AGU FALL MEETING
New Orleans, LA & Online Everywhere
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S51A-04
Predicting infrasound transmission loss using deep learning

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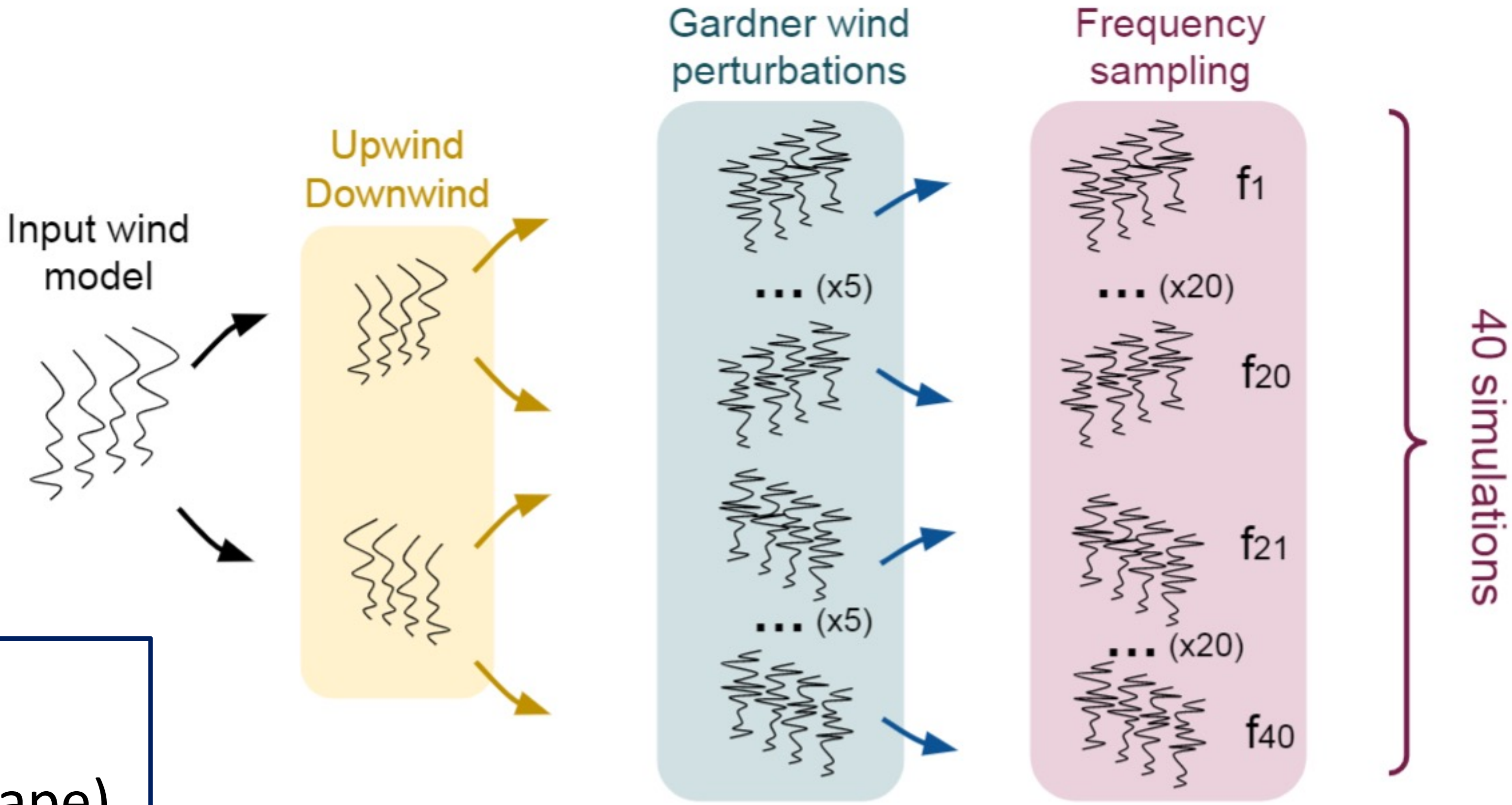
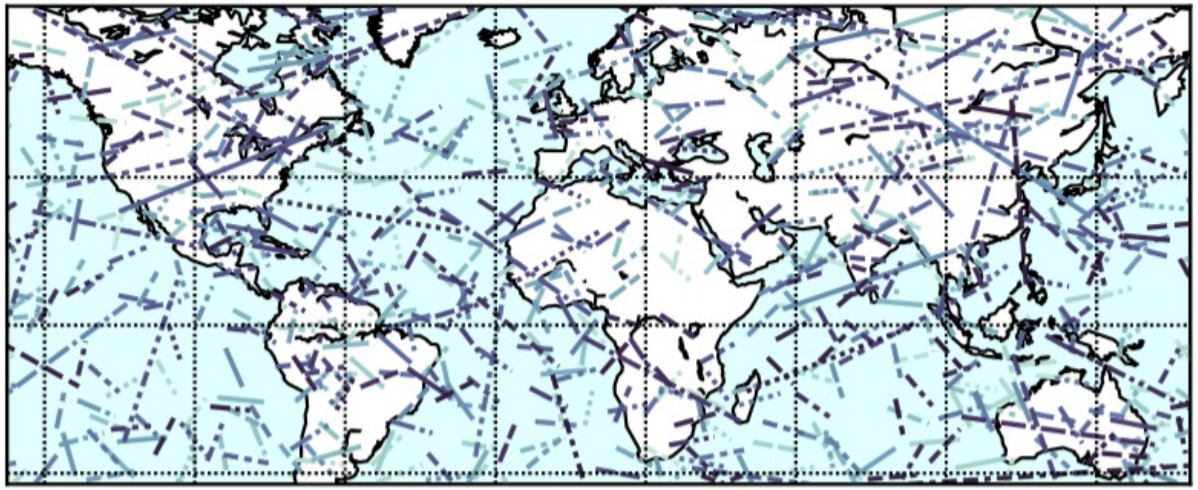
Goal

Fast infrasound amplitude predictor
⇒ **Transmission loss for any range-dependent atmospheric model**



Ground-truth dataset

- Massive PE simulations (NCPA ePape)
- Range-dependent:
  ERA5 & NRLMSIS-00/HWM13
- Randomization:
  - Slice locations
  - Time



Challenges with existing inversion framework

Full-waveform modeling: computationally expensive

⇒ inversions typically using empirical regression equations (Le Pichon, 2012, *referred in the following:* **LP12**)

LP12 optimized over an idealized set of Parabolic Equation (PE) simulations
⇒ TL as function of range

LP 12 regression equation:

Source frequency

$$A_P(f, V_{eff-ratio}) = \frac{1}{R} 10^{\frac{\alpha(f)R}{20}} + \frac{R^{\beta(f, V_{eff-ratio})}}{1 + 10^{\frac{\delta - R}{\sigma(f)}}}$$

Effective velocity ratio @ 50 km altitude

Neglects vertically and horizontally varying wind profiles

Generating models allowing for fast TL estimation

2 main computationally inexpensive approaches
to incorporate atmospheric variability into fast TL estimation:

S51A-01 presented by Alexis Le Pichon →

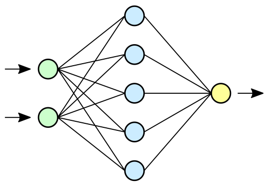
Analytical fitting approach

$$A_P(R, f, V_s) = A_0 R^{-\alpha(f,V_s)R}\, e^{-\beta(f,V_s)R}$$

Range-dependent analytical model

- Full control of predictive model parameters
- Explainability
- Simplicity
- Limited generalization for new data
- Difficult to introduce complexity in mapping function

Machine Learning (ML)



Machine learning

- Mapping with arbitrary complexity
- High accuracy
- "Black box"
- Costly training
- Tricky architecture optimization

← **S51A-04** **current paper**

NORSAR

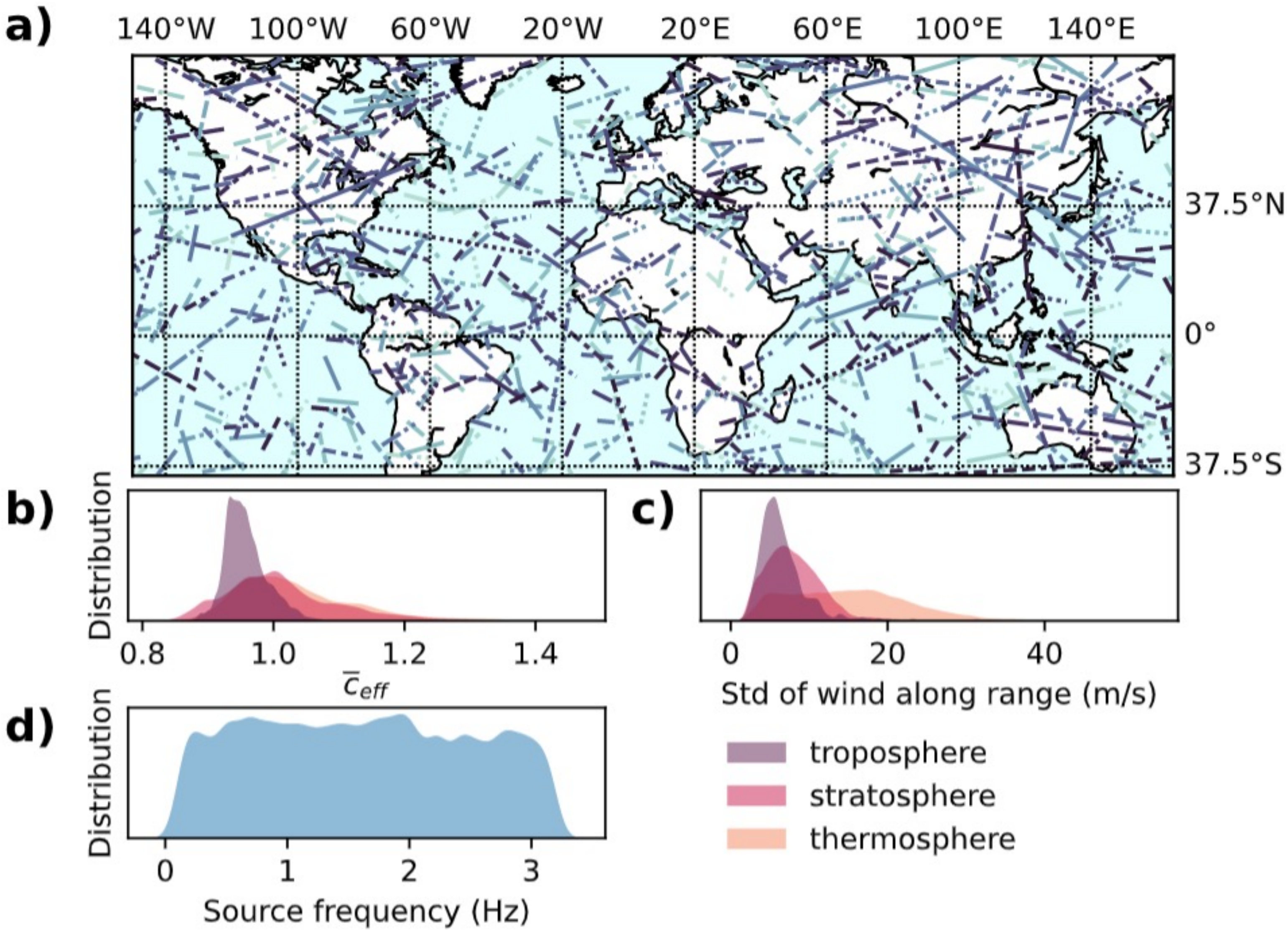
Creating a realistic Transmission-Loss dataset

Accurate ML model requires training over a dataset representative of the variability in winds and TLs

- Similar to LP12: generate synthetic dataset from PE simulations (NCPA ePape)
- Atmospheric **range-dependent** models: ERA5 & NRLMSIS-00/HWM13

Randomly sample:

- Slice locations
- Year
- Day



Learning TL from wind patterns using CNNs

Small and large-scale wind variations + frequency control the acoustic wavefield structure at the ground

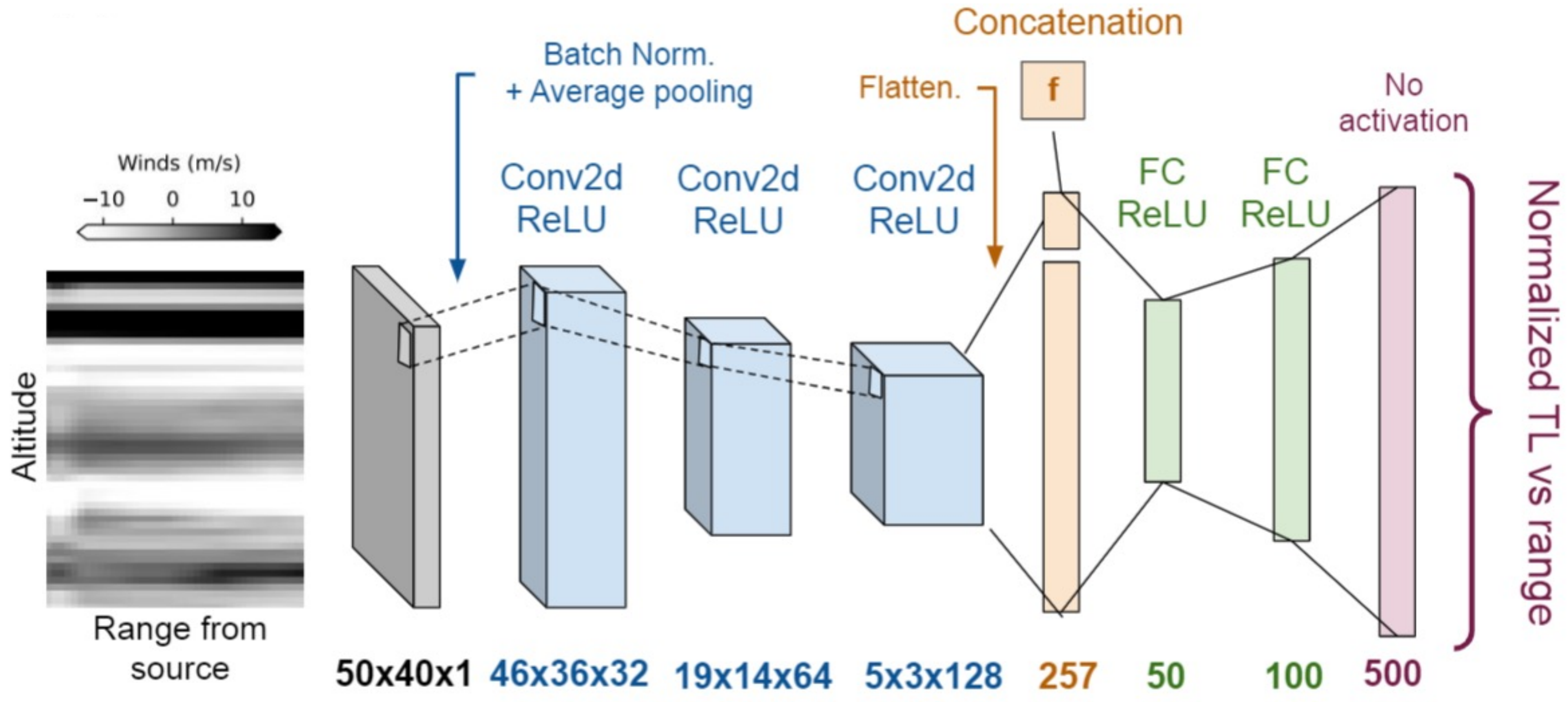
Convolutional Neural Networks (CNNs)

- Designed to extract local and global patterns.
  Several layers of convolutions with custom filters for prediction
- Here: TL from multi-dimensional input (2D wind maps)

Our approach

(1) extract wind patterns using 2D CNN

(2) find frequency-dependent TL relationship with wind models using a Fully-Connected layer



Training & validation

Training (75%) / validation (25%)

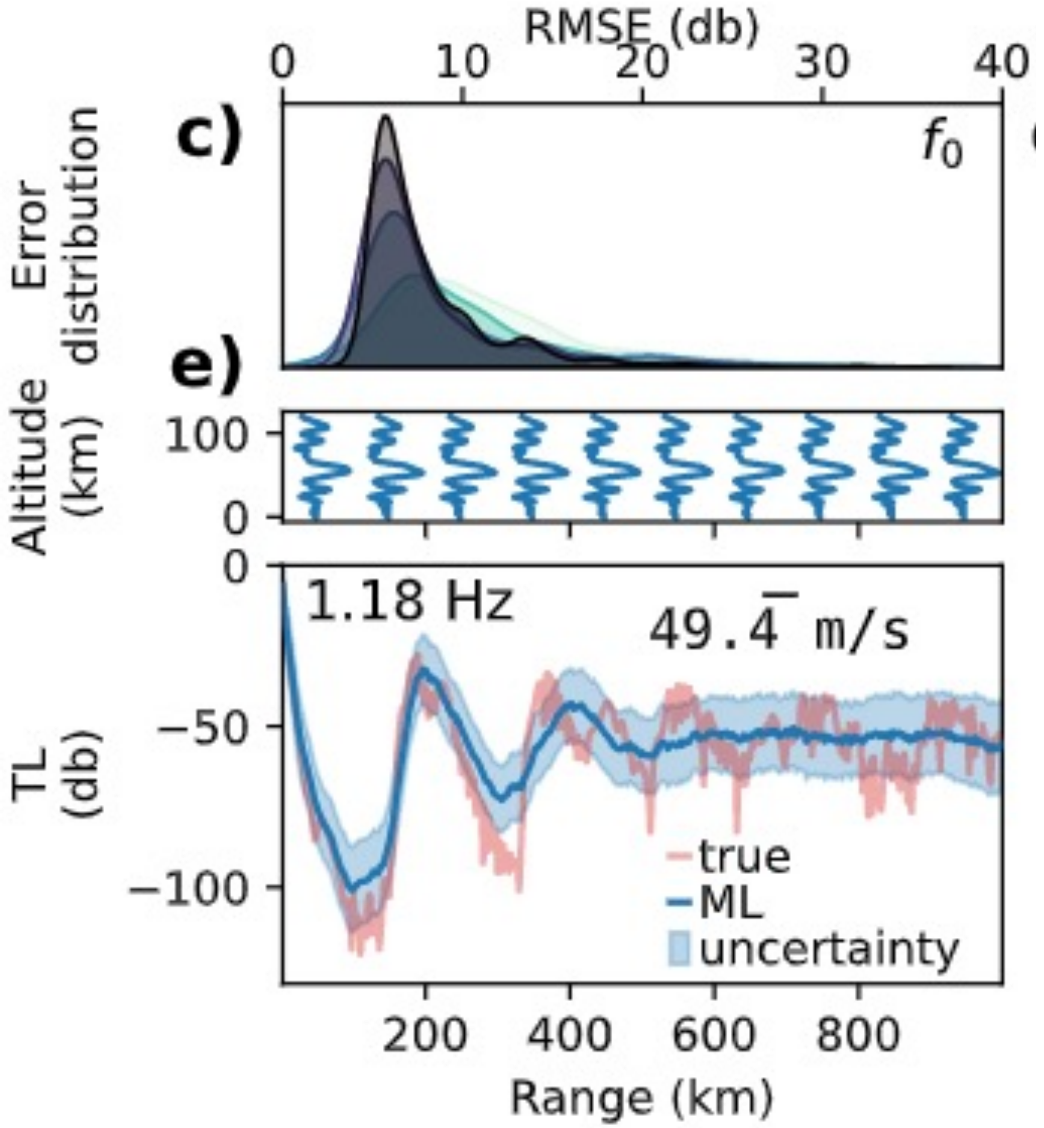
Training the ML using mini-batches (size 64)

⇒ 5 dB average accuracy over testing dataset

Once trained,
an ML-based TL estimate takes 0.05 s
(vs. 10 to 150 s with PE simulations)

Frequency-independent cost

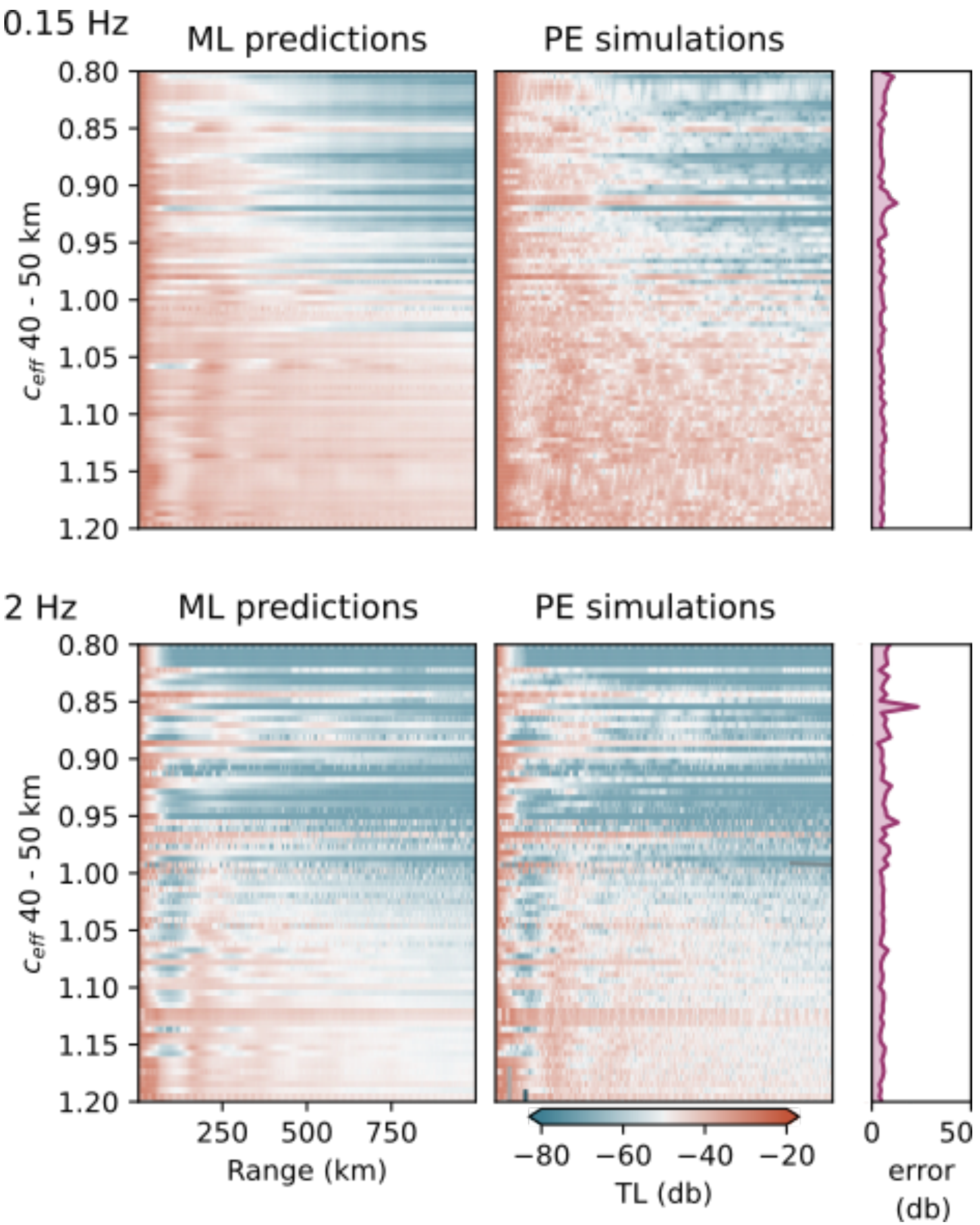
Uncertainty estimation:
Computing error vs. range made by the ML model over the testing dataset



Resulting model

ML captures main features:

- Multiple stratospheric shadow zones
- Tropospheric & thermospheric phases
- Low vs. high effective sound speed ratio
- Error within ~ 5 dB



Perspectives

ML-based inexpensive (0.05 s) & accurate (around 5 dB) alternative to full simulations

Plenty of applications benefitting from **rapid TL estimates,**
(near-) realtime atmospheric model diagnostics, event characterization, ++

E.g., microbarom modeling: **greater propagation range** (4000 – 6000 km).
⇒ new large-scale simulations to get new ground-truth & training

Enables rapid & **efficient amplitude-based inversion** procedures to retrieve source parameters
(e.g., explosion yield, ground pressure levels)

Future work:

Currently: range-**independent** Gardner perturbations
⇒ unrealistic beyond a few 100 km ⇒ **Range-dependent** to be incorporated

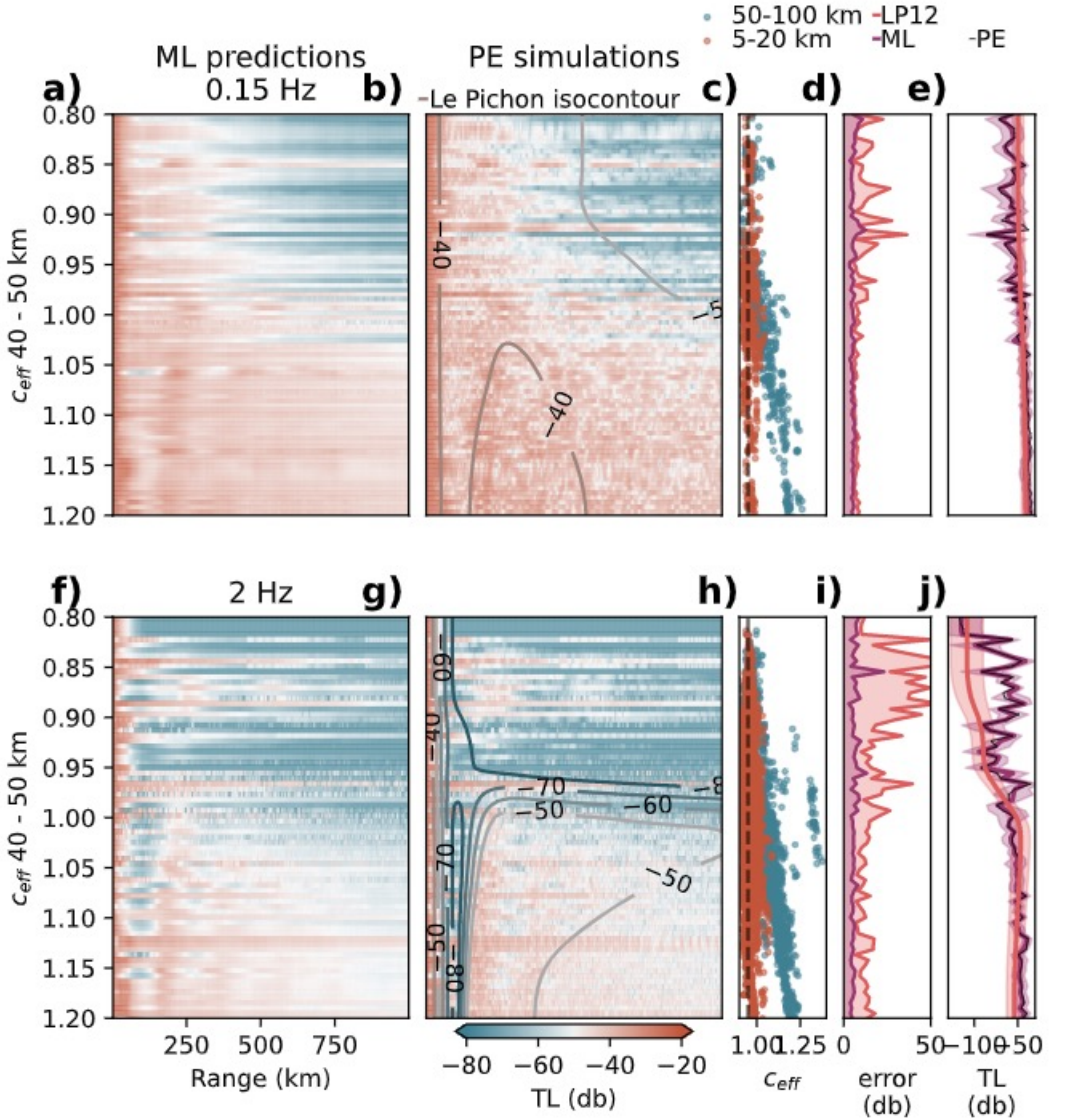
Explainable ML, e.g., Layer-wise Relevance Propagation (LRP)
⇒ relationship between specific atmospheric model regions & TL ⇒ **sensitivity kernels**

Ground truth from even more expensive & accurate codes (spectral-element / nonlinear propagation / …),
e.g., **taking cross-winds into account ++**

Code & synthetic data to be made available: https://github.com/QuentinBrissaud

Thank you!

ML vs. LP12



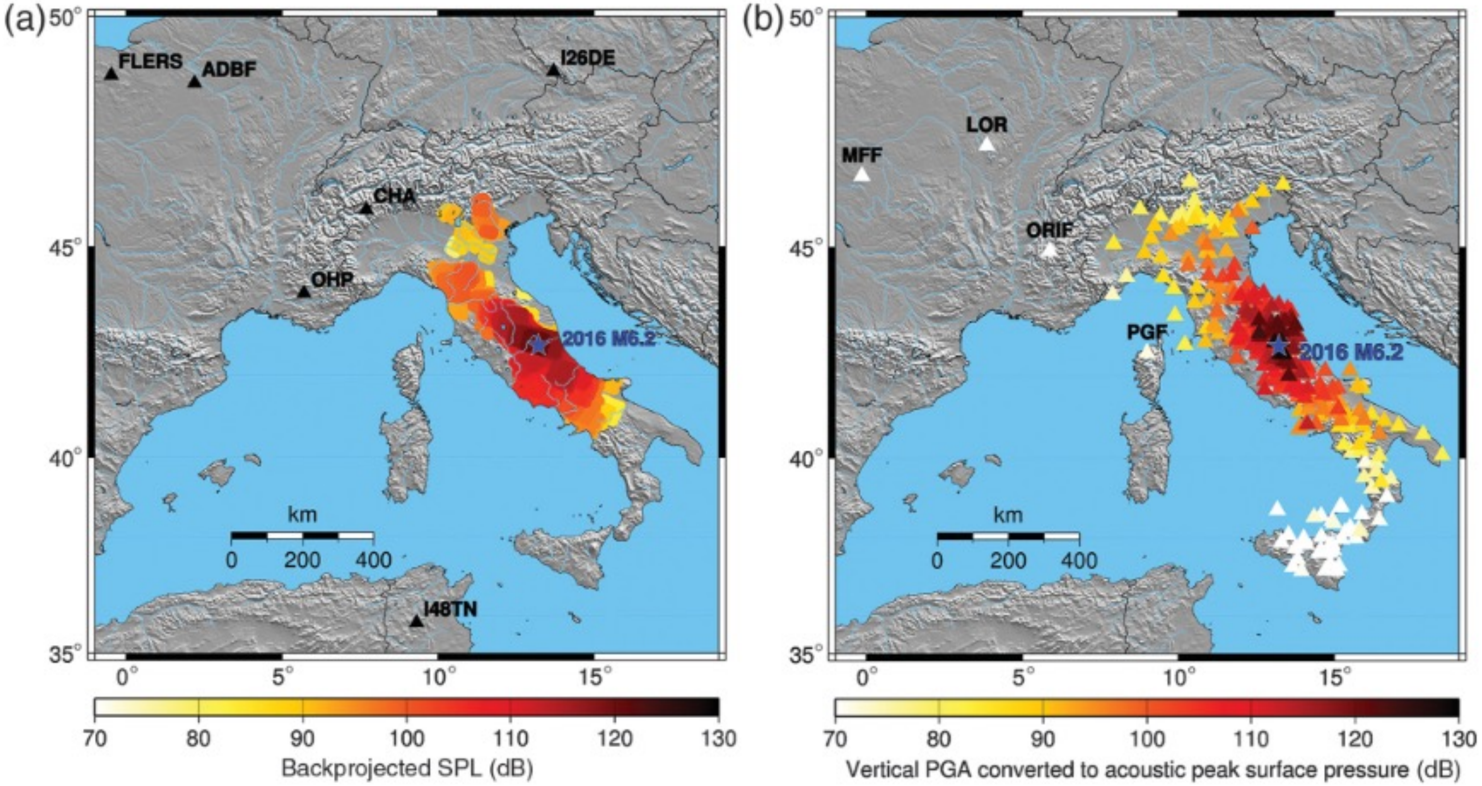
LP12 reproduces the main features

- First stratospheric shadow zone
- Low vs. high effective sound speed ratio

Infrasound to retrieve source parameters

Infrasound excited by surface sources can travel large distances and carry information about the source, e.g., surface pressure at the source after the 2016 Amatrice earthquake

Accurate estimation of **Transmission-Loss** (TL), i.e., infrasound amplitude decay with distance
⇒ opportunity to complement seismic data with acoustic data for remote sensing of surface processes



Reconstructed & measured surface pressure

(left) Backprojected infrasound (SPL, dB)

(right) Acoustic peak surface pressure (PSP, in dB); triangle = seismic station.

Hernandez, B., Le Pichon, et al. (2018). Estimating the Ground-Motion Distribution of the 2016 M w 6.2 Amatrice, Italy, Earthquake Using Remote Infrasound Observations. *Seismological Research Letters*, *89*(6), 2227-2236.

References

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Hernandez, B., Le Pichon, A., Vergoz, J., Herry, P., Ceranna, L., Pilger, C., ... & Bossu, R. (2018). Estimating the Ground-Motion Distribution of the 2016 M w 6.2 Amatrice, Italy, Earthquake Using Remote Infrasound Observations. Seismological Research Letters, 89(6), 2227-2236.

Waxler, R., C. Hetzer, J. Assink, and D. Velea (2021), chetzer-ncpa/ncpaprop-release: Ncpaprop v2.1.0, doi:10.5281/zenodo.5562713, last accessed on 29 October 2021.