Using Machine Learning to Improve Vertical Profiles of Temperature and Moisture for Severe Weather Nowcasting

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Problem and Motivation

Accurate boundary-layer thermodynamic and kinematic profiles are of paramount importance to meteorologists conducting near-term convective threat assessments.

The Storm Prediction Center **relies heavily** on Numerical Weather Prediction (NWP) models, but they include inherit errors and inaccuracies, which can lead to inaccurate forecasts.

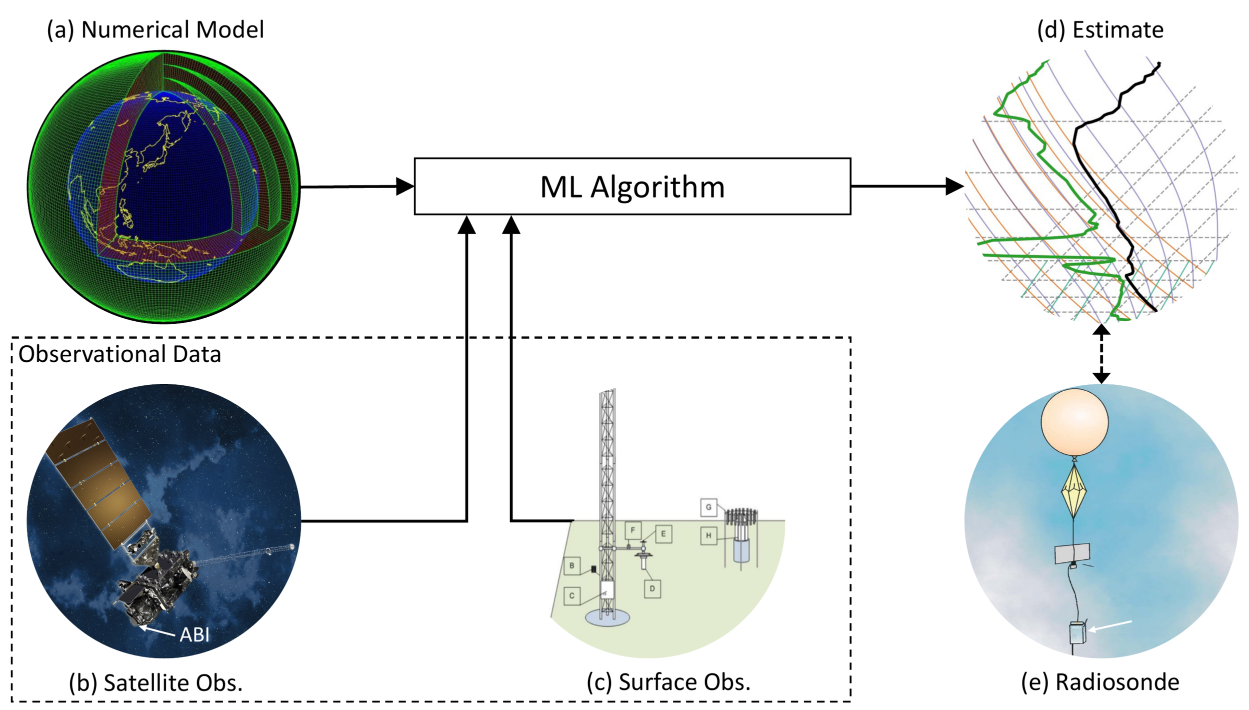

Figure 1: High level flow diagram and primary data sources for the proposed approach.

Scientific question: can vertical profiles of temperature and moisture in NWP models be corrected for and improved, especially near the surface, using machine learning?

Vertical Profiles

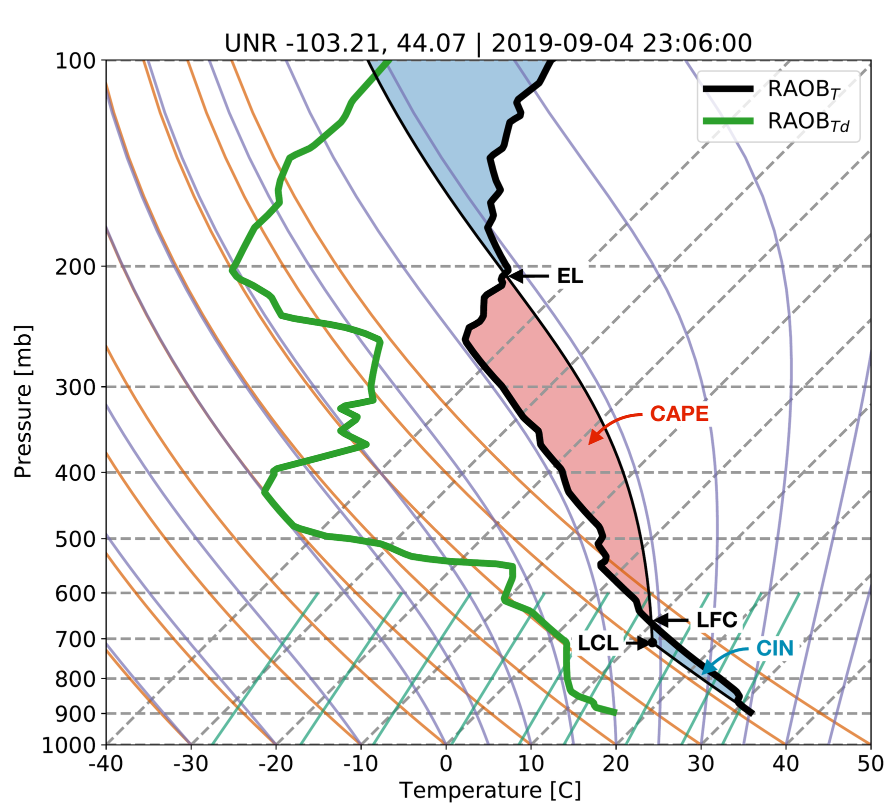

Figure 2: Skew-T Log-P digram of a radiosonde obs. with derived indices.

Datasets Details

A total of 38,373 **Radiosonde Observations (RAOB)s** from 18 locations in the Central U.S. are collected between Jan 1, 2017 — Aug 31, 2020. The following datasets are collocated using the launch metadata of the soundings:

- **The Rapid Refresh (RAP) NWP Model**
  - Temperature, Dewpoint Temperature, Pressure, and Geopotential Height
- **Geostationary Operational Environmental Satellite (GOES)-16 ABI**
  - Water Vapor Bands: 6.2, 6.9, 7.3 µm
  - Window Channels: 8.4, 10.3, 11.2, 12.3, 13.3 µm (near-surface)
- **The Real-Time Mesoscale Analysis (RTMA)**
  - Surface Temperature, Dewpoint Temperature, and Pressure

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Methodology

Our proposal: use deep learning algorithms to combine input from an NWP model, satellite data, and surface observations to produce a retrieval of temperature and moisture that is more like radiosonde observations.

1. Evaluate performance of neural networks over a range of architectures with **increasing complexity**: linear, fully-connected, convolutional, and residual u-net
2. Perform an ablation study over the input data to gain insight of **important features**: RAP ➟ RAOB; RAP/RTMA ➟ RAOB; RAP/GOES ➟ RAOB; RAP/RTMA/GOES ➟ RAOB
3. Quantitatively assess performance under **different meteorological conditions**:
   - Importance of GOES-16 ABI channels
   - Impact of cloud coverage
   - Influence of seasonality
   - Geographical discrepancies

Proposed U-Net Architecture

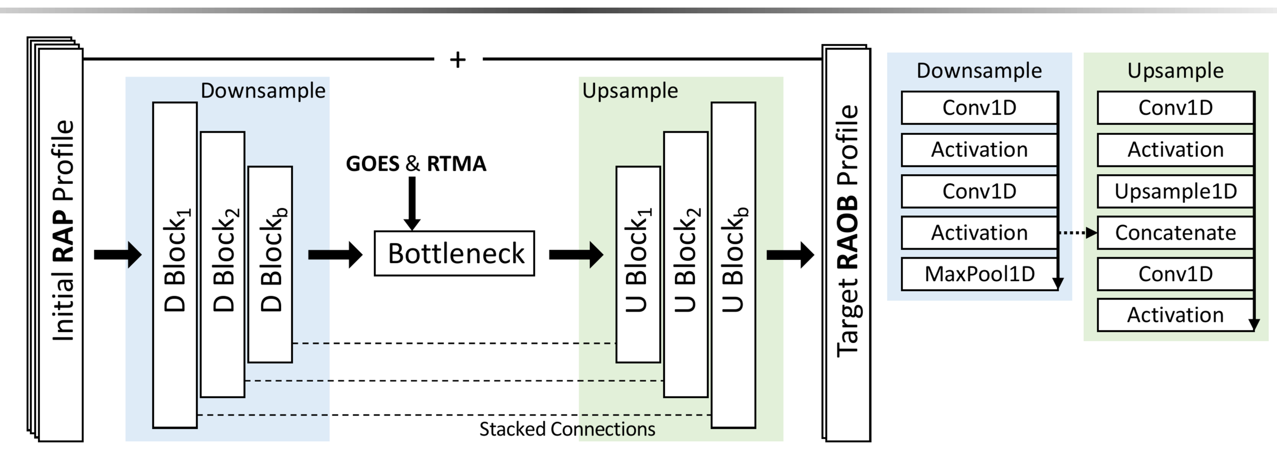

Figure 3: Abstract design of the residual u-net architecture.

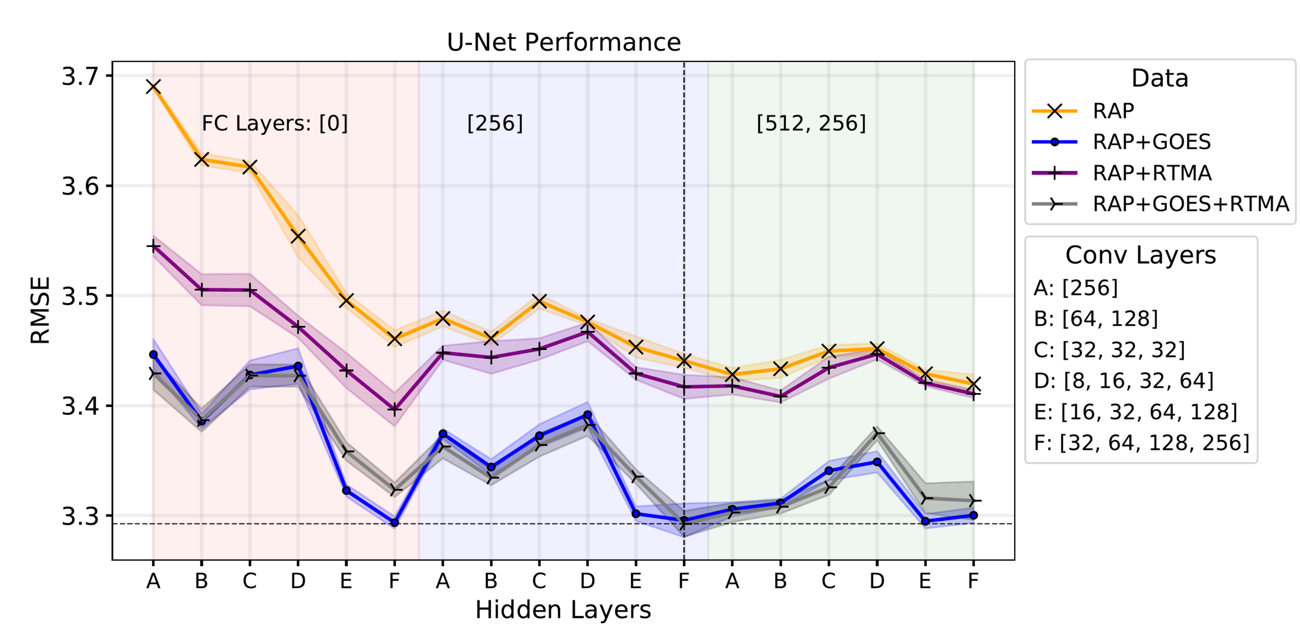

Figure 4: Network profile errors of different u-net architectures and input features.

Knowledge Guided Learning

Examine custom loss functions that capture important profile features and properties.

- Including derived **total precipitable water**, W, from the profiles:

$$W = \frac{1}{p_w g}\int_{p_{sfc}}^{p_{top}} r\,dp,$$

$$L_{tpw} = \frac{1}{n}\sum_{i=1}^{n}(W_{t_i} - W_{y_i})^2,$$

$$L_{tmae} = L_{mae} + \alpha L_{tpw}.$$

- Emphasizing errors of **near-surface** profile estimates:

$$L_{wmae} = \frac{1}{n}\frac{1}{k}\sum_{i=1}^{n}\sum_{j=1}^{k}(\alpha \exp(-\lambda j) + \beta)\,|\,t_{ij} - y_{ij}\,|,$$

General Profile Results

This is the **first known approach** that uses neural networks to improve on vertical profiles from an NWP model. The proposed architecture shows a **26.15% reduction in error** over the profile relative to RAP errors with the greatest improvements at mid- to upper-level moisture.

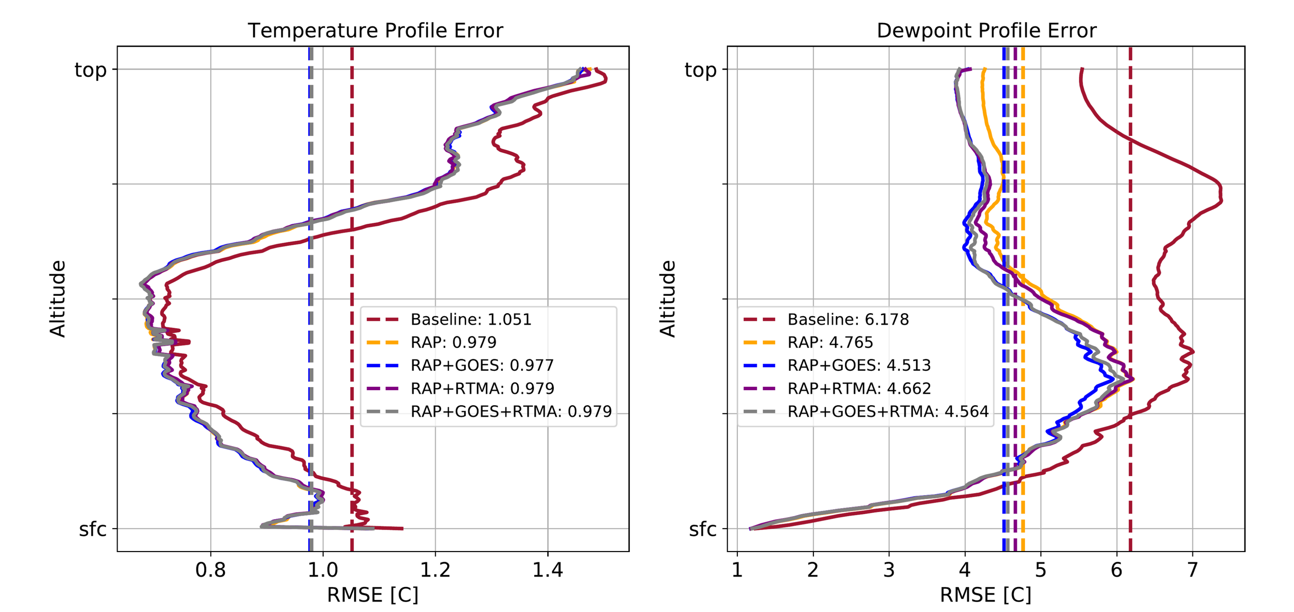

Figure 5: RMSE at every vertical level for models train using different input features.

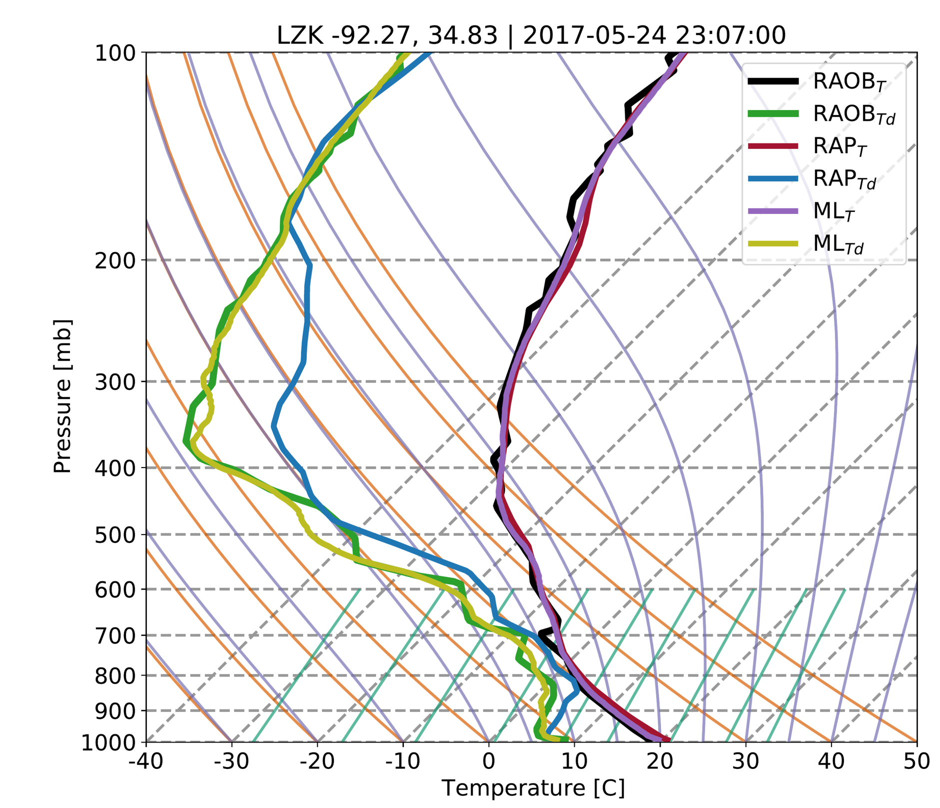

Figure 6: Example Skew-T Log-P digram with sounding estimate.

Evaluating Meteorological Conditions

Additional findings of modeling sounding profiles show:

- **Water vapor bands** (6.2, 6.9, 7.3 µm) from GOES improve the mid-level moisture
- Training with additional samples **even in cloudy conditions** is beneficial
- There is **no observable bias of seasonality** or autocorrelation of samples
- Sounding locations with **more samples** and higher errors have greater improvement

Modeling Sounding Products Directly

The accuracy of derived indices (e.g., CAPE/CIN) are essential to accurately predict and track severe weather events. Indices from ML profiles improve CAPE but not CIN; however, by **directly estimating** these products we see improvements to both indices.

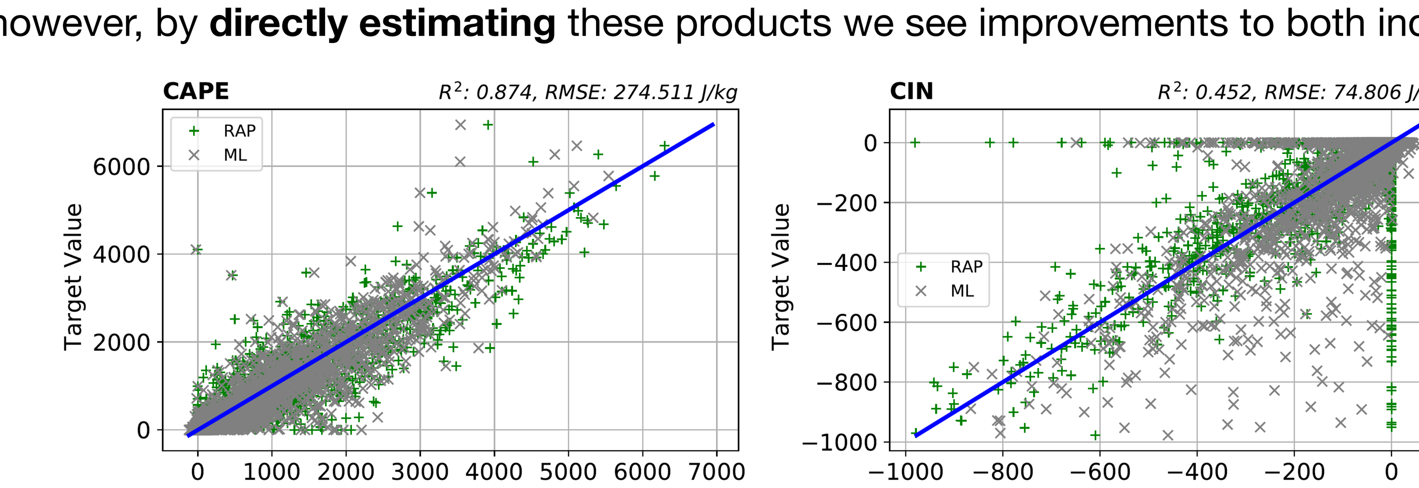

Figure 7: Target RAOB indices versus the RAP and direct ML estimates.