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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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?
Research Objectives

Science and mission planning questions:

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Observing System Simulation Experiment

Bart Forman

Observations
Objectives
OSSE
TAT-C
Hyperplanes
Eulerian Grid
Single Platform
Constellation
Trade-off Space
Machine Learning
Emulators
Variability
Experiments
Conclusions
Extra Slides
Observing System Simulation Experiment

Nature Run: LIS + MERRA2 - model-based representation

Snow Depth & SWE over North America

TAT-C

Sub-sample in space / time

Permutation of Orbit(s) + Sensor(s)
Observing System Simulation Experiment

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Permutation of Orbit(s) + Sensor(s)
Sub-sample in space / time

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)

LIS Assimilation
Open Loop (i.e., no assimilation)

Mission cost estimate and risk analysis
T_{B}, \sigma_{o}, and \delta h Operators
Machine Learning "Emulators"
Synthetic Obs.
Observing System Simulation Experiment

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

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

Mission cost estimate and risk analysis

TAT-C: Operators

Machine Learning "Emulators"

Synthetic Obs.
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“Comb” Viewing ↔ Single Platform
“Comb” Viewing $\mapsto$ Constellation
**Trade-off Space: Coverage vs. Resolution**

- 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”

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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

Xue and Forman, 2015
Remote Sensing of Environ.
Machine Learning “Emulators”

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spectral difference
18V - 36V
18H - 36H
10V - 36V
10H - 36H

Xue and Forman, 2015
Remote Sensing of Environ.

atmosphere

T2-meters

vegetation

Tskin

LAI

snow

SWE

ρ(z)

T(z)

SLWC

grain size

soil

Tsurf

moisture

TAT-C

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Multi-frequency, Multi-polarization Training Targets
Spatiotemporal Variability
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
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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For parameters $C > 0$ and $\varepsilon > 0$, the standard (primal) form is:

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

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.