Towards the Development of a Global, Satellite-based, Terrestrial Snow Mission Planning Tool

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Satellite-derived Snow “Information”
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Radiometer, $T_b$

RADAR, $\sigma_0$
Satellite-derived Snow “Information”
Science and mission planning questions:

1. What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?

2. How might observations be coordinated (in space and time) to maximize this utility?

3. What is the additional utility associated with an additional observation?

4. How can future mission costs be minimized while ensuring Science requirements are fulfilled?
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Research Objectives

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Observing System Simulation Experiment

Nature Run

Snow Depth & SWE over North America

LIS + MERRA2 - model-based representation
Observing System Simulation Experiment
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- **Nature Run**: Snow Depth & SWE over North America
  - LIS + MERRA2 - model-based representation

- **TAT-C**: Permutation of Orbit(s) + Sensor(s)
  - Sub-sample in space / time

- **TAT-C**: Mission cost estimate and risk analysis
  - \( T_B, \sigma_0, \text{ and } \delta h \)
  - Operators
  - Machine Learning “Emulators”

- **LIS Open Loop**: LIS + GLDAS
  - apply representative B.C. error
  - no assimilation (a.k.a., Open Loop)
  - with assimilation (merge with observations from suite of sensors)

- **Synthetic Obs.**
Observing System Simulation Experiment

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- with assimilation (merge with observations from suite of sensors)

LIS Assimilation
- Open Loop (i.e., no assimilation)
- Data Assimilation
  (Bayesian merger w/ synthetic obs.)

TAT-C
- Mission cost estimate and risk analysis
- $T_B$, $\sigma_0$, and $\delta$h Operators

Synthetic Obs.

Machine Learning
- Emulators
- Variability
- Experiments

Conclusions
Extra Slides
TAT-C Orbital Simulator
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Observations
Objectives
OSSE
TAT-C
Hyperplanes
Eulerian Grid
Single Platform
Constellation
Trade-off Space
Machine Learning
Emulators
Variability
Experiments
Conclusions
Extra Slides
“Comb” Viewing $\rightarrow$ Single Platform
“Comb” Viewing $\mapsto$ Constellation

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Extra Slides
• Explore trade-off between engineering and science
  ▶ Field-of-View (FOV)?
  ▶ Platform altitude?
  ▶ Repeat cycle?
  ▶ Single platform vs. constellation?
  ▶ Orbital configuration(s)?

• How do we get the most scientific bang for our buck?
Machine Learning “Emulators”

Physically-based Land Surface Model(s)

Observation Operator
(Forman et al., 2013; Forman and Reichle, 2014; Forman and Xue, 2016)

Multi-frequency, Multi-polarization Training Targets

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Multi-frequency, Multi-polarization Training Targets

Xue and Forman, 2015
Remote Sensing of Environ.
Spatiotemporal Variability
Spatiotemporal Variability

Tundra

Taiga

Maritime

Alpine

Prairie

Ephemeral
Relevancy Scenarios

- **Scenario 1**: Benchmark Analysis
  - Passive MW Assimilation only
- **Scenario 2**: Comparative Analysis
  - Passive MW vs. Active MW vs. LIDAR
- **Scenario 3**: Multi-sensor Analysis
  - single-sensor platform
  - multi-sensor platform
  - constellation of sensors
Research Summary

- Global snow mission will require evidence of achievable science via OSSE ... or some other means
- NASA LIS provides “nature run” plus assimilation framework
- TAT-C provides spatiotemporal sub-sampling of observations, including cost estimates and risk assessments
- Machine learning maps model state(s) into observation space (i.e., $T_b$ and $\sigma_0$)
  - Enables integration of $T_b$, $\sigma_0$, and $\delta h$ in geophysical realm (i.e., SWE and snow depth)
  - Multiple frequencies/polarizations/observations allow for flexibility and modularity in DA framework
- Snow OSSE is on-going → open to ideas + suggestions!
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Thank You.

Questions and/or Comments?

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SVM Mathematical Framework (1 of 2)

For parameters $C > 0$ and $\varepsilon > 0$, the standard (primal) form is:

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^{m} (\xi_i + \xi_i^*) \\
\text{subject to} & \quad \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle + \delta - z_i \leq \varepsilon + \xi_i \\
& \quad z_i - \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle - \delta \leq \varepsilon + \xi_i^* \\
& \quad \xi_i, \xi_i^* \geq 0, \ i = 1, 2, \ldots, m.
\end{align*}
\]

where $m$ is the available number of $T_b$ measurements in time (for a given location in space), $z_i$ is a $T_b$ measurement at time $i$, and $\xi$ and $\xi^*$ are slack variables.
Primal optimization is commonly solved in **dual form** as:

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \sum_{i,j=1}^{m} (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) \langle \phi(x_i) \cdot \phi(x_j) \rangle \\
& \quad + \varepsilon \sum_{i=1}^{m} \alpha_i + \alpha_i^* - \sum_{i=1}^{m} z_i (\alpha_i - \alpha_i^*) \\
\text{subject to} & \quad \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) = 0, \\
& \quad \alpha_i, \alpha_i^* \in [0, C], \; i = 1, 2, \ldots, m
\end{align*}
\]

where $\alpha_i$ and $\alpha_i^*$ are Lagrangian multipliers, $\langle \phi(x_i) \cdot \phi(x_j) \rangle$ is the inner dot product of $\phi(x_i)$ and $\phi(x_j)$, $\varepsilon$ is the specified error tolerance, and $C$ is a positive constant that dictates a penalized loss during training.