Retrieving temperature and relative humidity profiles from hyperspectral radiations via deep learning

Maosi Chen [1,†], Chaoshun Liu [2], Zhibin Sun [1], Wei Gao [1,3]

[1] USDA UV-B Monitoring and Research Program, Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, Colorado 80523, USA
[2] Key Laboratory of Geographic Information Science, Ministry of Education, East China Normal University, Shanghai 200062, China
[3] Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, Colorado 80523, USA

† maosi.chen@colostate.edu
+1-970-491-3604

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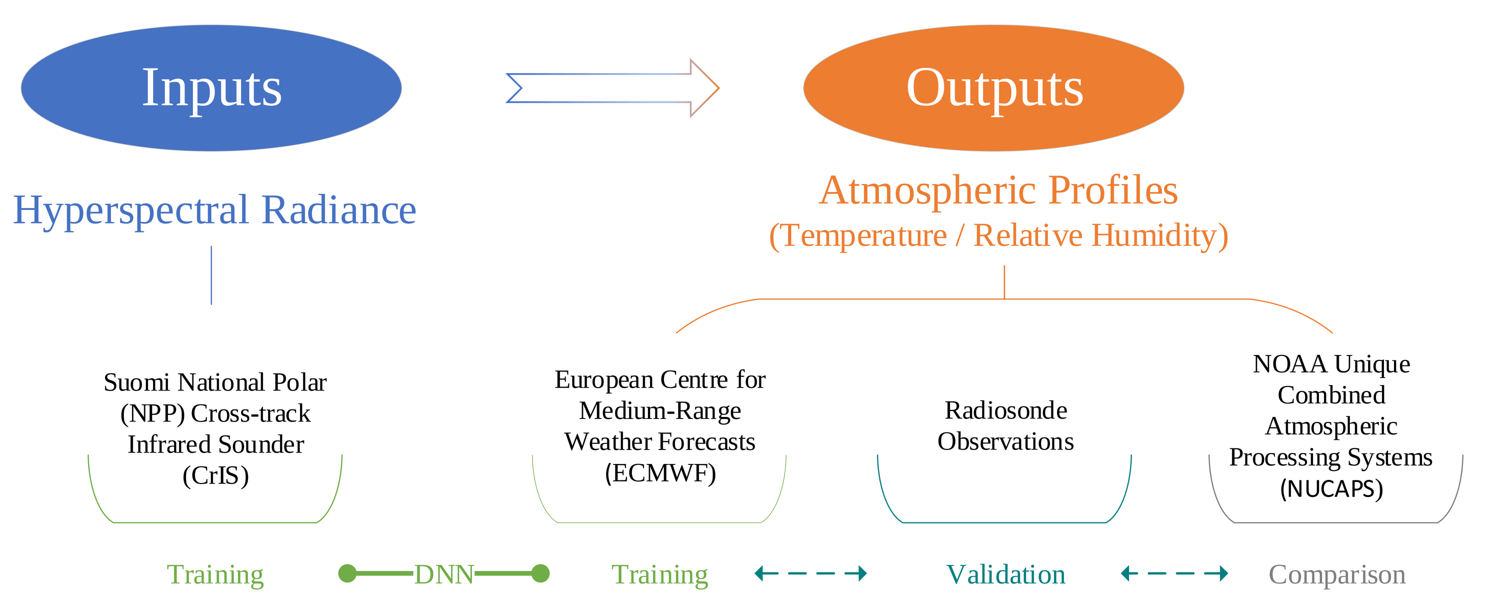
Introduction

Atmospheric temperature and relative humidity profiles are fundamental for atmospheric research such as numerical weather prediction and climate change assessment. Hyperspectral satellite data contain a wealth of relevant information and have been used in many algorithms (e.g. regression-based methods) to retrieve these profiles. Deep Learning or Deep Neural Network (DNN) is capable of finding complex relationships (functions) between pairs of input and output variables by assembling many simple non-linear modules together and learning the parameters therein from large amounts of observations. DNN has been successfully applied in many fields (such as image classification, object detection, language translation). In this study, we explored the potential of retrieving atmospheric profiles from hyperspectral satellite radiation data using DNN. The requirement for applying the DNN technique is satisfied with large amount of hyperspectral radiance data provided by United States Suomi National Polar (NPP) Cross-track Infrared Sounder (CrIS) and the reanalyzed atmospheric profiles data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The proposed DNN consists of two consecutive parts. In the first part, the first 1245 bands of the NPP CrIS hyperspectral radiance data (648.75 to 2555 cm^{-1}) are compressed into a 300-element vector representing their key features by stacked AutoEncoders. Then, in the second part, the multi-layer Self-Normalizing Neural Network (SNN) is used to map the compressed vector (of 300 elements) into 55-layer temperature and relative humidity profiles. The DNN trainable variables are optimized by minimizing the difference of its predictions and the matched ECMWF temperature and humidity profiles (53230 samples). Finally, the DNN retrieved atmospheric temperature and relative humidity profiles and those provided by the NOAA Unique Combined Atmospheric Processing System (NUCAPS, the official retrieval products for CrIS) are compared with the matched radiosonde observations at one location.

1. Datasets



NUCAPS

- Available Variables: T, rh, O_3, CH_4, CO_2, CO, SO_2, HNO_3, N_2O
- Layers: 101 (original) → 55 pressure levels (96-1014 mb)
- Resolution: 0.5° x 0.5° (3 x 3 FOV array), daily
- Algorithm: eigenvector regression + infrared physical retrieval
- Training dataset: NPP CrIS, NPP ATMS (microwave), ECMWF analysis
- Archive: Comprehensive Large Array-Data Stewardship System (CLASS): www.nsof.class.noaa.gov
- Cloud Mask: < 15%
- Date range: June to September in 2014, 2015, 2016

NPP CrIS

- Instrument: Fourier transform spectrometer, 2200 km swath width, 30 Earth-scene views. Each field consists of 9 fields of view (3x3 array).
- Bands: long-wave IR (LWIR, 717 bands, 648.75-1096.75 cm^{-1}, freq. incr.: 0.625 cm^{-1},), mid-wave IR (MWIR, 437, 1207.5-1752.5 cm^{-1}, freq. incr.: 1.25 cm^{-1}), short-wave IR (SWIR, 2150-2555 cm^{-1}, freq. incr.: 2.5 cm^{-1}). First 1245 bands used.
- Resolution: 15 km x 15 km (single FOV), daily.
- Archive: CrIS SDR files are archived in NOAA Comprehensive Large Array-data Stewardship System (CLASS).
- Cloud Mask: < 15%
- Date range: June to September in 2014, 2015

Radiosonde

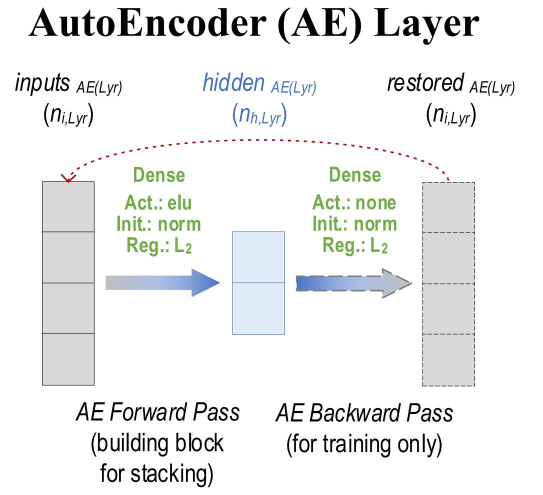
- Station: Baoshan (31.4° N, 21.45° E)
- Layers: interpolated to 55 pressure levels (96-1014 mb)
- Resolution: Twice a day (00:00, 12:00 UTC)
- Archive: China Meteorological Administration
- Date range: June to September in 2014, 2015, 2016

ECMWF

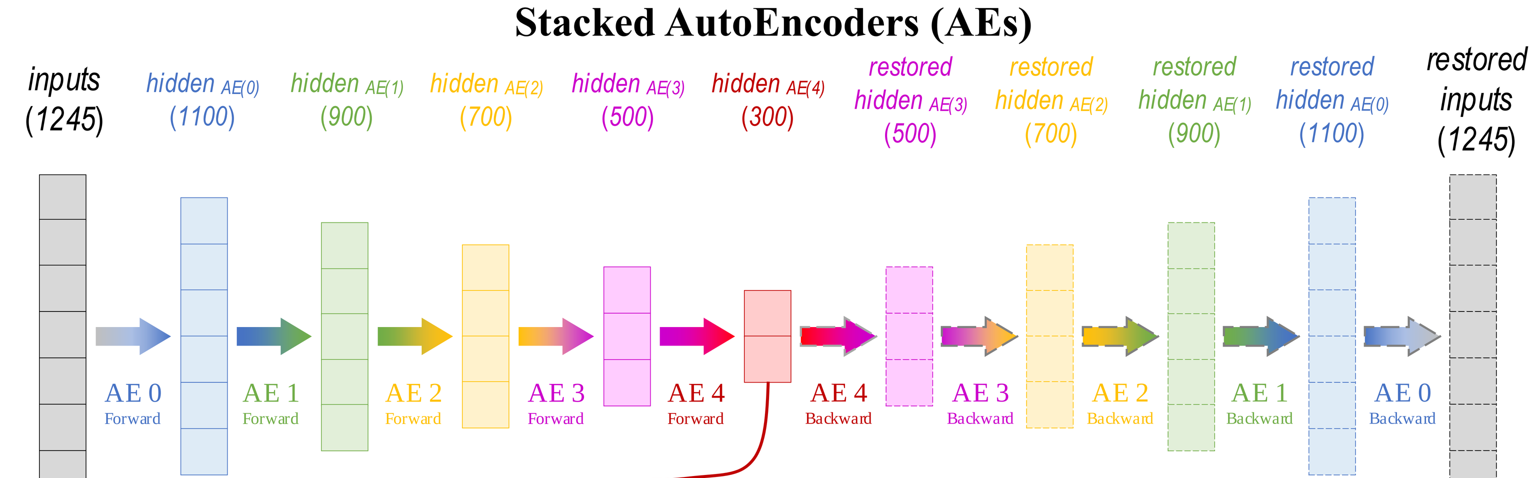
- Dataset name: ERA-Interim, daily
- Layers: 60 (original) → 55 pressure levels (96-1014 mb)
- Resolution: 0.125°, 4 times a day (use the one at 6:00 UTC).
- Archive: ECMWF Public Datasets web interface, apps.ecmwf.int/datasets/data/interim-full-daily/
- Cloud Mask: < 15%
- Date range: June to September in 2014, 2015

2. The DNN model (AEs + SNN)

AutoEncoder (AE) Layer



Stacked AutoEncoders (AEs)



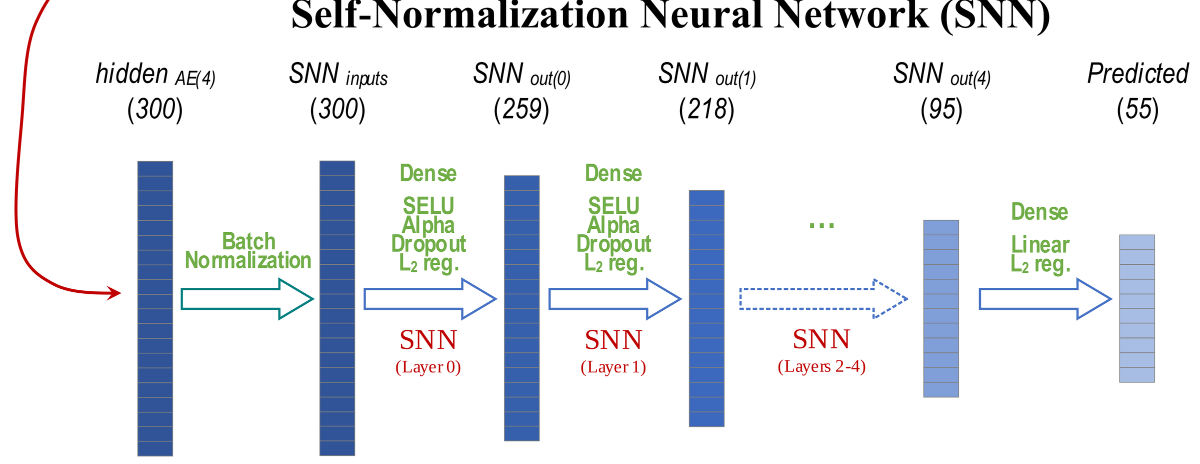
AEs & SNN Training parameters

- λ_{AE}, λ_{SNN}: 0.01 (init.)
  - *decay steps:* 30 epochs
  - *decay rate:* 0.84
  - *scaling:* $1/(n_{in} \times n_{out})$
- *dropout rate:* 0.05
- *Optimizer:* Adam
- *learning rate:* 3×10^{-5} (init.)
  - *decay steps:* 30 epochs
  - *decay rate:* 0.96
- *Batch size:* 200
- *Buffer size:* 60,000
- *Read ahead epochs:* 1
- *Training samples:* 53230
- *Training epochs:* 300
- *Validation samples:* 20
- *Validation freq. (epochs):* 5

$$Loss_{AE(Lyr)} = MSE(restored_{AE(Lyr)}, inputs_{AE(Lyr)}) + \lambda_{AE} \cdot L_2(weights_{AE(Lyr)})$$

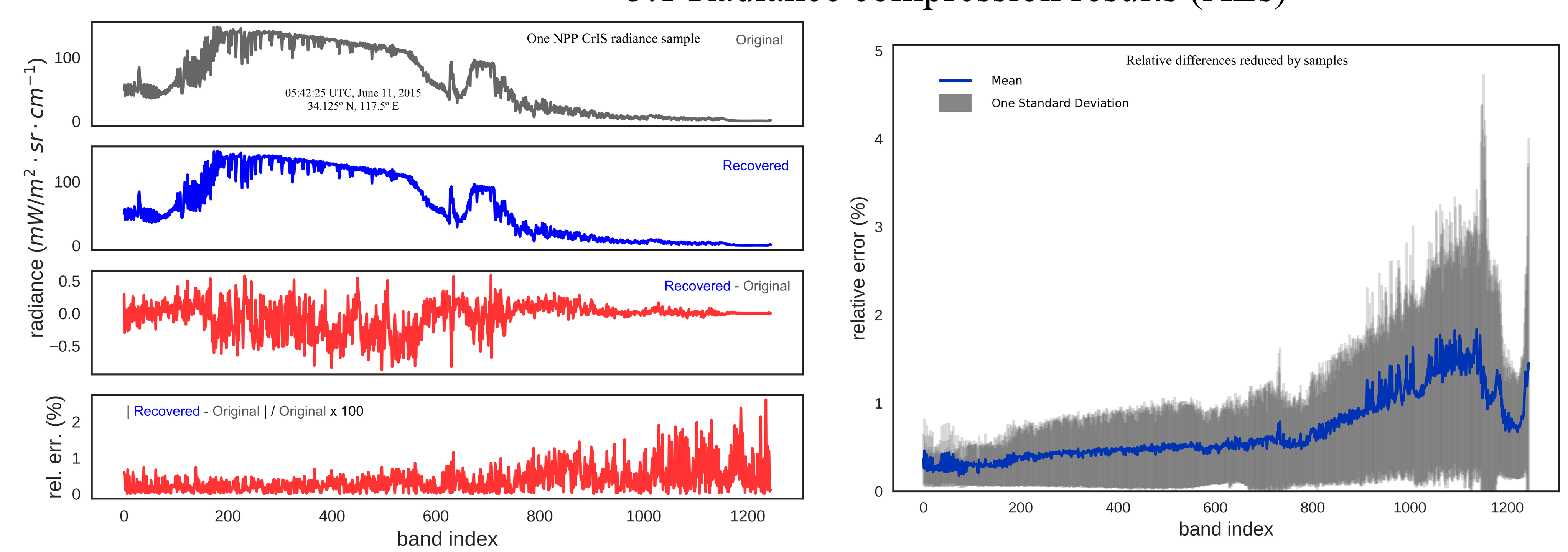
$$Loss_{SNN} = MSE(predicted, observed) + \lambda_{SNN} \cdot L_2(weights_{SNN})$$

Self-Normalization Neural Network (SNN)



3. Results

3.1 Radiance compression results (AEs)

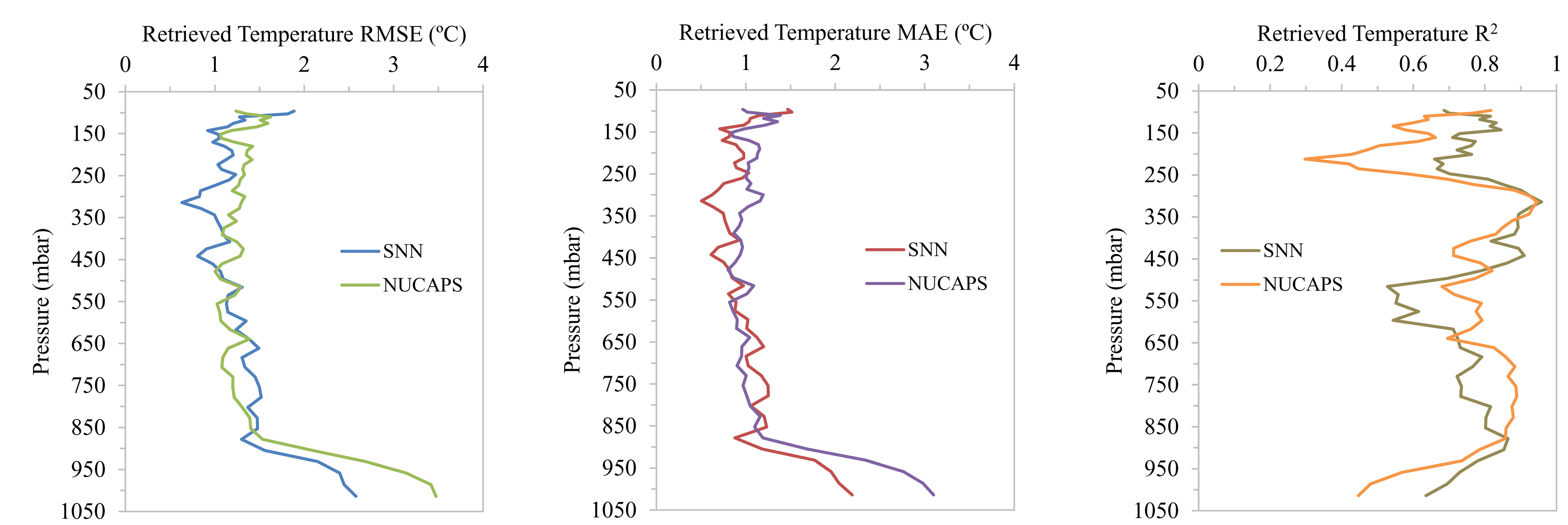


Radiance

Statistics for all bands and samples

- relative difference
  mean: 0.0055
  std. dev.: 0.0063
- correlation coefficient
  mean: 0.9974
  std. dev.: 0.0014

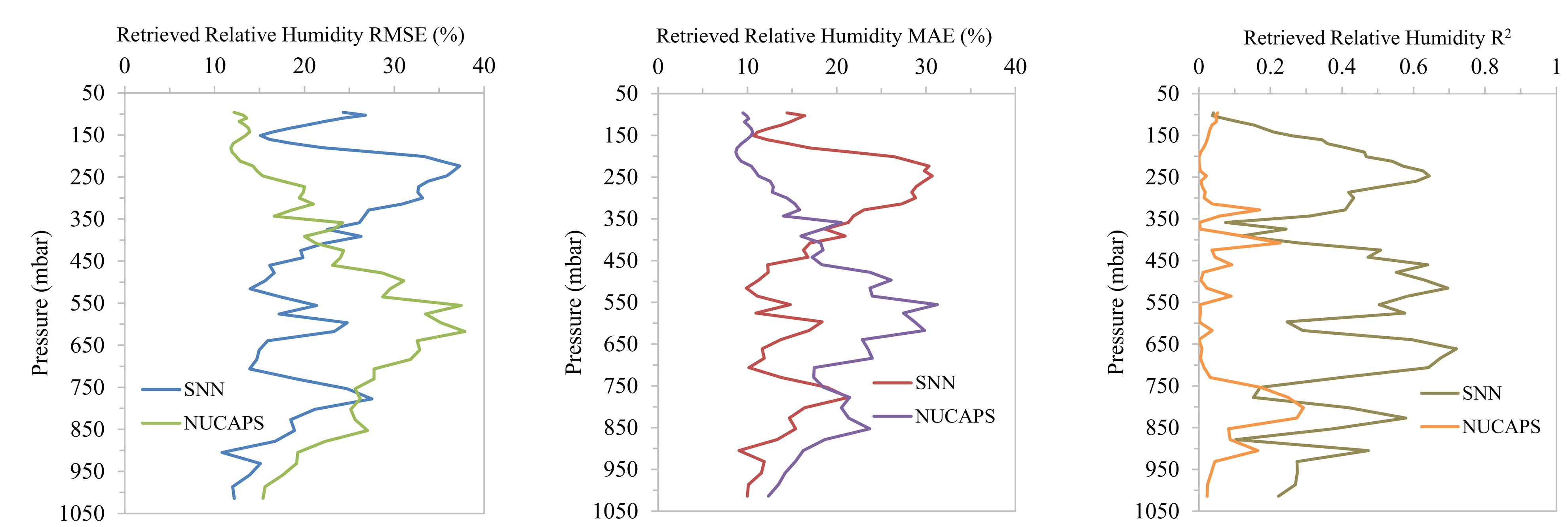
3.2 Temperature and Relative Humidity retrieval results (SNN)



Temperature

Statistics for all layers and samples

- RMSE
  SNN: 1.3358°C
  NUCAPS: 1.5100°C
- MAE:
  SNN: 1.0161°C
  NUCAPS: 1.1591°C
- R^2:
  SNN: 0.9982
  NUCAPS: 0.9980



Relative Humidity

Statistics for all layers and samples

- RMSE
  SNN: 23.299%
  NUCAPS: 22.549%
- MAE:
  SNN: 17.289%
  NUCAPS: 16.527%
- R^2:
  SNN: 0.4071
  NUCAPS: 0.3096

Summary

- AEs reduced the dimension of radiance data from 1245 to 300 with a small loss.
- SNN-retrieved temperature profiles showed slightly better validation results than those from NUCAPS (especially in lower atmospheric layers). SNN-retrieved relative humidity profiles showed mixed results: lower layers had improved performance comparing with NUCAPS, while the upper layers displayed an opposite pattern.
- The poorer performance on relative humidity is because its distribution from ECMWF is significantly different from the radiosonde counterparts.
- The attribution of the radiance to the predicted atmospheric profiles will be analyzed in the future.

References

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USDA
UV-B Monitoring and Research Program
NREL NATURAL RESOURCE ECOLOGY LABORATORY
Department of ECOSYSTEM SCIENCE & SUSTAINABILITY
Colorado State University
ECNU GIS