and GRACE
- Effectively **add vertical resolution to GRACE TWS**
- Multiple frequencies/polarizations allow for flexibility in DA framework
  - Transferable methodology to SSM/I and AMSR2
Research Summary

- 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**
- **Bridge spatial / temporal scales** between PWM $T_b$ and GRACE
- Effectively **add vertical resolution** to GRACE TWS
- **Multiple frequencies/polarizations** allow for flexibility in DA framework
  - Transferable methodology to SSM/I and AMSR2
Research Summary

• 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
• Bridge spatial / temporal scales between PWM $T_b$ and GRACE
• Effectively add vertical resolution to GRACE TWS
• Multiple frequencies/polarizations allow for flexibility in DA framework
  ▶ Transferable methodology to SSM/I and AMSR2
Thank You.

Questions and/or Comments?

Partial financial support provided by the NASA New Investigator Program (NNX14AI49G)