A FAST NEURAL NETWORK-BASED APPROACH FOR JOINT MID-IR AND FAR-IR SURFACE SPECTRAL EMISSIVITY RETRIEVAL

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Motivations

Why surface emissivity?

- Surface emissivity (ε) is a pivotal factor in the analysis of Earth's radiation budget and its impact on climate.
- Unobserved far-IR (15–100μm) surface emissivity in polar regions impacts simulated mean-state polar climate; which motivated the Polar Radiant Energy in the Far-InfraRed Experiment (PREFIRE) mission [1].

What can be improved?

- Existing optimal-estimation (OE)-based methods are computationally intensive and too slow to keep up with the data stream from the PREFIRE measurements.

Data Collection

Synthetic data

- 6.2 million synthetic clear-sky PREFIRE spectra data were generated using 4 months of 2005 of ERA-5 6-hourly reanalysis data [2-3] and surface emissivity data [4].
- We focused on estimating the surface spectral emissivities at the 14 PREFIRE channels (6 in mid-IR and 8 in far-IR).

Train-test split

- 70% training (4,314,437 samples); 30% testing (1,849,045 samples).

Methodology

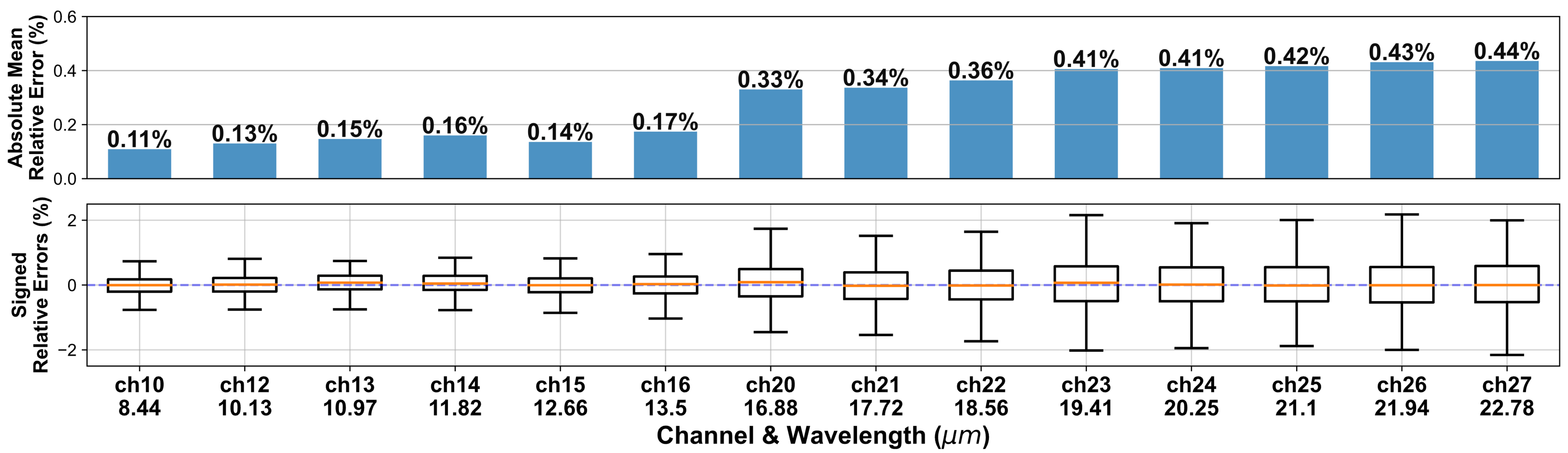
Channel-wise Neural Networks (NNs) Architecture (2L MLP)

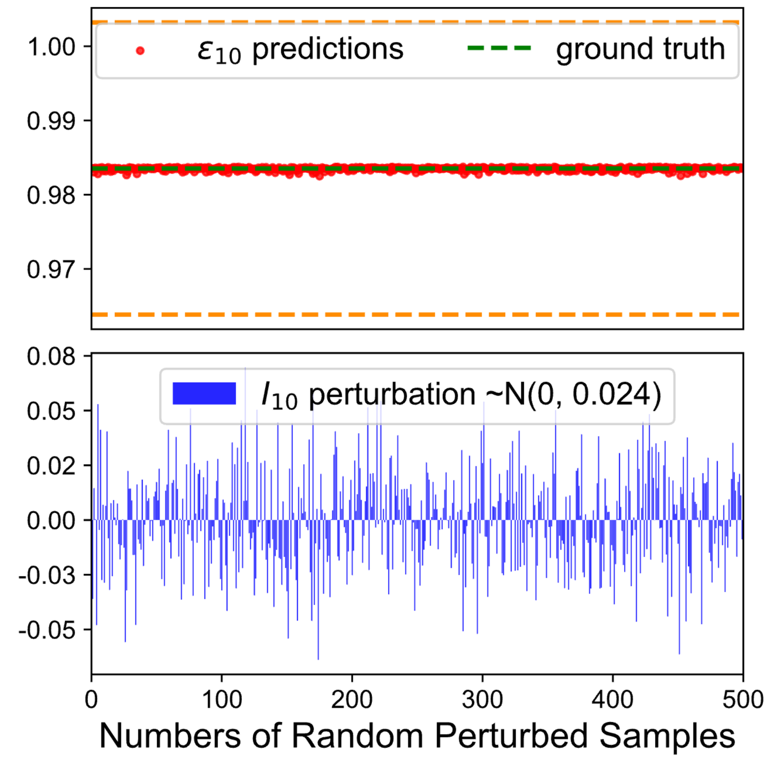
- **Input features: 115** (Standardized channel radiance (I_n) + other standardized parameters including temperature, water vapor, and ozone profiles at 37 levels, surface temperature, surface pressure and CO_2)
- **Hidden layer #1: 57 neurons** => batch normalization => ReLU activation
- **Hidden layer #2: 28 neurons** => batch normalization => ReLU activation
- **Output: 1** (Standardized channel emissivity)

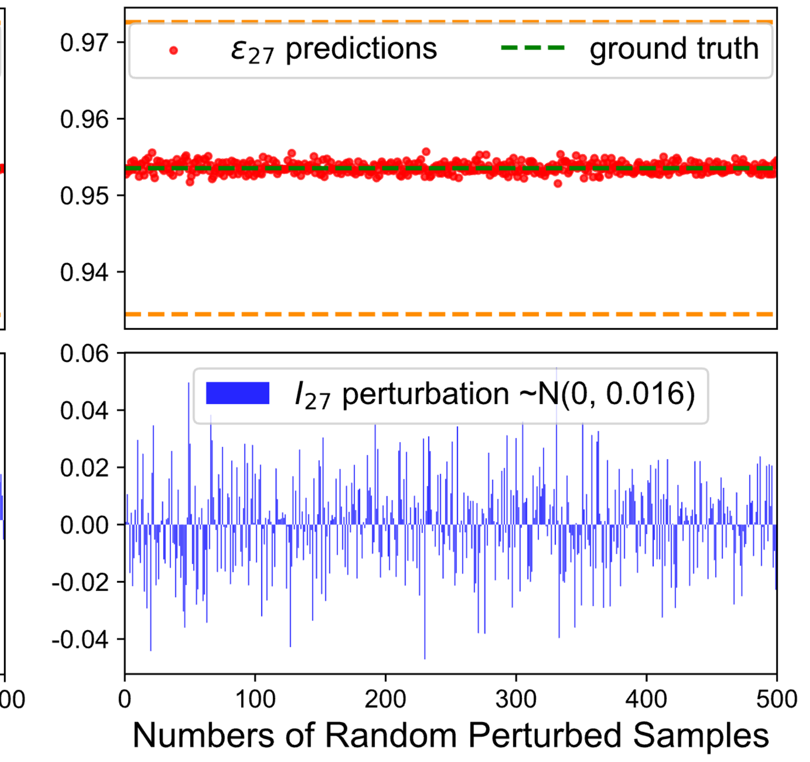
Experiment setup (a single NN training takes around 5 hours on CPU)

- Utilizing the Adam optimizer with a 0.0001 learning rate and MSE loss function, we trained all 14 channel-wise models over 10 epochs.
- Evaluated the predicted emissivity against the established ground truth emissivity.

Retrieval Performance







Overall retrieval performance

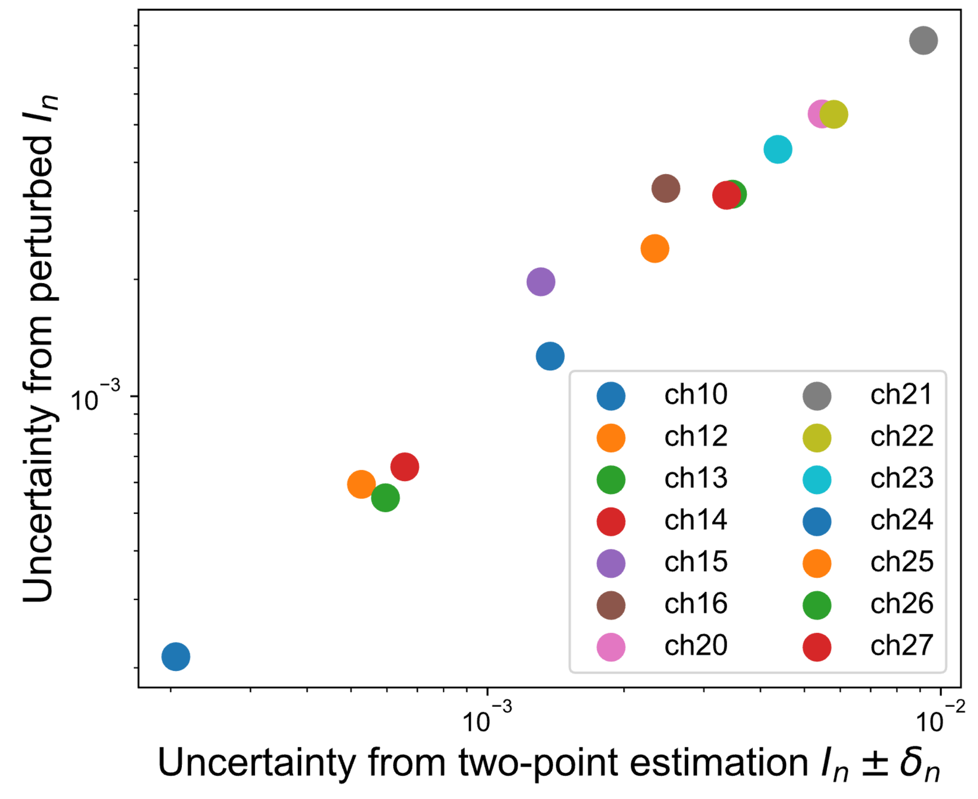
- Achieved a mean error of 0.0028 with a standard deviation of 0.0013, comparable to the OE-based retrieval [2].

Performance under perturbations

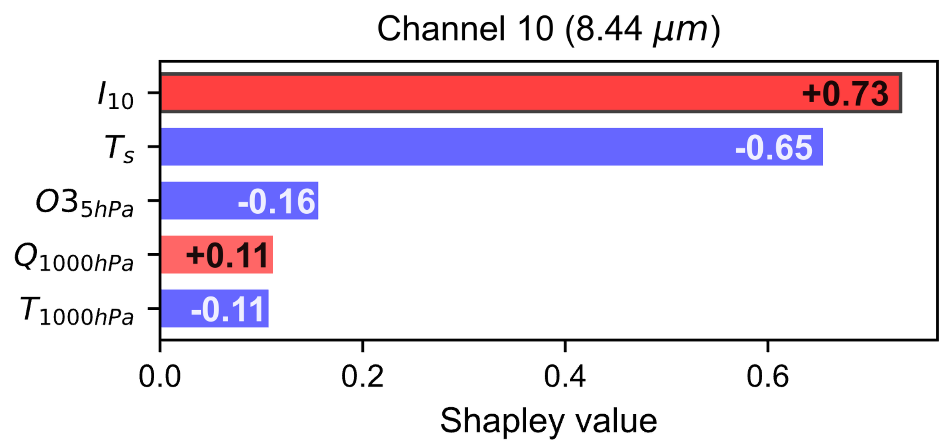
- Less than ±2.5% prediction changes.
- Changes are consistently centered around the ground truth emissivity.

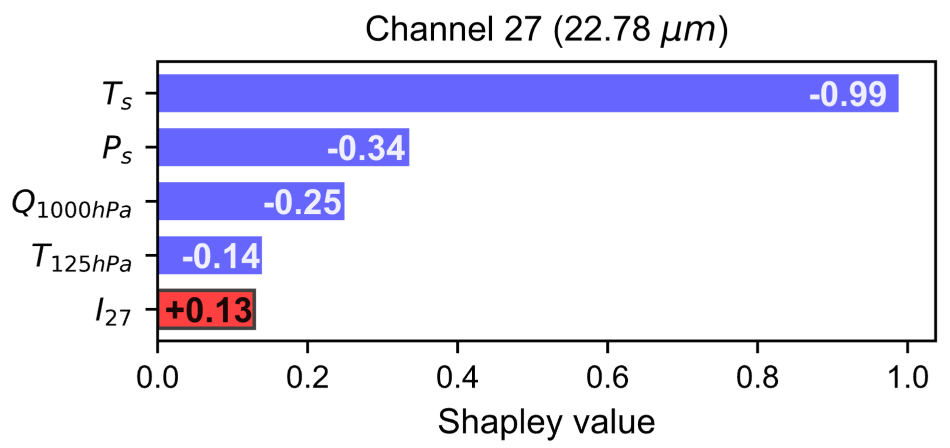
Uncertainty estimation given NeSRs (δ_n)

- Nearly a 1:1 correspondence between the uncertainty estimated using $I_n \pm \delta_n$ and randomly perturbed radiances.



Shapley Value Analysis





Conclusion

A simple yet effective NN-based approach for estimating mid-infrared and surface spectral emissivity retrieval

- Achieved a comparable retrieval performance to OE-based methods, with a computational time saving by a factor of 10^5.
- Uncertainty estimation can be done using a two-point average ($\pm\delta_n$).
- Shapley value analysis confirms feature contribution to emissivity estimation, aligning with our physical understanding.

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References

- **[1]** T.S. L'Ecuyer, B.J. Drouin, J. Anheuser, M. Grames, D.S. Henderson, X. Huang, B.H. Kahn, J.E. Kay, B.H. Lim, M. Mateling, A. Merrelli, N.B. Miller, S. Padmanabhan, C. Peterson, N.-J. Schlegel, M.L. White, and Y. Xie, "The polar radiant energy in the far infrared experiment: A new perspective on polar longwave energy exchanges," Bulletin of the American Meteorological Society, 2021.
- **[2]** Y. Xie, X. Huang, X. Chen, T.S. L'Ecuyer, B.J. Drouin, and J. Wang, "Retrieval of Surface Spectral Emissivity in Polar Regions Based on the Optimal Estimation Method," Journal of Geophysical Research (Atmo- spheres), 2022.
- **[3]** Cameron Bertossa, Tristan L'Ecuyer, Aronne Merrelli, Xianglei Huang, and Xiuhong Chen, "A neural network–based cloud mask for PREFIRE and evaluation with simulated observations," Journal of Atmospheric and Oceanic Technology, 2023.
- **[4]** Huang, X. L., X.H. Chen, D. K. Zhou, X. Liu, An observationally based global band-by-band surface emissivity dataset for climate and weather simulations, Journal of the Atmospheric Sciences, 2016.