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

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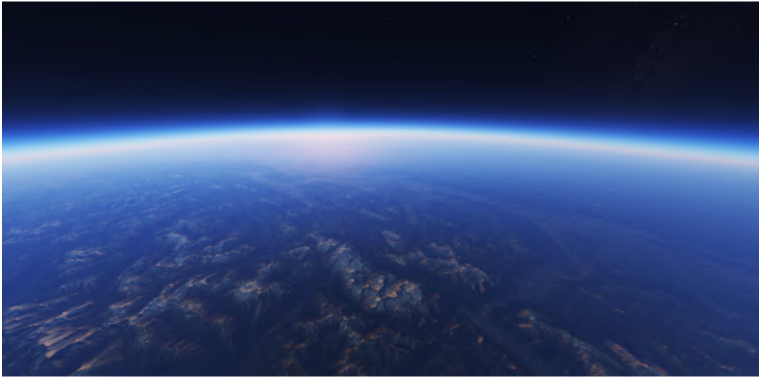
June 7th, 2017

Satellite-derived Snow "Information"



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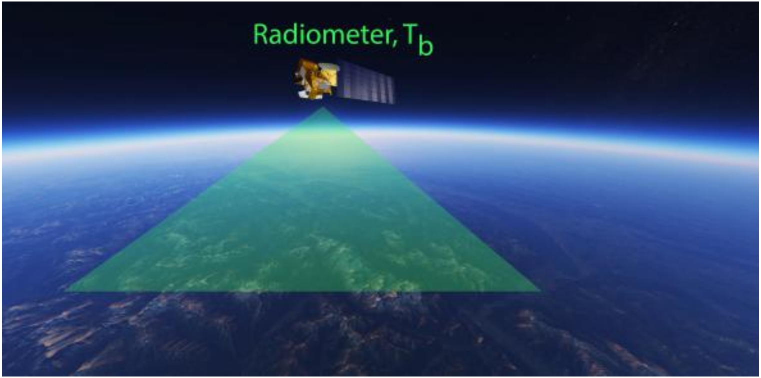

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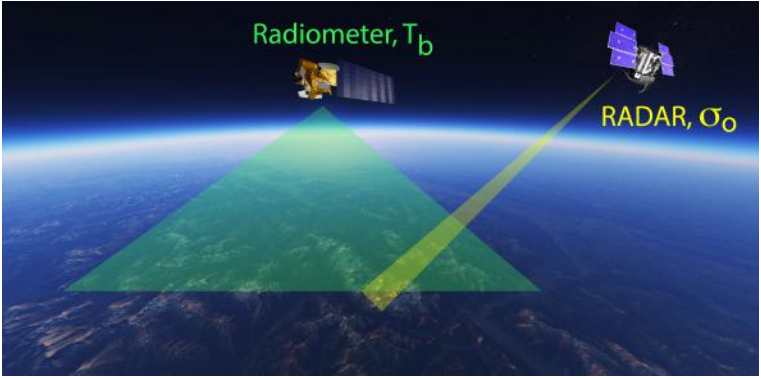

Satellite-derived Snow "Information"

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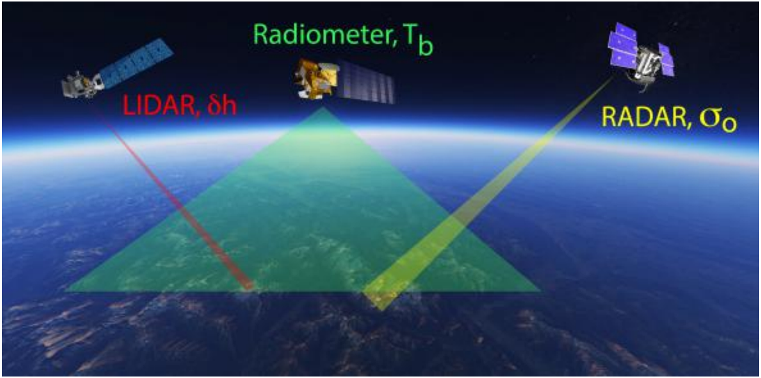

Science and mission planning questions:

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?

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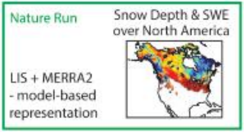

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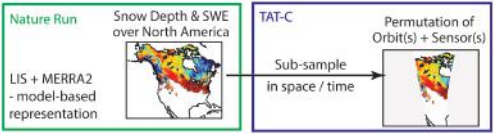

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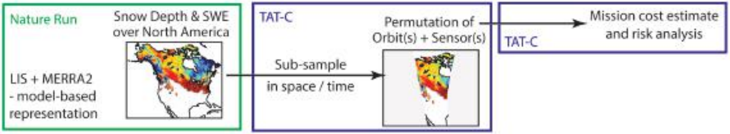

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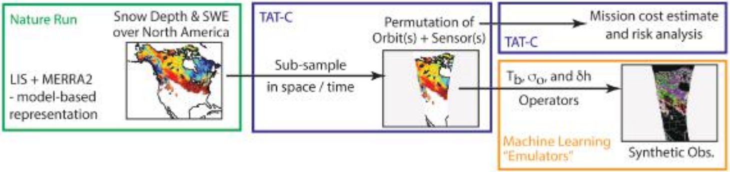

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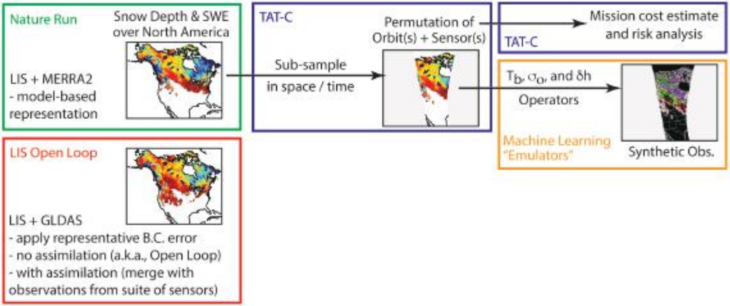

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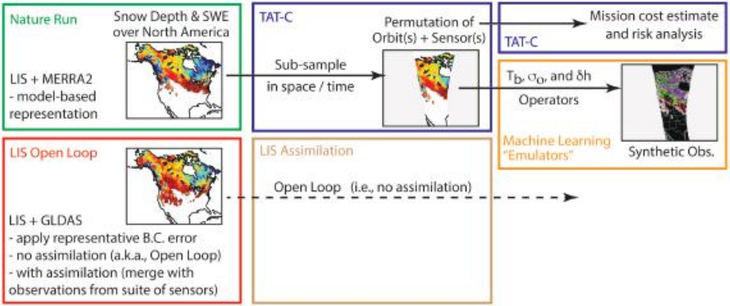

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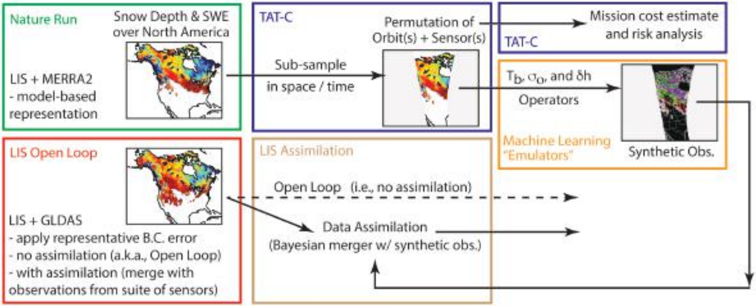

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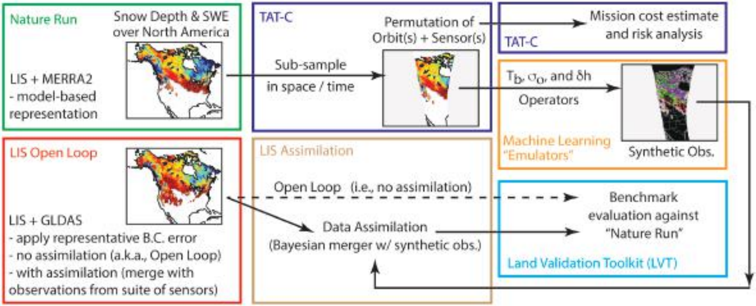
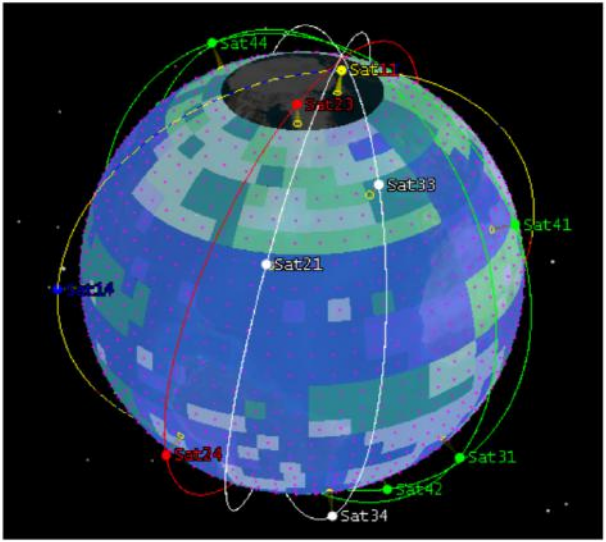


TAT-C Orbital Simulator



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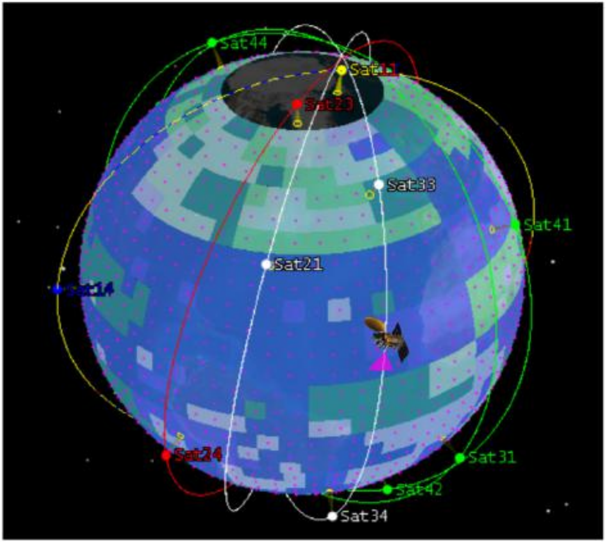

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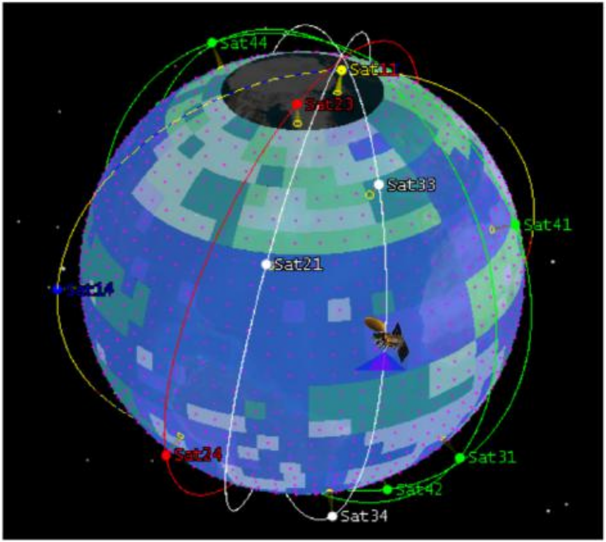

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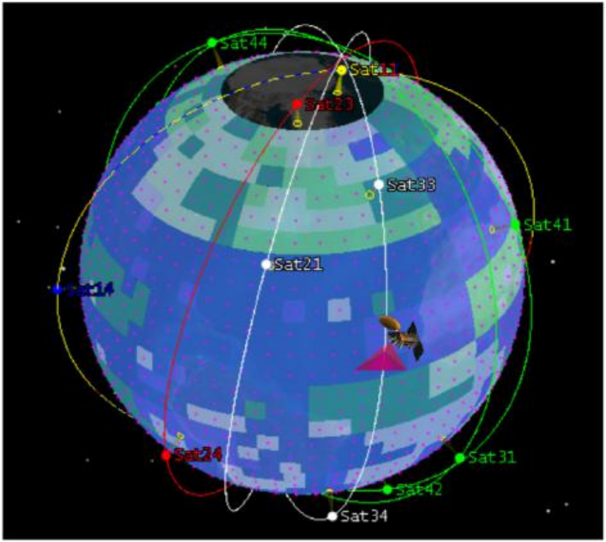

TAT-C Orbital Simulator

"Comb" Viewing $\mapsto$ Single Platform

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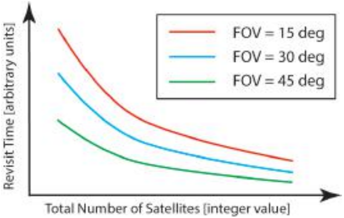
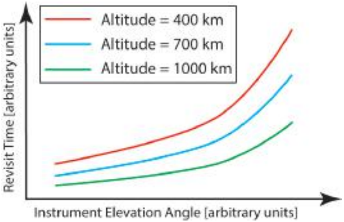
“Comb” Viewing $\mapsto$ Constellation

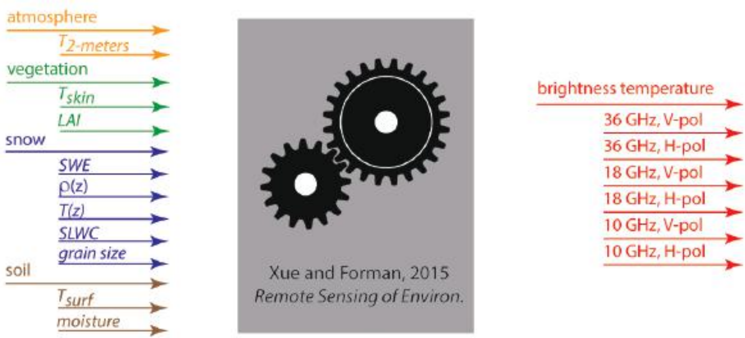
Trade-off Space: Coverage vs. Resolution





- 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"



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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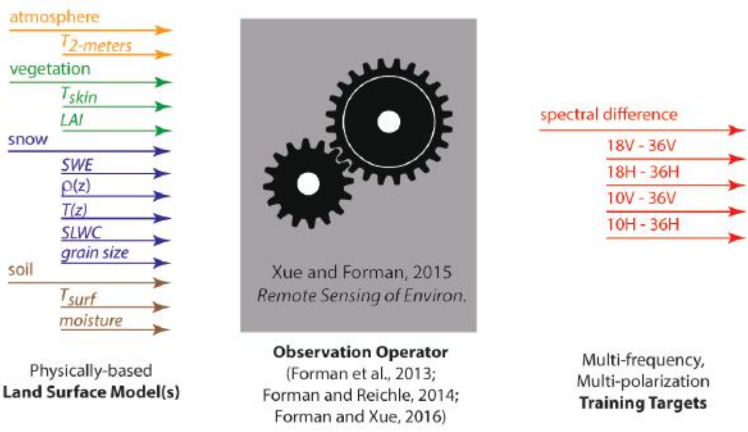

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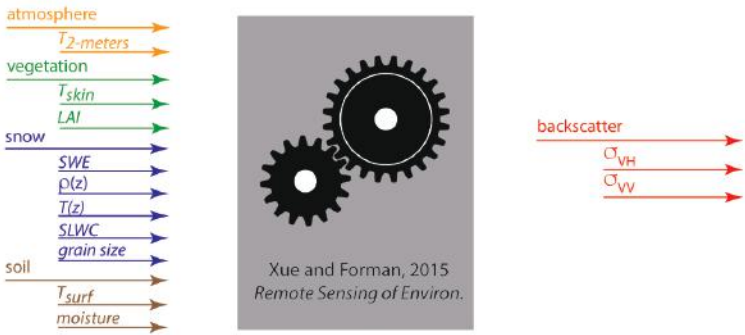

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Spatiotemporal Variability

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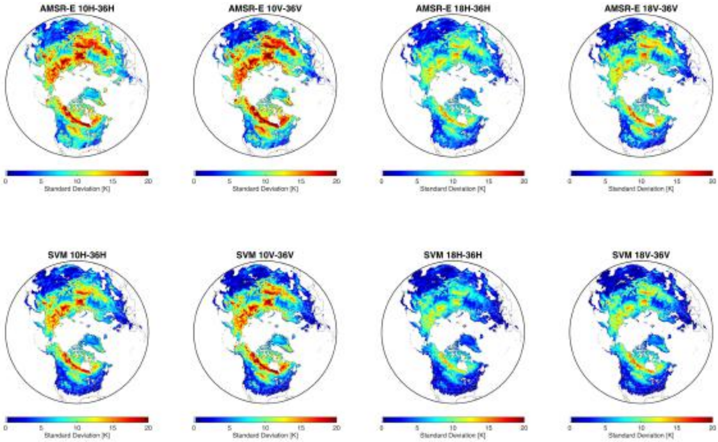

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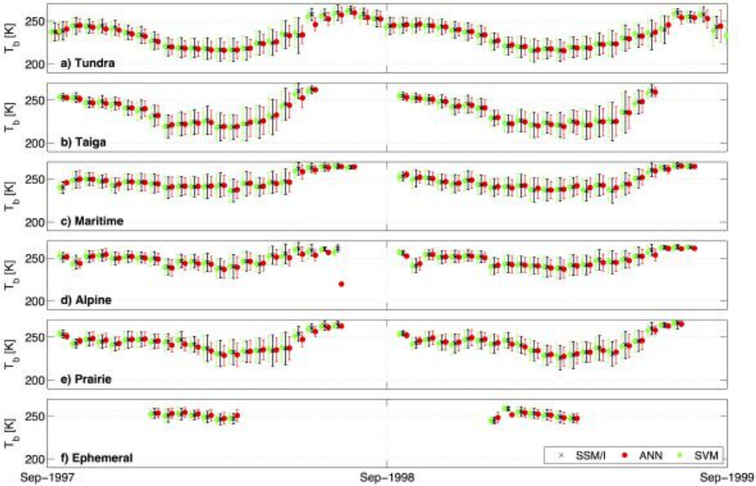

Relevancy Scenarios

- **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 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 σ_0)
  - Enables integration of T_b, σ_0, and δh 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 $\longrightarrow$ open to suggestions!

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Thank You.

Questions and/or Comments?

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