

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

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## Abstract

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<sup>-1</sup>) 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.



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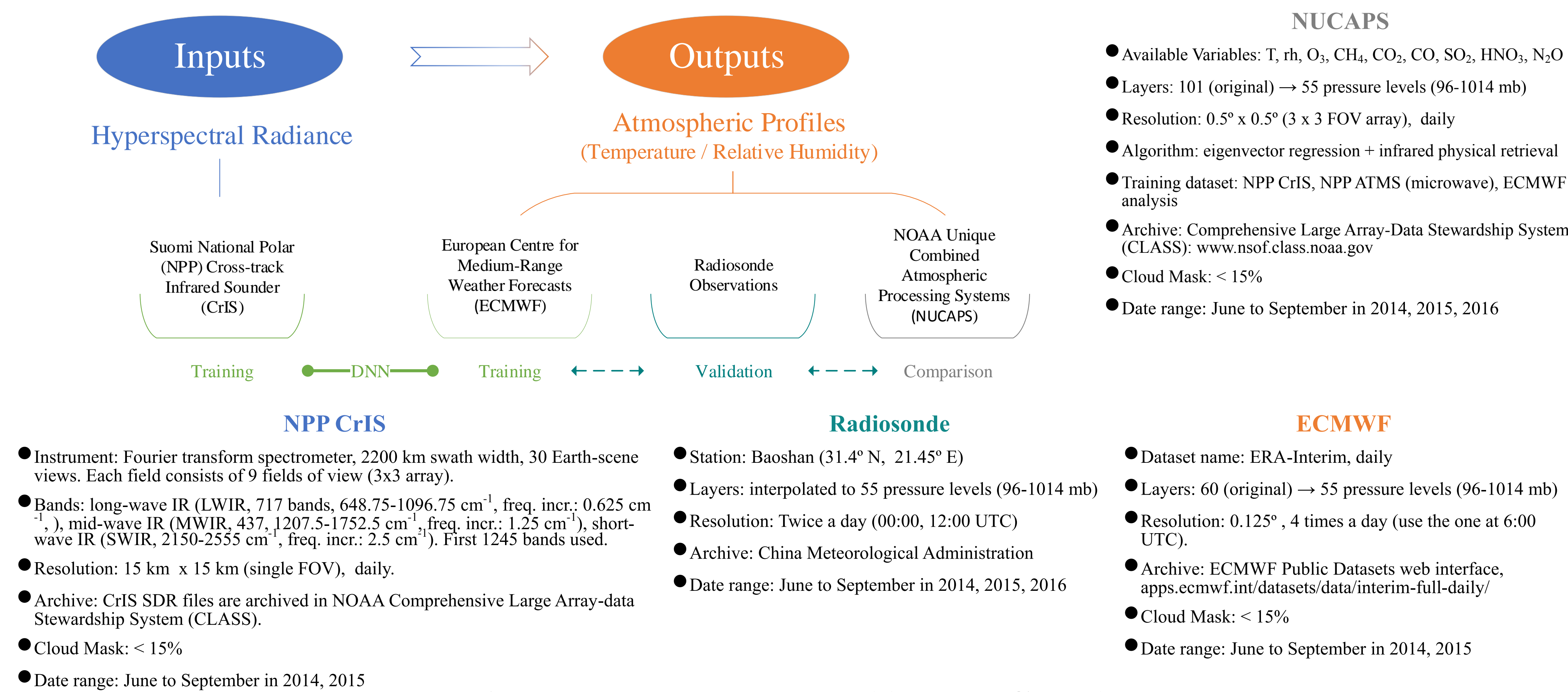
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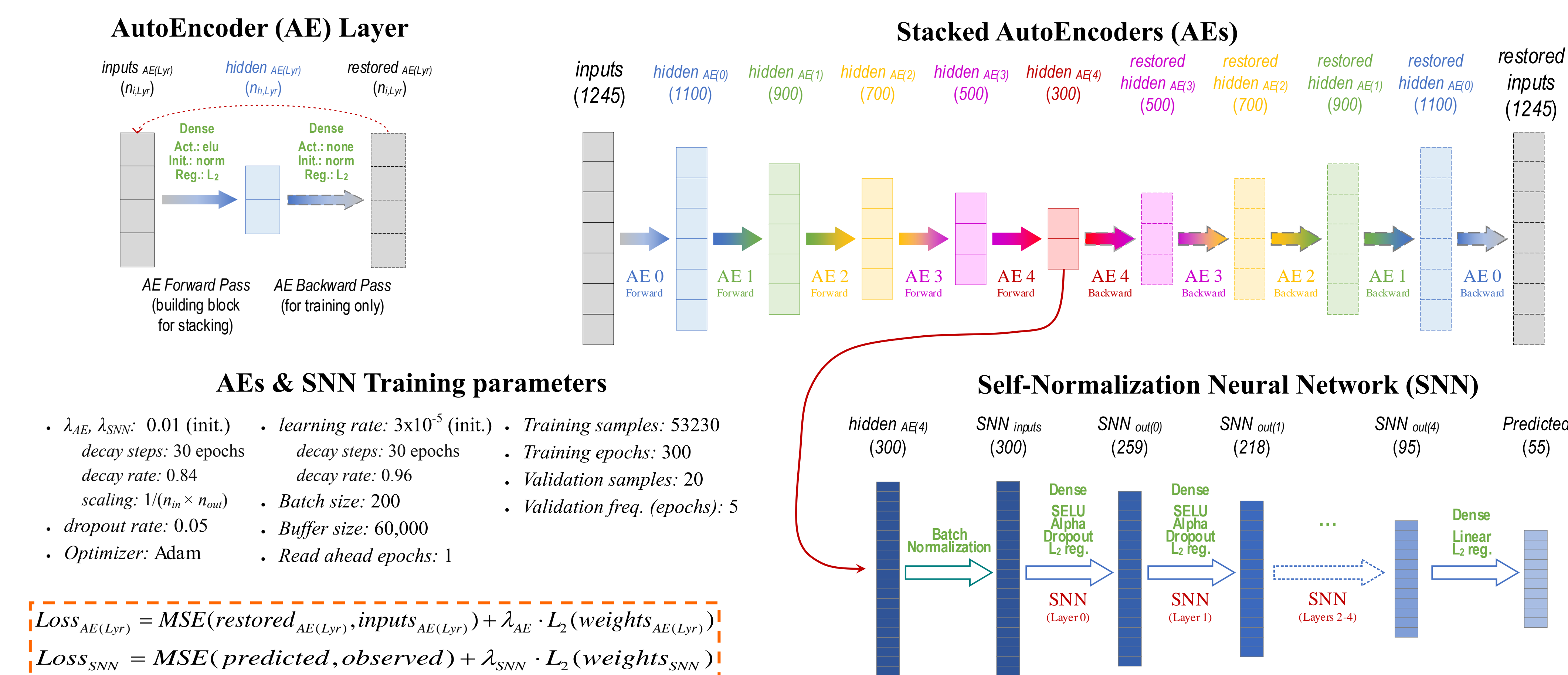
## Introduction

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  $2555\text{ cm}^{-1}$ ) 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

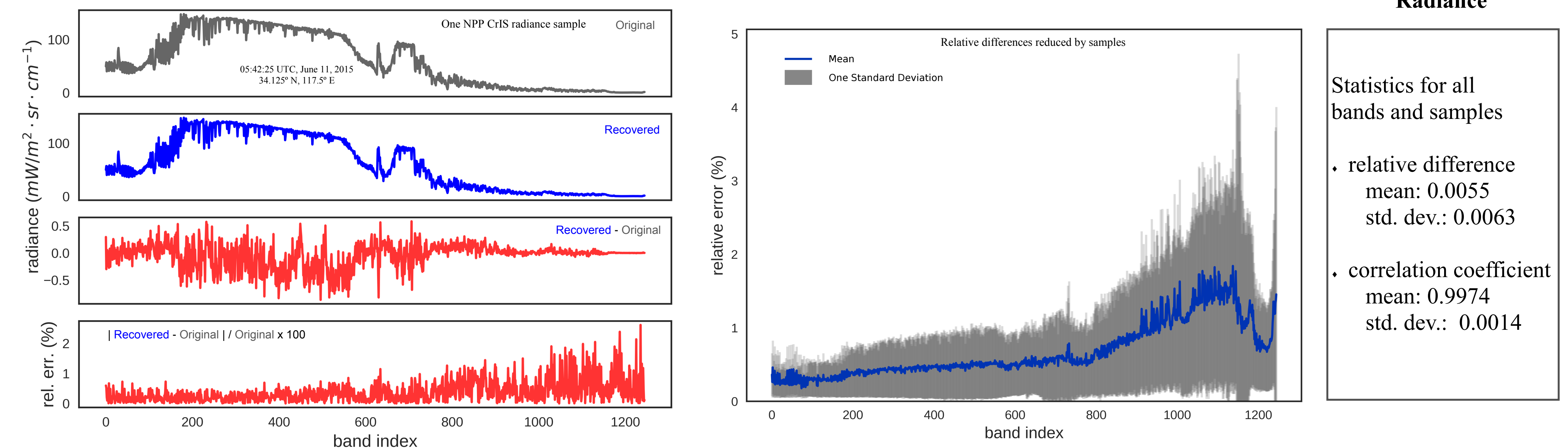


## 2. The DNN model (AEs + SNN)

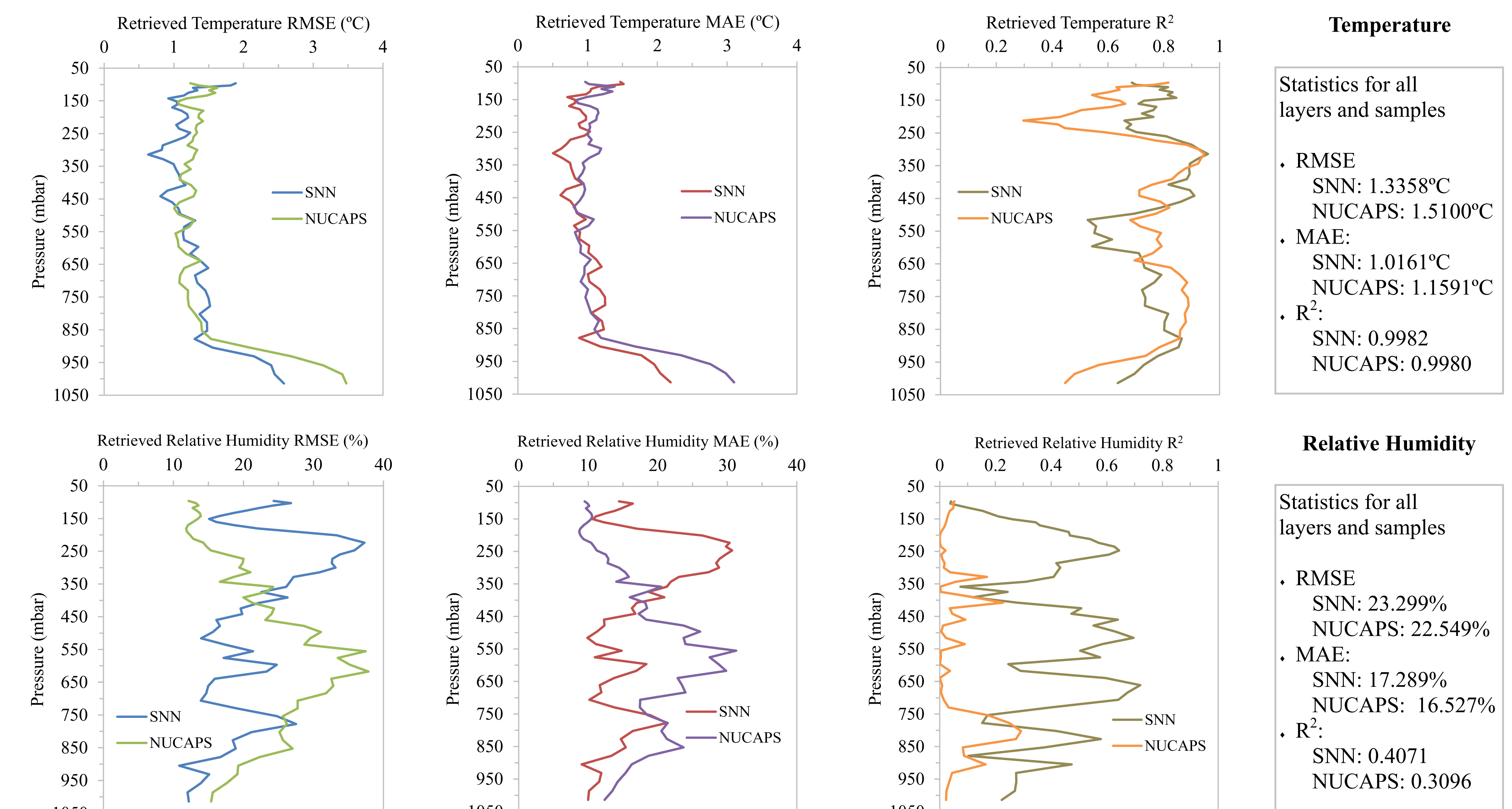


## 3. Results

### 3.1 Radiance compression results (AEs)



### 3.2 Temperature and Relative Humidity retrieval results (SNN)



### 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

- Klambauer et al. 2017. Self-Normalizing Neural Networks. arXiv:1706.02515
- Géron 2017. Hands-On Machine Learning with Scikit-Learn and TensorFlow. Concepts, Tools, and Techniques to Build Intelligent Systems (1st Edition). ISBN-13: 978-1491962299.
- Danijar 2018. Patterns for Fast Prototyping with TensorFlow. Blog post. <https://danijar.com/patterns-for-fast-prototyping-with-tensorflow>
- Chen et al. 2018. Spatial interpolation of surface ozone observations using deep learning. Proc. SPIE. Volumn 10767, 107670C. doi: 10.1117/12.2320755
- Sundararajan, et al. 2017. Axiomatic attribution for deep networks. arXiv:1703.01365.

