Dynamic Surface-Background Estimation for Passive-Microwave Snowfall Retrieval

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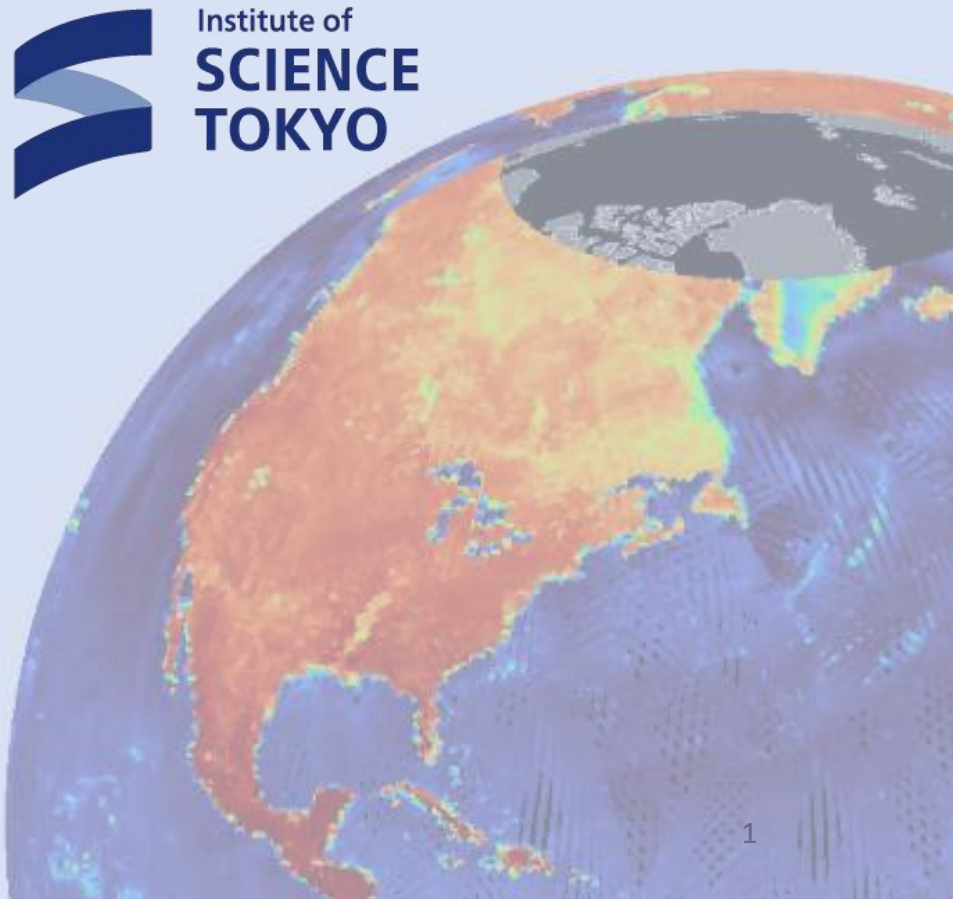
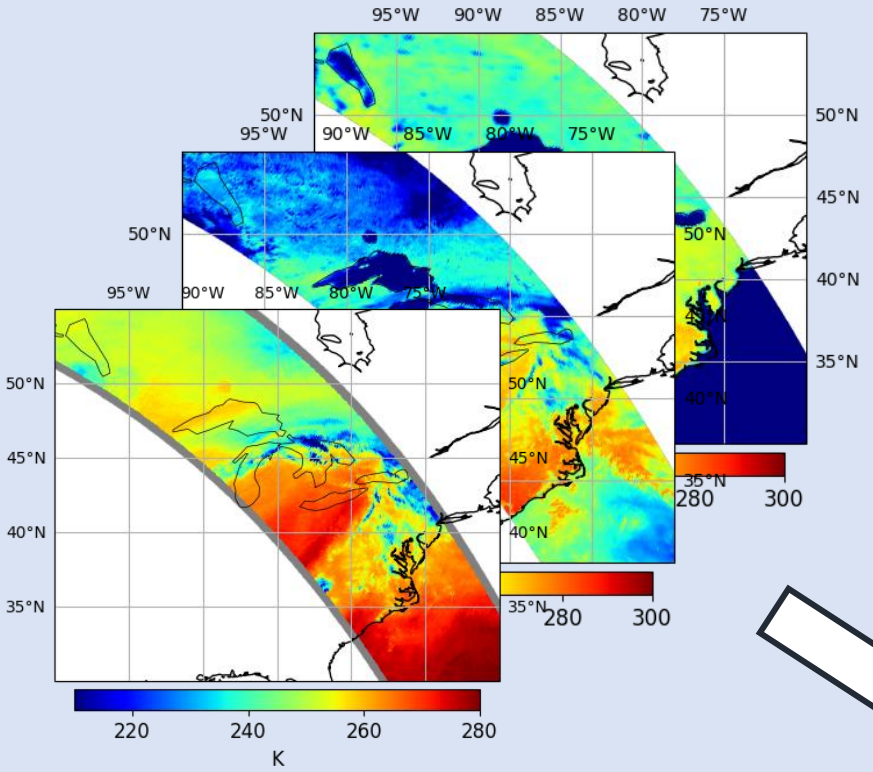


(I) Near-surface snowfall retrieval

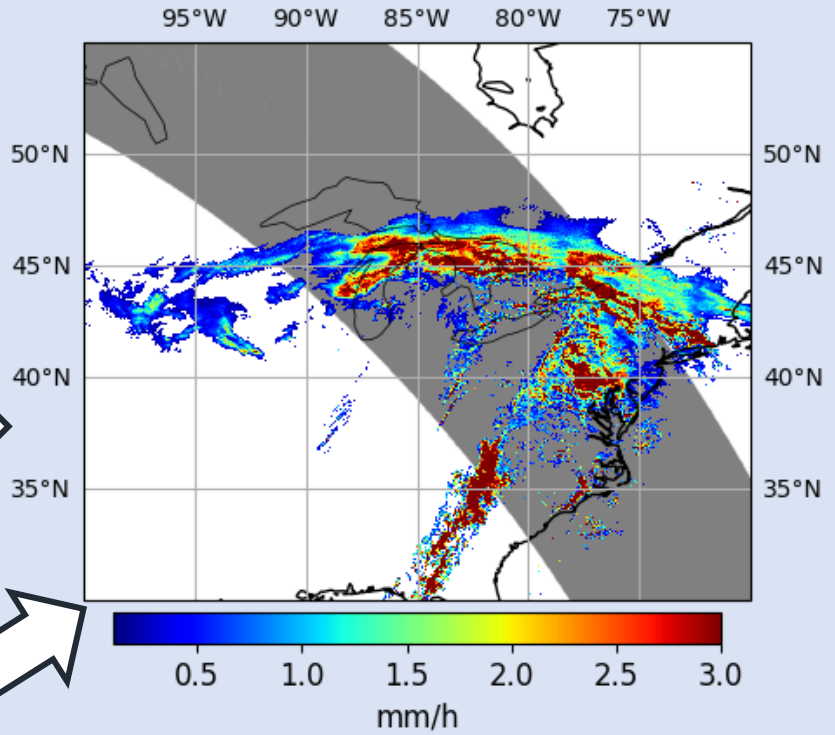


Model inputs:

Multichannel brightness temperatures (TBs)

Machine learning

Radiometric and surface-context features



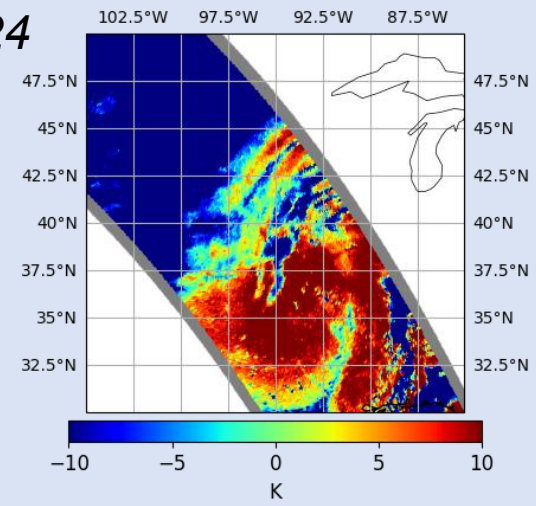
Expected output:

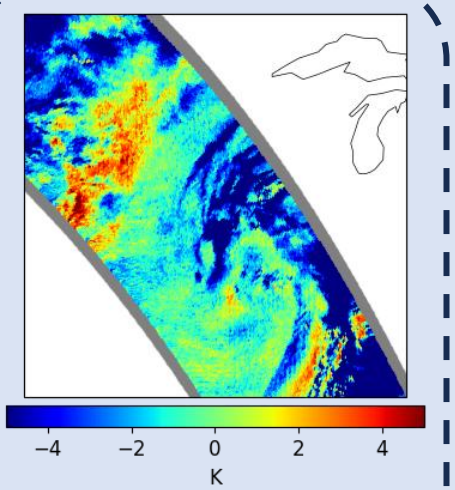
Snowfall probability and rate

(I) Candidates for new features

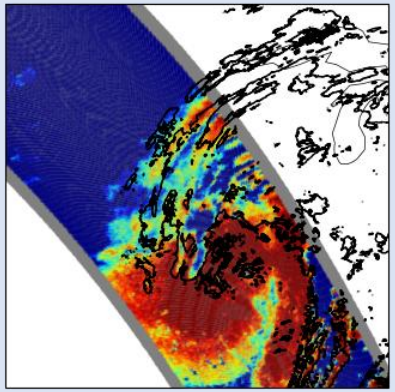
13 Jan 2024

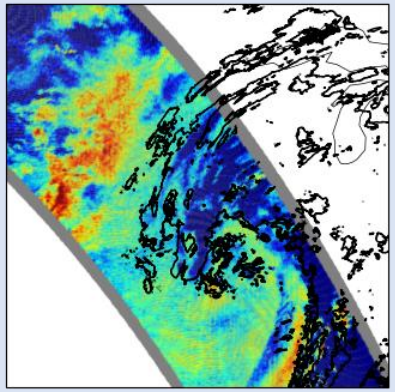
New feature:





New feature with MRMS mask:





Difference between channels:

166 V – 166 H

Difference with surface emission:

Observed – estimated surface (166 V)

- Estimate surface emission using machine learning (ML)
- Calculate from emissivity and temperature (simplified Rayleigh–Jeans):

$$T_B \approx \varepsilon T_{\text{skin}}$$

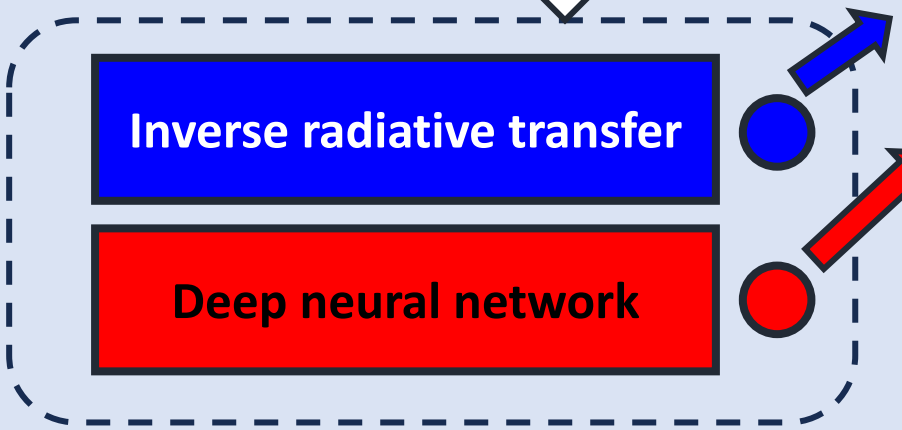
Sources of emissivity

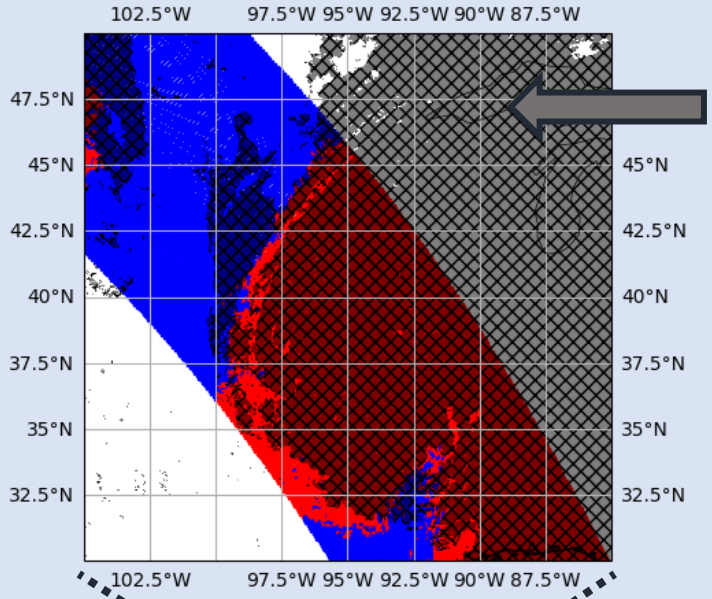
- **Climatological atlases:** TELSEM
- **Dynamic estimation:** inverse radiative-transfer modeling and machine learning
- **Surface classification:** GMI/DPR, PESCA

(I) Surface Emissivity and Temperature Retrieval Algorithm (SETRAP)

Inputs

- Observed TBs (x11)
- Near-surface ancillary variables:
  - Temperature
  - Humidity
  - Pressure



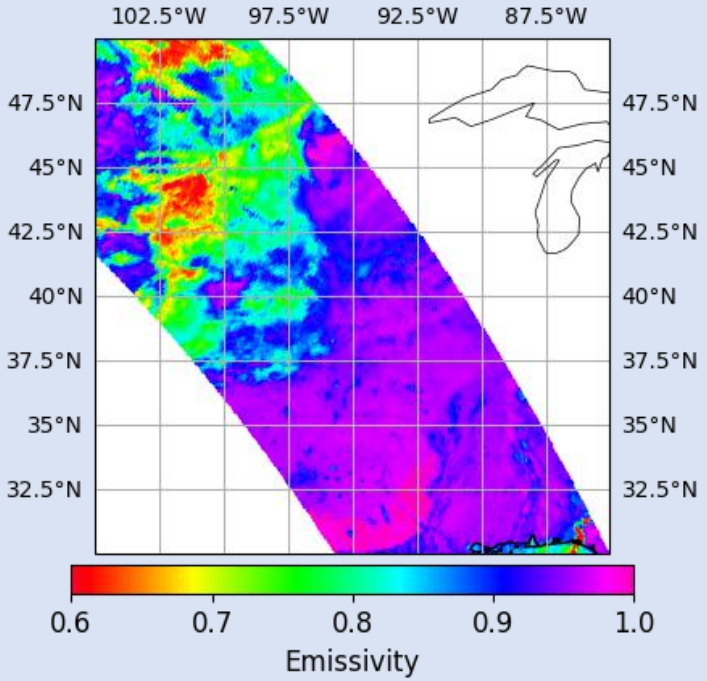


Deep neural network is selected for cloud-masked locations for [166 GHz (H)] according to the **GOES** cloud mask.

Emissivity branch selection

- Independent per channel
- Determined from transmittance

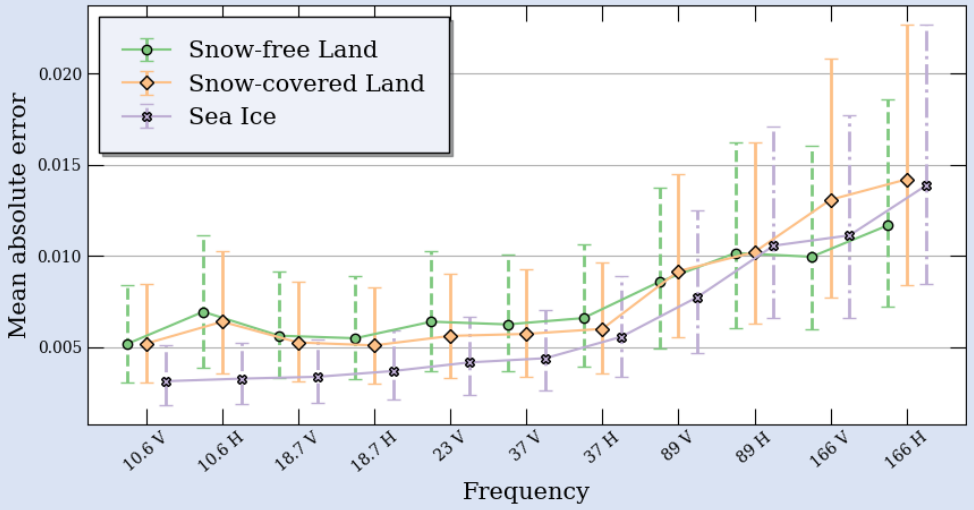
Outputs



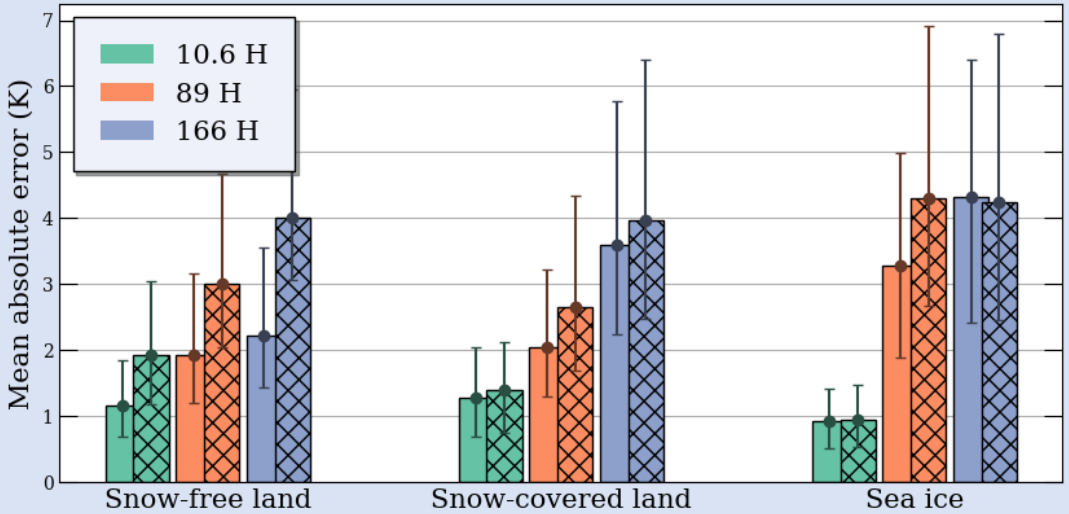
- Surface emissivity (x11)
- Skin temperature

(I) SETRAP performance

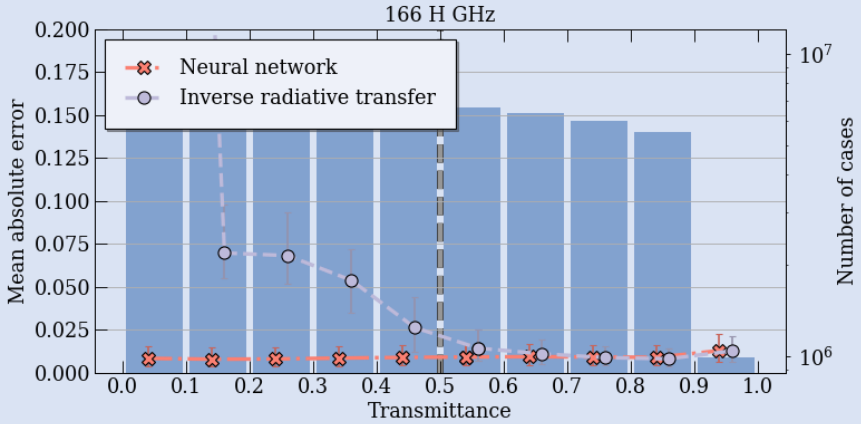
Validation against training database



Validation against observed TB

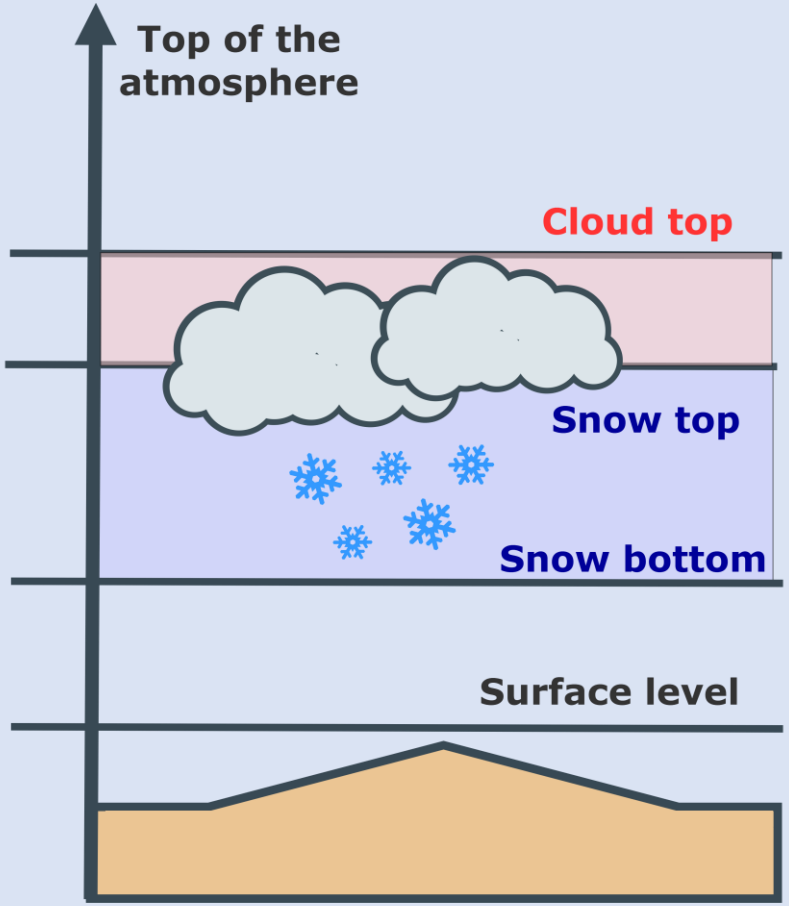


Validation with threshold



- Less than **0.015** MAE for emissivity
- Less than **5K** MAE between simulations with new emissivity source and observed TB
- Performance depends on the correct threshold for model switch

(II) Machine learning for snowfall

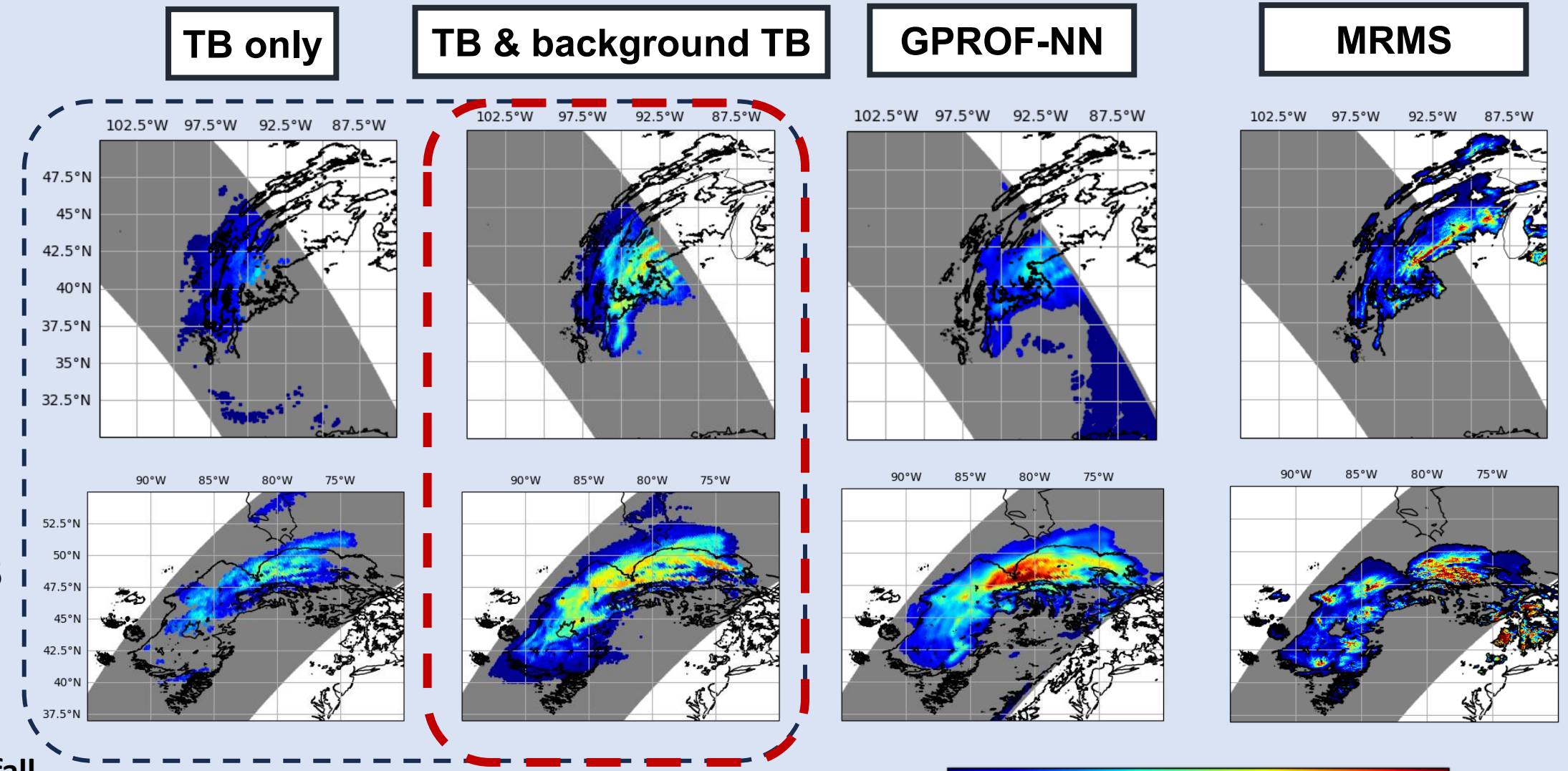


- Deep neural network with a vertical-profile representation:
  1. Cloud presence and cloud top location
  2. Snow presence and snow top/bottom locations
  3. Near-surface snowfall presence and rate

- For inputs, vertical profiles of temperature, humidity and pressure (**ERA5**) are added in addition to observed TB and background TB

- **CloudSat Level-2** products were used as ground truth:
  - 2C-SNOW-PROFILE
  - 2C-PRECIP-COLUMN

(II) Validation with GPROF-NN and MRMS

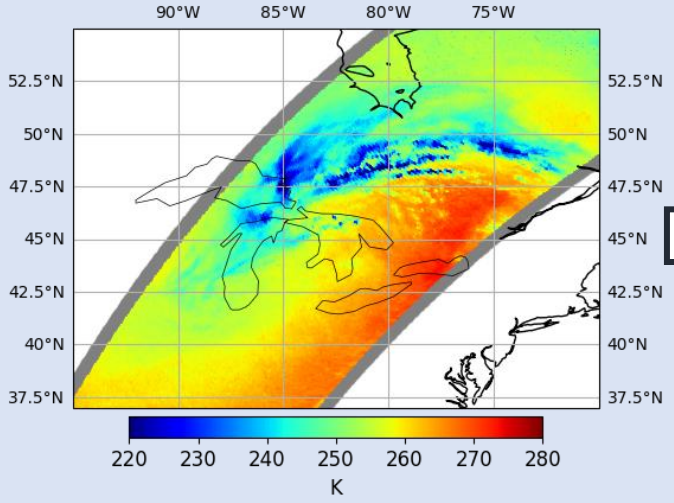


Surface snowfall

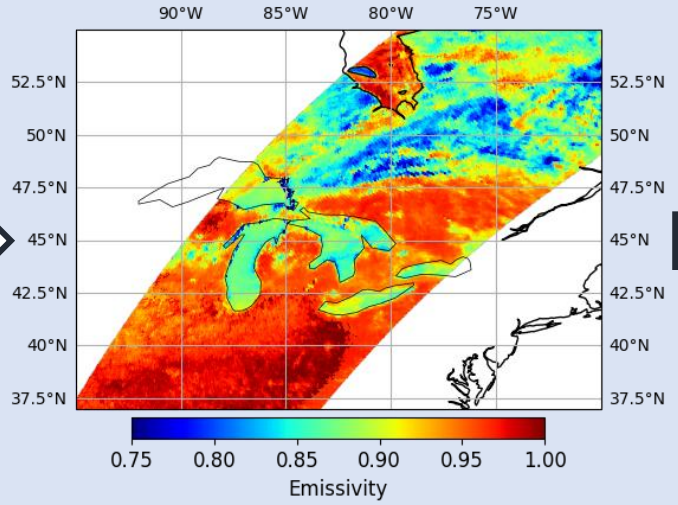
Classification:	HSS: 0.55	HSS: 0.64 ↑
Regression:	RMSE: 0.063	RMSE: 0.057 ↓

(III) Summary

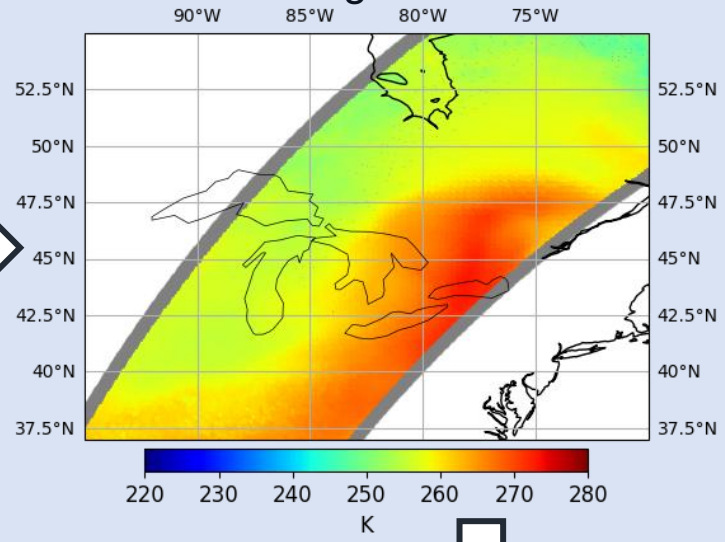
TB measurements



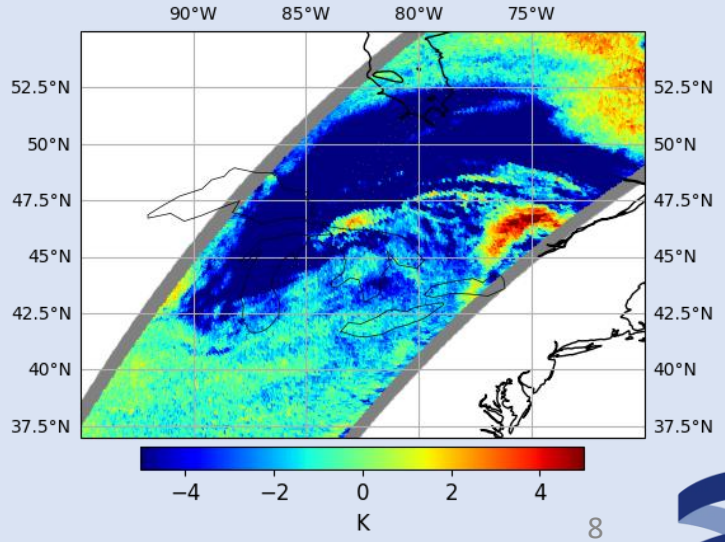
Surface emissivity retrieval (SETRAP)



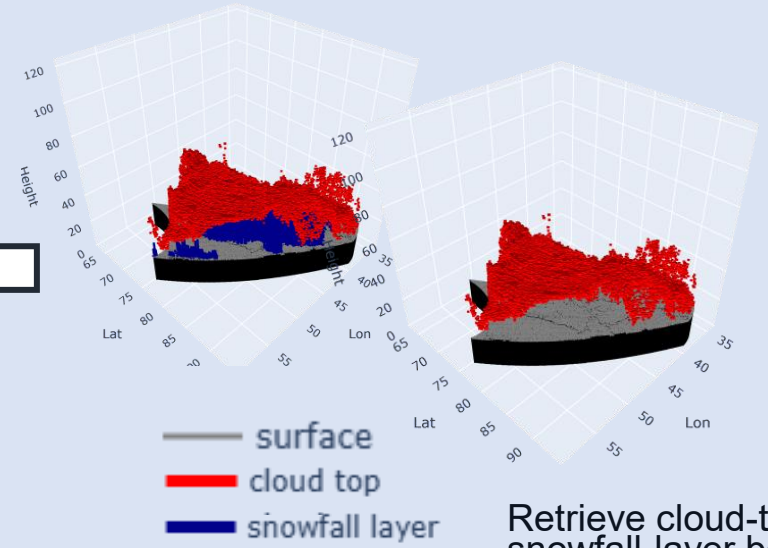
Surface-background TB estimation



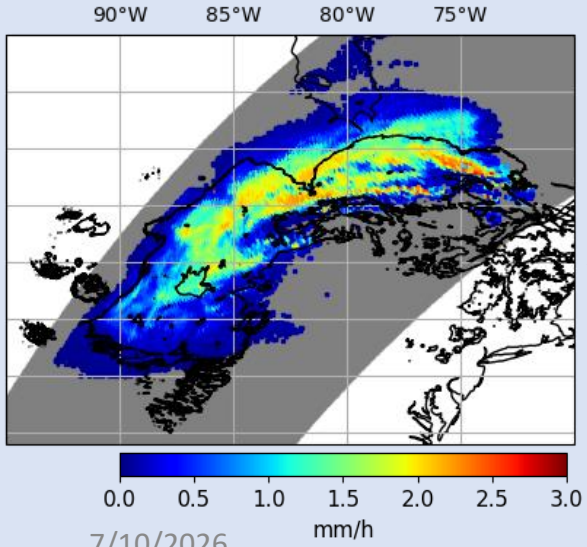
Compute observed - background TB



Retrieve cloud-top and snowfall-layer boundaries



Near-surface snowfall retrieval



(III) Conclusions and future work

Take-home messages

- Land-surface emissivity is an important surface-context feature.
- SETRAP provides channel-specific dynamic surface-background TB estimates under clear and cloudy conditions.
- Adding background TB raises HSS from 0.55 to 0.64 and reduces RMSE from 0.063 to 0.057 in the validation.

Future work

- Integrate **EarthCARE-GPM** coincidence data into training and validation.
- SETRAP-derived land-surface emissivity datasets will be released:
  - Full **2015 GMI swath** dataset
  - **CloudSat-GPM** coincidence dataset

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Laboratory website