



#### Global Snow from Space: Development of a Satellitebased, Terrestrial Snow Mission Planning Tool

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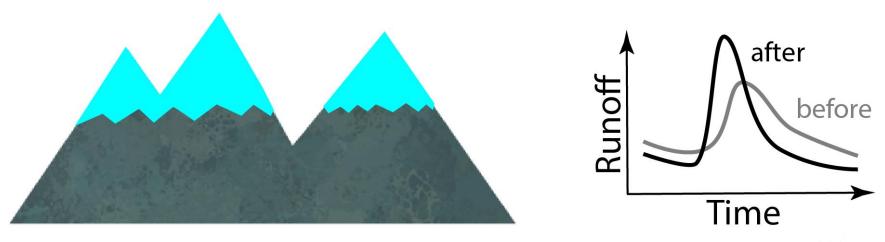
Earth Science Technology Forum, Silver Spring, MD June 12-14, 2018







- Snow is a **significant contributor** to terrestrial freshwater supply
  - Up to 80% of runoff in some Western states
- Vital resource for **~billion people** worldwide
  - Not exactly sure **how much snow** is out there
  - **Difficult to measure**; significant uncertainty;
- Global warming  $\rightarrow$  rising snow line
  - reduced virtual reservoir; accelerated hydrologic cycle;









- Global warming  $\rightarrow$  rising snow line  $\rightarrow$  reduced virtual reservoir
- Goal is to improve snow mass estimation at regional / continental scales
  - No dedicated snow mission
  - Water security  $\rightarrow$  food+energy security  $\rightarrow$  national security

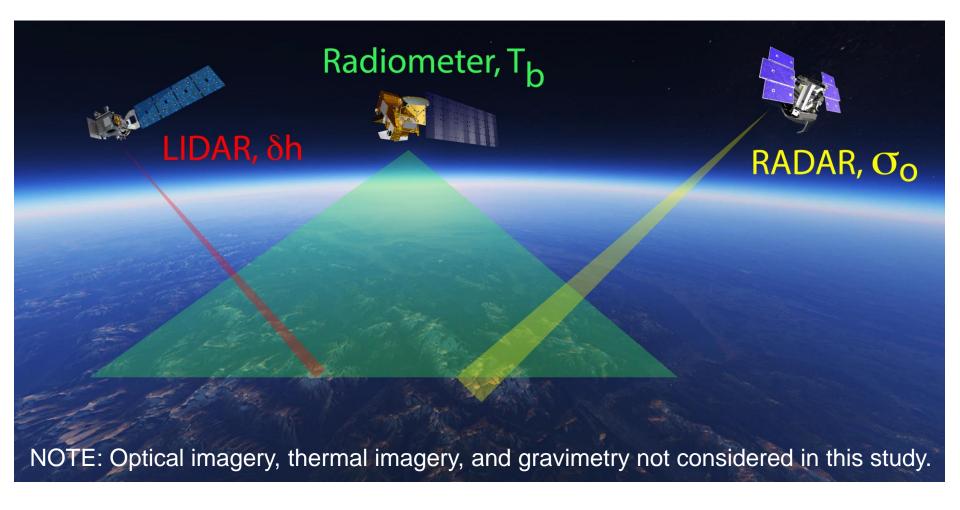
Science and Applications	Science and Applications Questions
Area	Addressed by <b>MOST IMPORTANT</b> Objectives
Coupling of the Water and Energy Cycles	<ul> <li>(H-1) How is the water cycle changing? Are changes in evapotranspiration and precipitation accelerating, with greater rates of evapotranspiration and thereby precipitation, and how are these changes expressed in the space-time distribution of rainfall, snowfall, evapotranspiration, and the frequency and magnitude of extremes such as droughts and floods?</li> <li>(H-2) How do anthropogenic changes in climate, land use, water use, and water storage interact and modify the water and energy cycles locally, regionally and globally and what are the short- and long-term consequences?</li> </ul>

 TABLE S.1 Science and Applications Priorities for the Decade 2017-2027















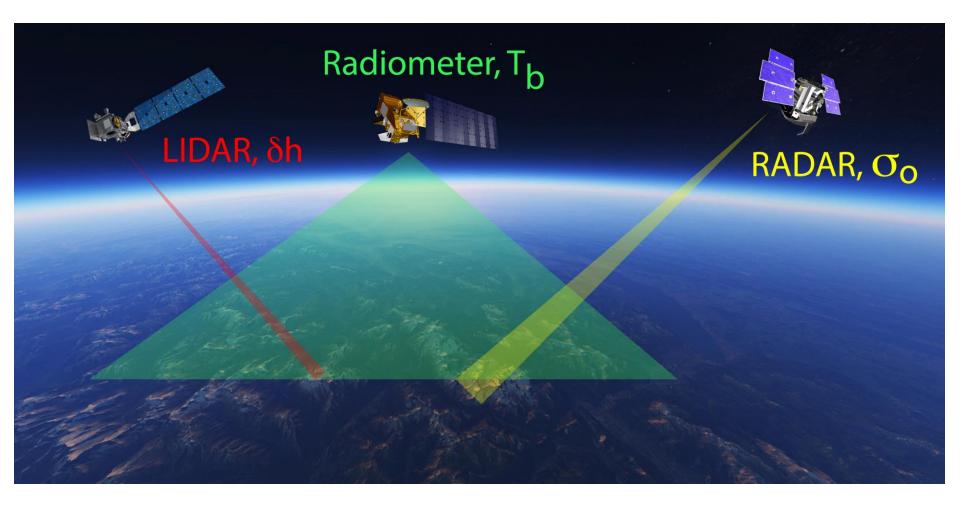
### Science and mission planning questions

- 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?













SNOW



## Global land surface models lack → → → → fidelity as required by RTMs and more ... Physically-based

**Electromagnetic Response** 

Inputs from **Snow Hydrology Model**  Tb Observation Operator

**Microwave Emission Model** (a.k.a., Radiative Transfer)

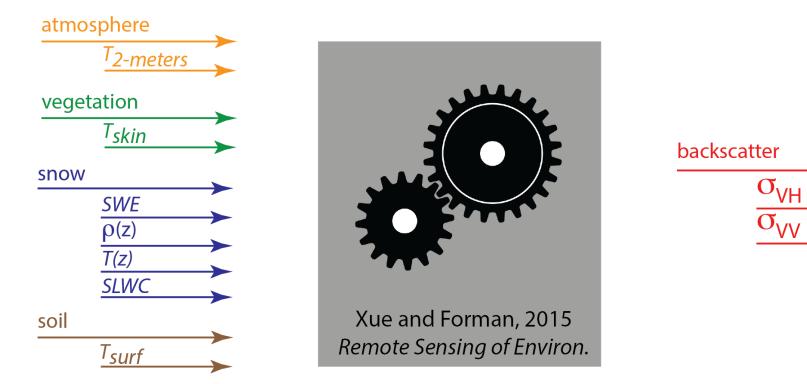
Multi-frequency, Multi-polariztion **Brightness Temperatures** 





#### **Machine Learning "Emulators"**





NASA Catchment **Land Surface Model** (Koster et al., 2000)

#### **Tb Observation Operator**

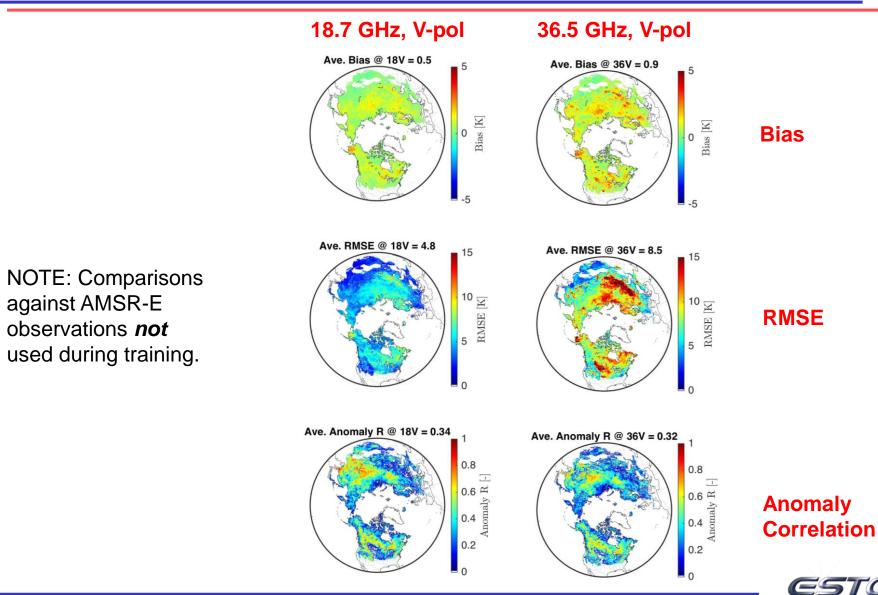
(Forman et al., 2014; Forman and Reichle, 2014; Forman and Xue, 2016) Multi-frequency, Multi-polariztion **Training Targets** 





#### **Machine Learning Performance**

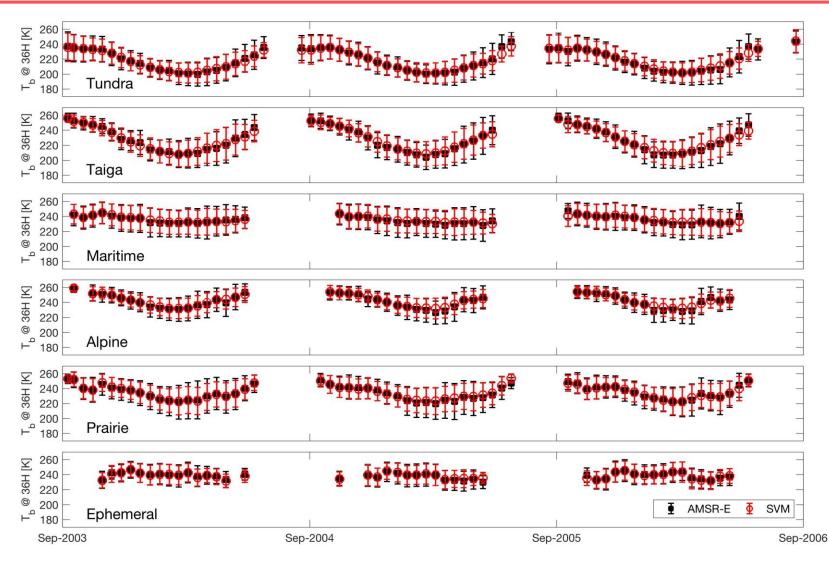






#### **Spatiotemporal Variability**



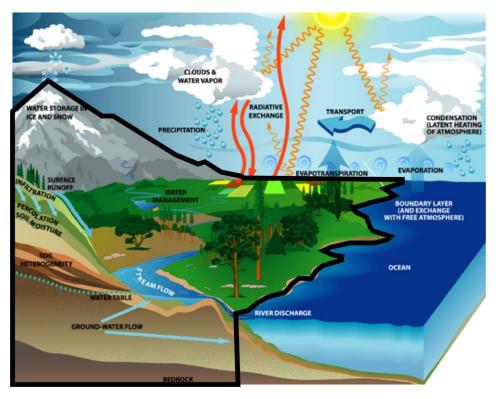








- Models land surface processes (including snow)
- Integrates satellite-based **observational data** products with land surface **modeling and data assimilation techniques**

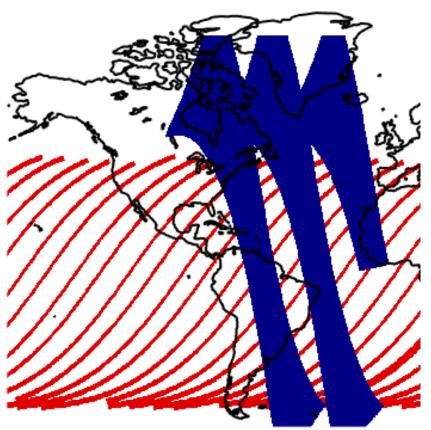


Kumar et al. (2006), Land Information System: An interoperable framework for high resolution land surface modeling, Environmental Modeling and Software









- Explore **trade-off** between engineering and science
  - Field-of-View (FOV)?
  - Platform altitude?
  - Orbital configuration(s)?
  - Single platform vs. constellation?
  - Repeat cycle?
  - How do we get the most **scientific bang** for our buck?

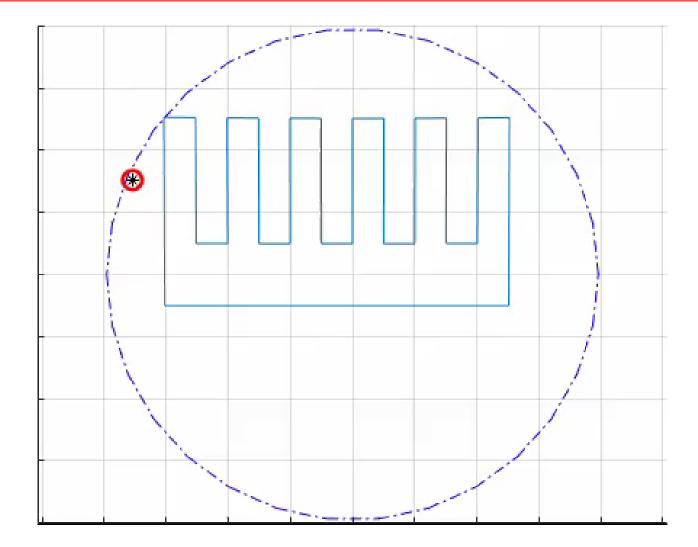
4-hour Radiometer Viewing in Polar Orbit (Ascending Overpasses Only, e.g.)4-hour RADAR Viewing in Inclined Orbit (Descending Overpasses Only, e.g.)





#### **TAT-C: "Comb Viewing" via Single Platform**



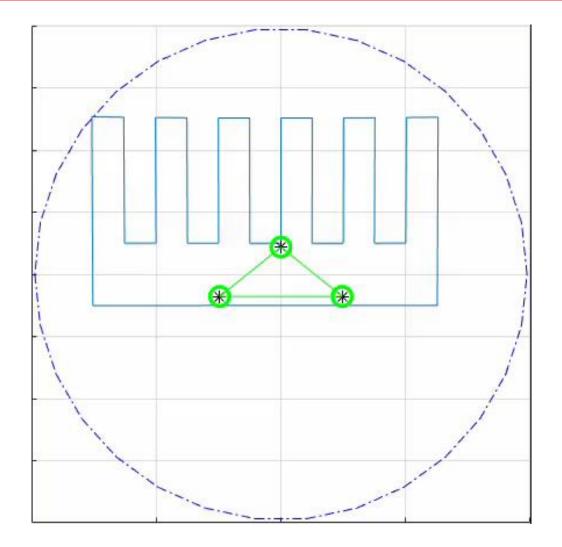






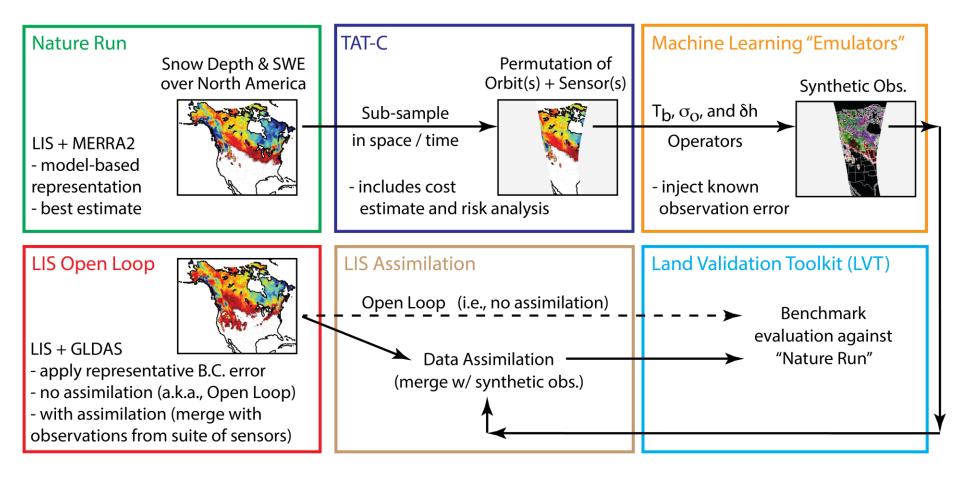
#### **TAT-C: "Comb Viewing" via Constellation**







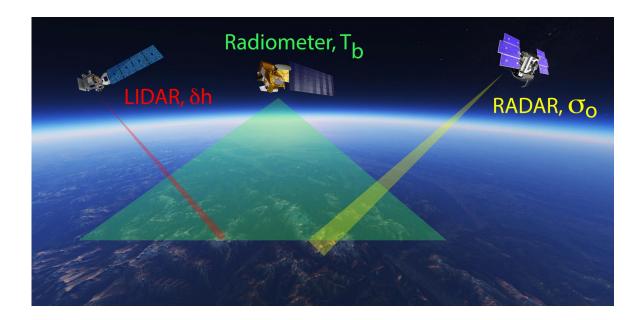


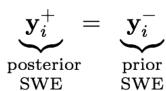


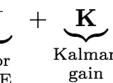












Kalman gain



LIDAR snow depth and/or C-band SAR and/or K-,Ka-,X-band PMW



operator spatiotemporal  $\mathbf{H}$ and/or  $\sigma_0$  machine learning and/or  $T_b$  machine learning



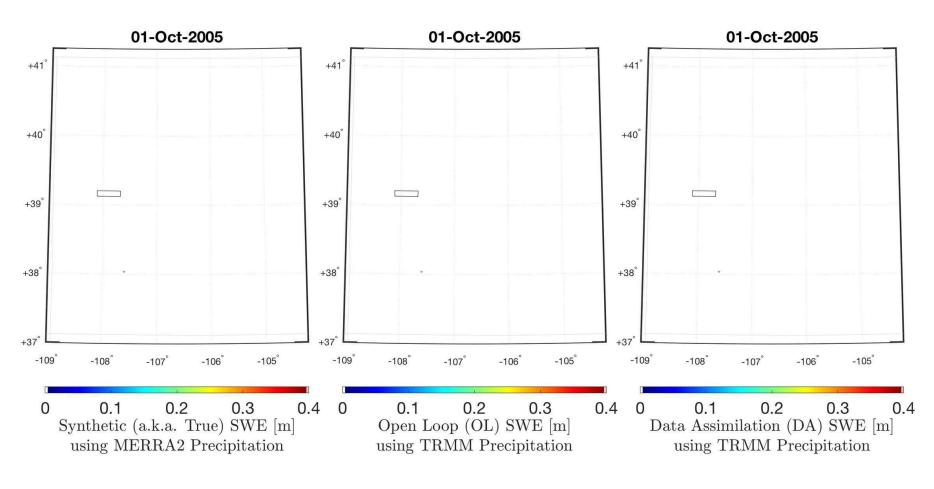


OL



DA

"Truth"









- 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  $\sigma_0$ )
- Snow **OSSE is on-going** . . . open to ideas + suggestions!







# **Thank You!**

# Questions and/or comments?





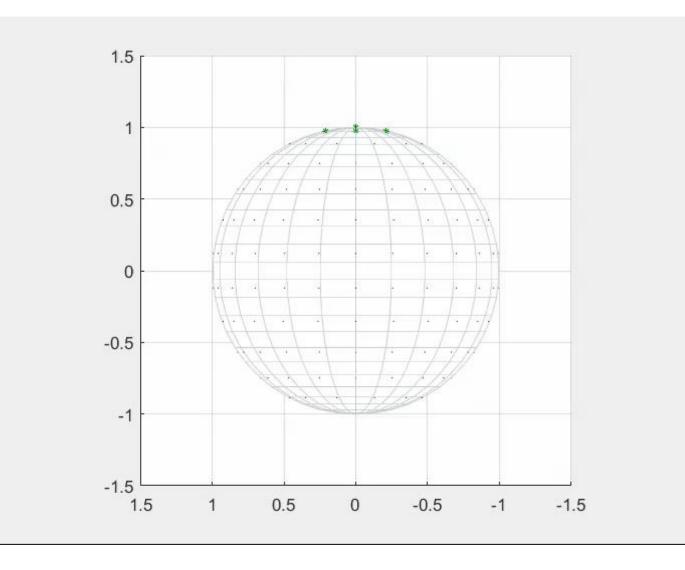






#### **TAT-C Orbital Simulator**

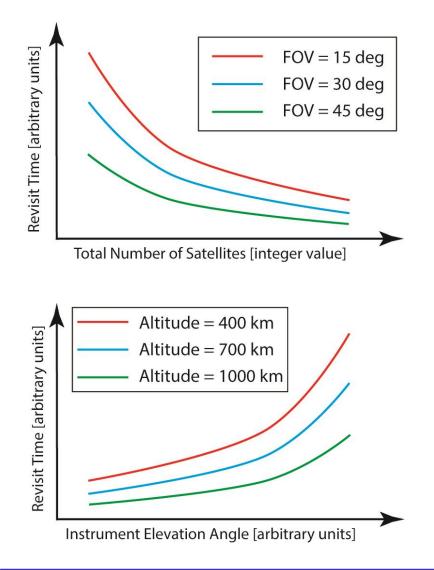












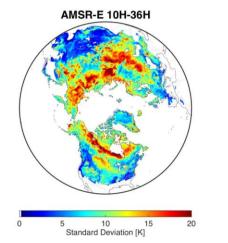
- Explore **trade-off** between engineering and science
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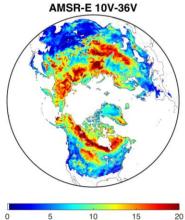




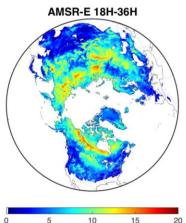
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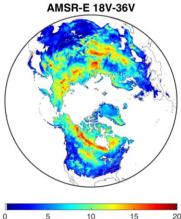




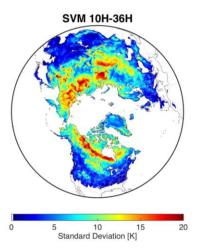
5 10 15 Standard Deviation [K]

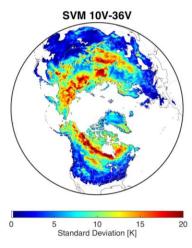


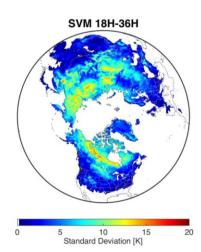


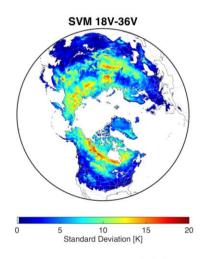


5 10 15 20 Standard Deviation [K]















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

$$\begin{array}{ll} \underset{\mathbf{w}, \, \delta, \, \boldsymbol{\xi}, \, \boldsymbol{\xi}^*}{\text{minimize}} & \frac{1}{2} \langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^m \left( \xi_i + \xi_i^* \right) \\ \text{subject to} & \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle + \delta - z_i \leq \varepsilon + \xi_i \\ & z_i - \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle - \delta \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, m. \end{array}$$

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  $\boldsymbol{\xi}$  and  $\boldsymbol{\xi}^*$  are slack variables.







Primal optimization is commonly solved in **dual form** as:

$$\begin{split} \underset{\alpha_{i}, \ \alpha_{i}^{*}}{\text{minimize}} & \quad \frac{1}{2} \sum_{i,j=1}^{m} \left( \alpha_{i} - \alpha_{i}^{*} \right) \left( \alpha_{j} - \alpha_{j}^{*} \right) \left\langle \phi(\mathbf{x}_{i}) \cdot \phi(\mathbf{x}_{j}) \right\rangle \\ & \quad + \varepsilon \sum_{i=1}^{m} \left( \alpha_{i} + \alpha_{i}^{*} \right) - \sum_{i=1}^{m} z_{i} \left( \alpha_{i} - \alpha_{i}^{*} \right) \\ \text{subject to} & \quad \sum_{i=1}^{m} \left( \alpha_{i} - \alpha_{i}^{*} \right) = 0, \\ & \quad \alpha_{i}, \ \alpha_{i}^{*} \in [0, \ C], \ i = 1, 2, \dots, m \end{split}$$

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

