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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Observation Types
Objectives
OSSE
TAT-C
Hyperplanes
Eulerian Grid
Single Platform
Constellation
Trade-off Space
Machine Learning
Emulators
Variability
Experiments
Conclusions
Research Objectives

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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TAT-C Orbital Simulator
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TAT-C Orbital Simulator
“Comb” Viewing $\leftrightarrow$ Single Platform
“Comb” Viewing ↔ Constellation

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• 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)

Xue and Forman, 2015
Remote Sensing of Environ.

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

Multi-frequency, Multi-polarization Training Targets

brightness temperature

36 GHz, V-pol
36 GHz, H-pol
18 GHz, V-pol
18 GHz, H-pol
10 GHz, V-pol
10 GHz, H-pol

atmosphere
$T_2$-meters
vegetation
$T_{skin}$
LAI
snow
SWE
$p(z)$
$T(z)$
SLWC
grain size
soil
$T_{surf}$
mobility

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p(z)
T(z)
SLWC
grain size
soil
Tsurf
moisture

backscatter
\(\sigma_{VH}\)
\(\sigma_{VV}\)
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 planning will require evidence of achievable science via OSSE

- Land Information System (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 suggestions!
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Thank You.

Questions and/or Comments?

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