Infrasound Technology Workshop, Ponta Delgada, Açores

Rapid estimation of ground-to-ground infrasonic transmission loss using a recurrent neural network

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Modelling & Network Processing session, S3.1 / contribution 92
Tuesday 31 January 2023

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Exploring the Earth

Motivations

- **Long-range transmission loss** (TL) useful:
  Explosive source characterization & location, *& beyond*
- Simulations: expensive, especially at high frequency

Objective: Avoid running costly simulations:
Have "table lookup" using the atmospheric specification

Methodology

1) Massive simulated TL dataset from range-dependent atmospheric **ERA5 specifications**
2) Train a **neural net** to learn TL from atmospheric models & synthetics

⇒ Get TL **almost instantaneously**

Existing rapid TL framework (Le Pichon et al. 2012, **LP12**)

- **Empirical regression TL equations** fit to idealized Parabolic Equation (PE) simulations, neglecting atmospheric range-dependency

- Low complexity & impressingly robust

Frequency

Effective velocity ratio
@ 50 km altitude

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

Recent rapid TL estimation enhancements

Analytical fitting

Le Pichon et al. *in preparation*

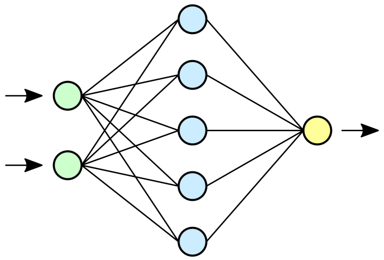
$$A_P(R, f, V_s) = A_0 R^{-\alpha(f,V_s)R}\, e^{-\beta(f,V_s)R}$$

Range-dependent analytical model

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

Machine Learning (ML)

Current study



- Arbitrary complexity
- Higher accuracy
- "Black box"
- Costly training
- Tricky architecture optimization

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2021 — **NORSAR internal**
proof of concept

Early 2022 — **Paper submission**

Geophysical Journal International
Geophys. J. Int. (2023) **232,** 274–286
https://doi.org/10.1093/gji/ggac307
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GJI Seismology

Predicting infrasound transmission loss using deep learning

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Spring 2022 — **Student internship**
Edouard Forestier, ENSTA Paris
Better accuracy & longer range

2023 — **Open-source code / data release**
& beyond

Synthetic ground-truth

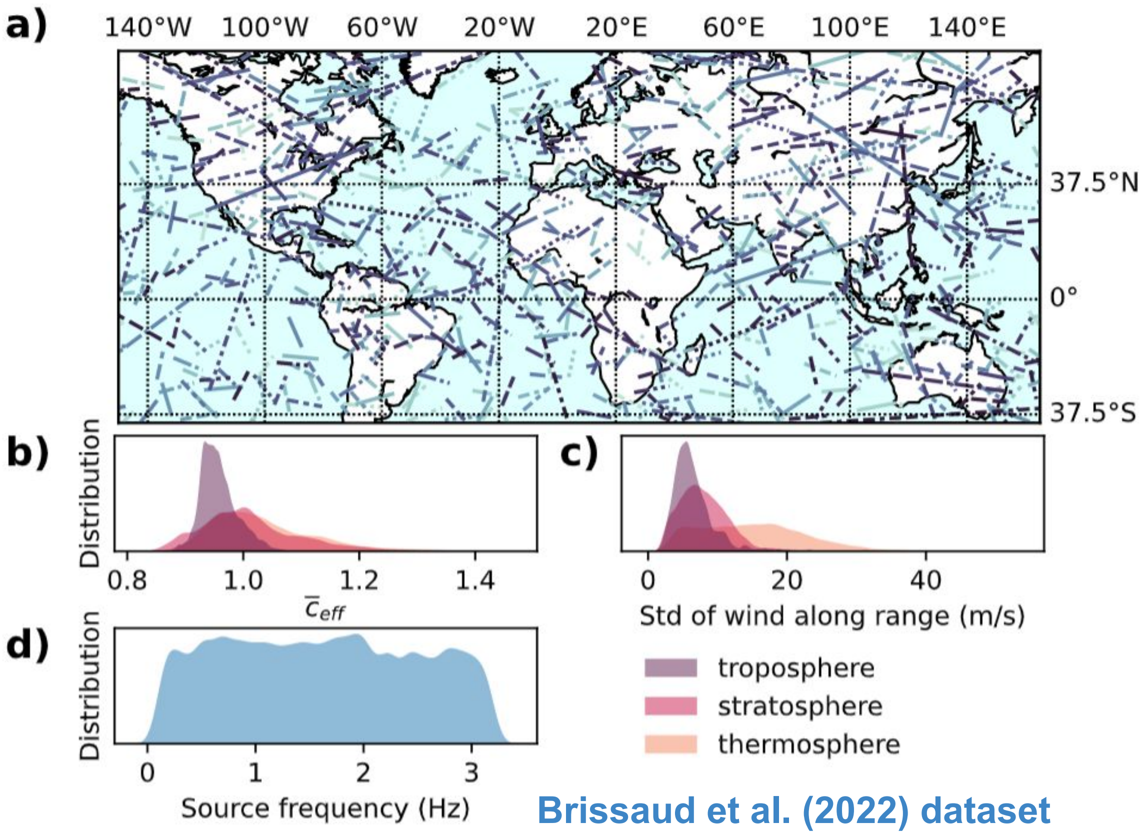
- **ML:** requires training over **data with representative wind & TL variability**

- **PE datasets:**

1) **Proof of concept** (Brissaud et al., 2023): 1000 km w/ range-**independent** gravity-wave perturbations
2) **Longer range** (Forestier et al., 2022): 4000 km w/ range-**dependent** gravity-waves

Characteristics

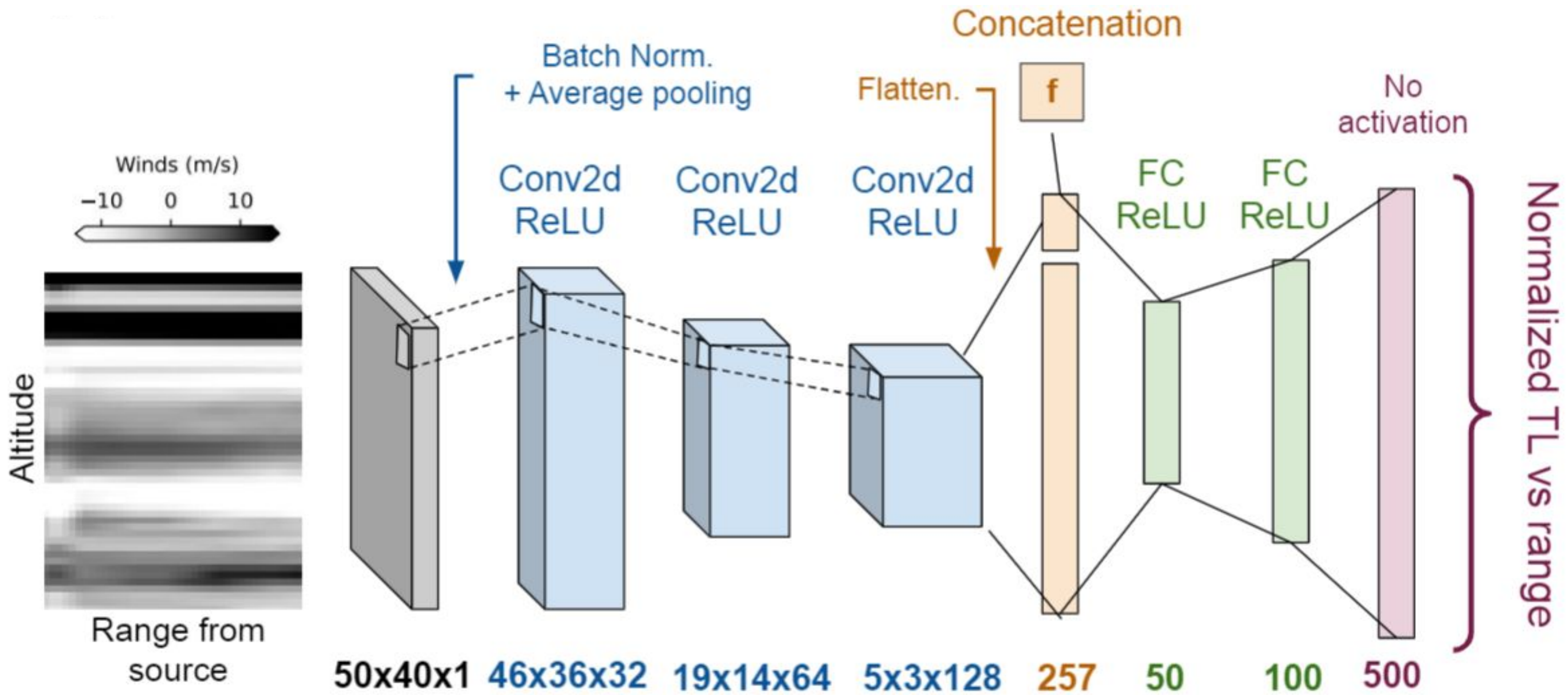
- NCPA ePape PE code
- Range-dependent atmosphere: ERA5 re-analysis & NRLMSIS-00 / HWM14
- Gardner-type gravity-wave perturbations
- Slices sampled randomly in location & time
- Random input frequencies 0.1–3.2 Hz



Brissaud et al. (2022) dataset

CNN: learning to get TL from wind models & wave frequency

1) **Input**: 2-D distance vs altitude wind
2) Condense wind patterns w/ 2-D Convolutional Neural Networks (CNN)
3) Frequency-dependent TL relation with wind: from additional neural net
4) **Output: TL as function of range**



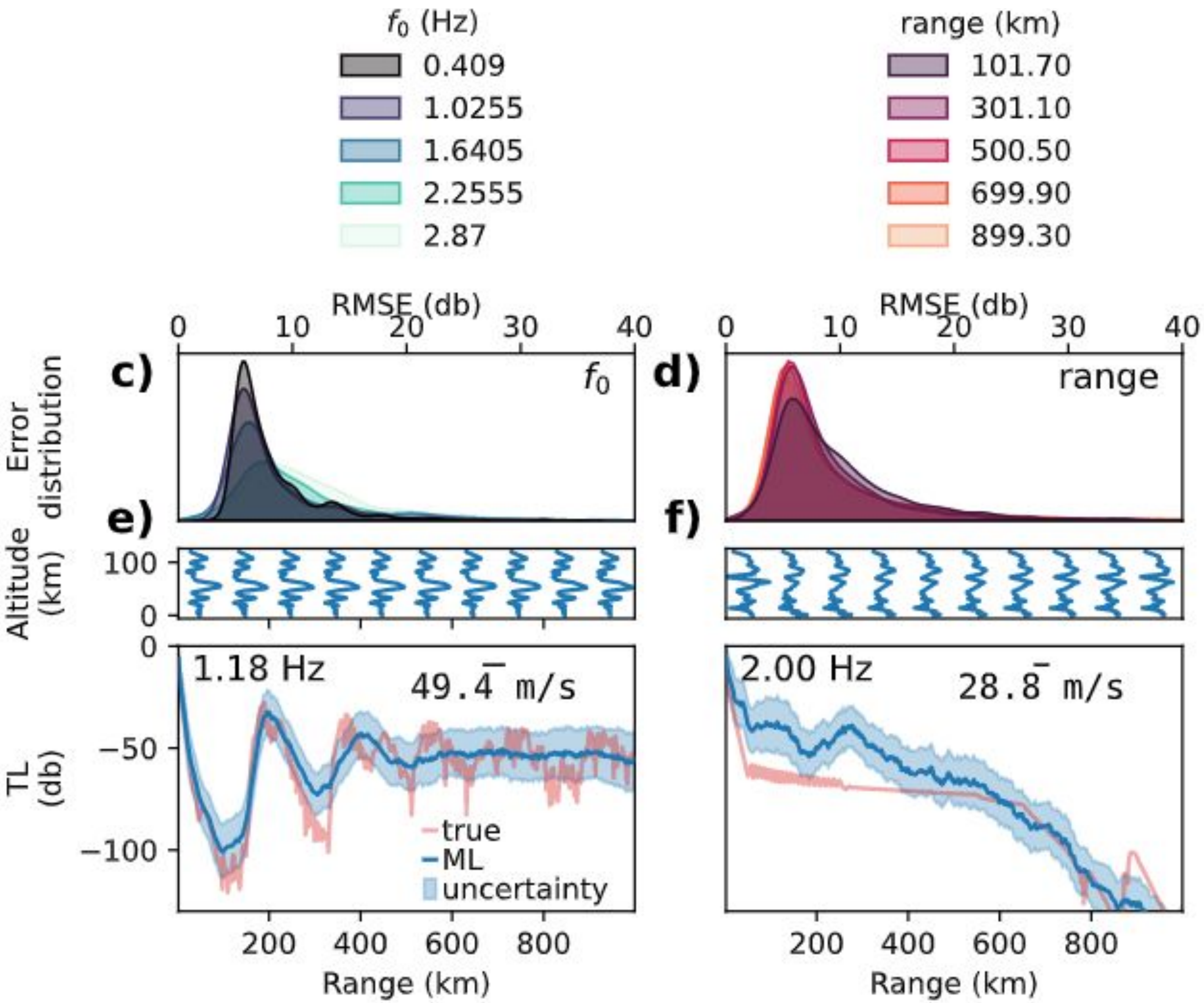
Training & validation

Characteristics

- 42 000 simulations.
  Training (75%) & validation
- Mini-batches (size 64)
- Early stopping

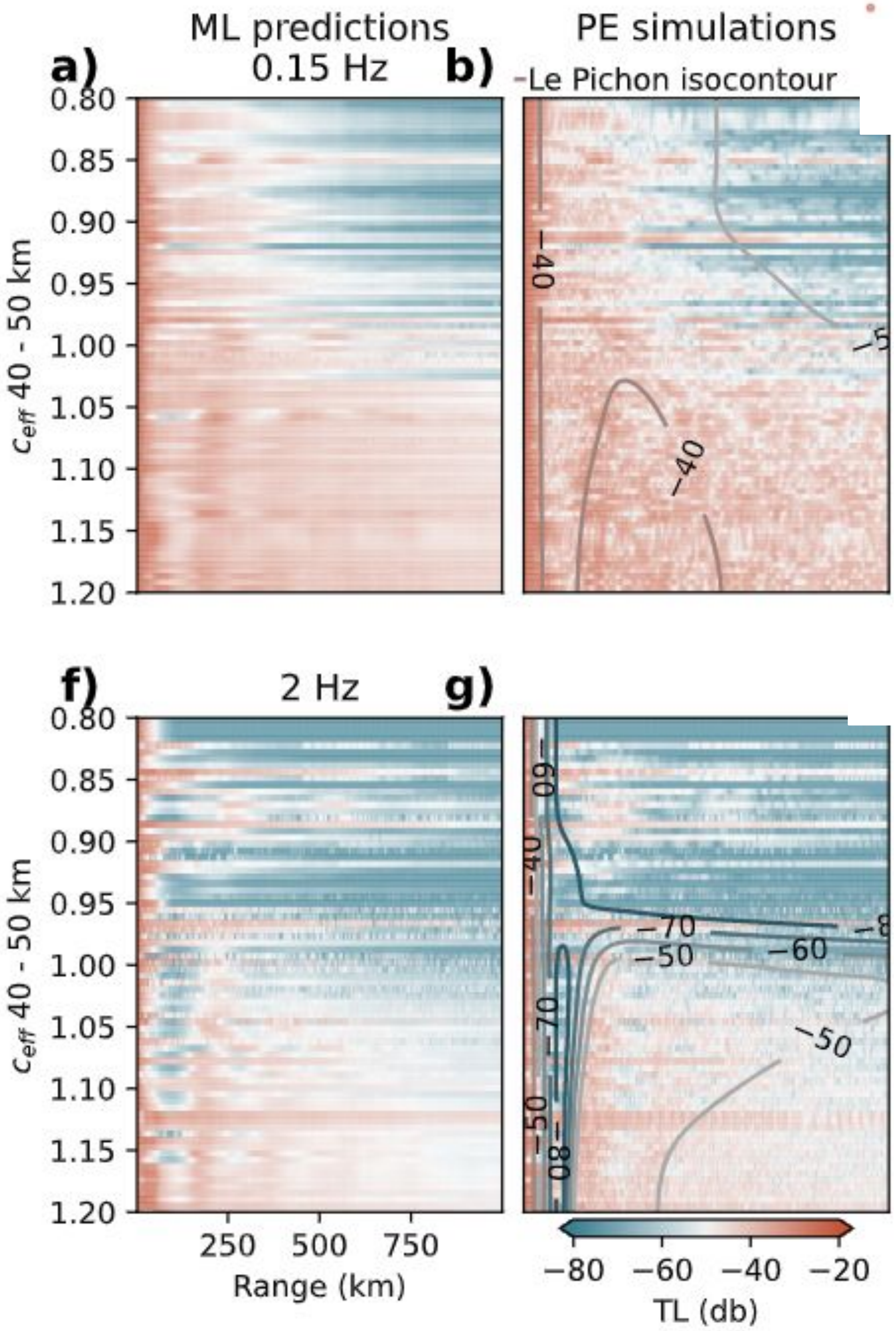
Results

- 5 dB average accuracy
- 0.05 s computation
  (10 − 150 s PE simulations for high freq.)



Reproduces main propagation features

- Stratospheric shadow zone
- Low vs. high effective sound speed ratio



Recurrent Neural Network (RNN) approach

- **2-D CNN ignores “*spatial causality*”**,
  wind beyond a range should **not** influence TL at closer ranges
- Incorporating causality,
  informing about physics, ⇒ **enhanced learning**
- **Recurrent Neural Networks**:
  Good for learning causality in sequential data
  Involves feedback (à la IIR)
- Use 1-D CNN + Gated Recurrent Units (GRUs)
  as RNN, building *“spatially causal”* framework

Edouard Forestier

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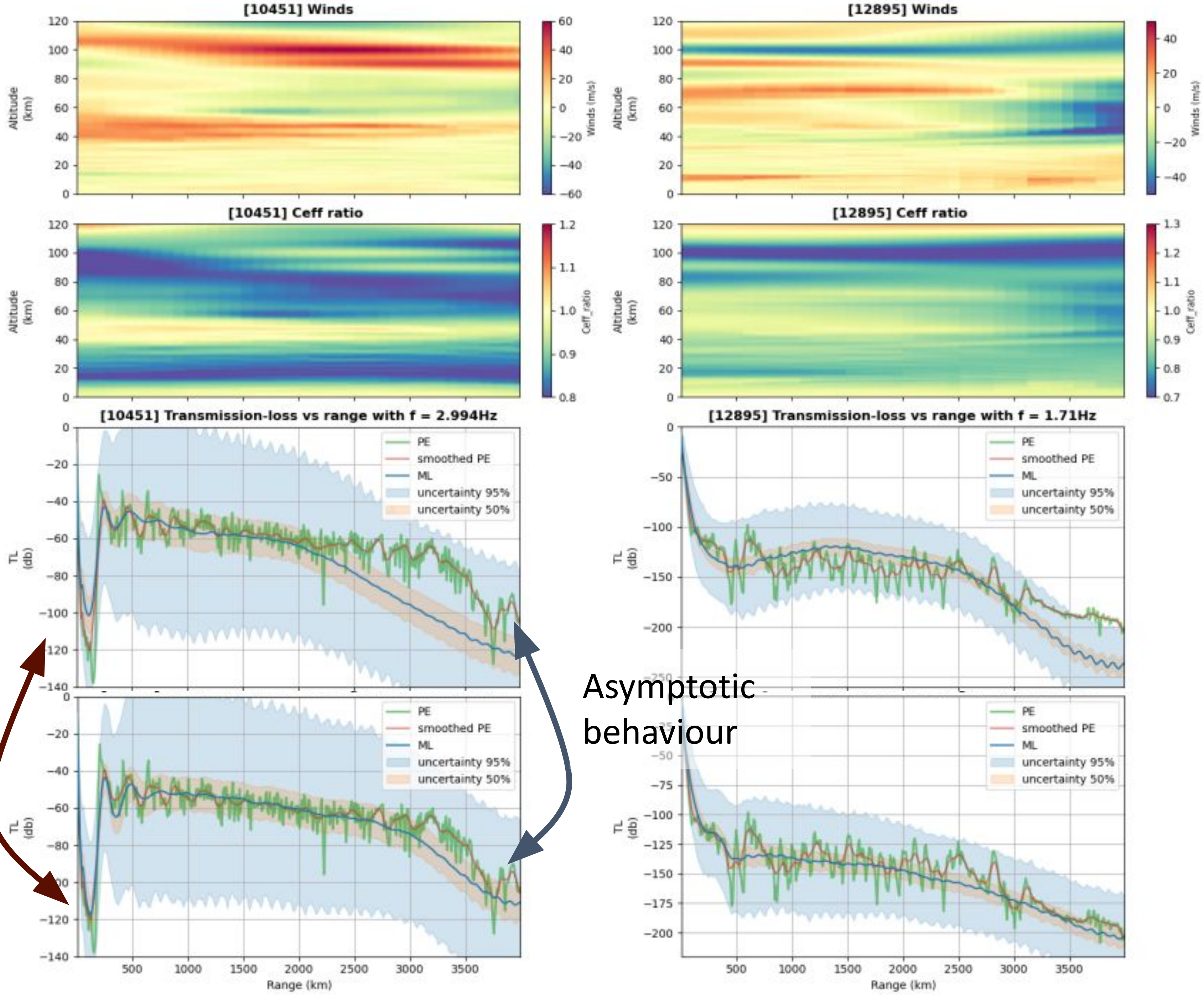
Comparisons



CNN

RNN

Shadow zone

Asymptotic behaviour

Perspectives

- **Inexpensive** (0.05 s) & **accurate** ($\sim$ 5 dB) alternative to PE
- **Plenty of applications** benefitting from **rapid** TL estimate, (near-) realtime atmospheric model diagnostics, microbarom propagation, event analysis, …
- **Rapid amplitude-based inversion** $\Rightarrow$ **source parameters** (e.g., yield, ground pressure level)
- How accurate do we need to be? Must consider the **atmospheric model uncertainty context**

Ambitions

- Explainable ML, e.g., Layer-wise Relevance Propagation
  $\Rightarrow$ relations between atmospheric model regions & TL
  $\Rightarrow$ **sensitivity kernels**
- ERA5: **ensemble** allowing for **probabilistic simulations** & **uncertainty propagation**
- Building **stochastic models for propagation**
- Compose full-waveform or **Green's function** from multi-frequency complex-valued ML-based TL

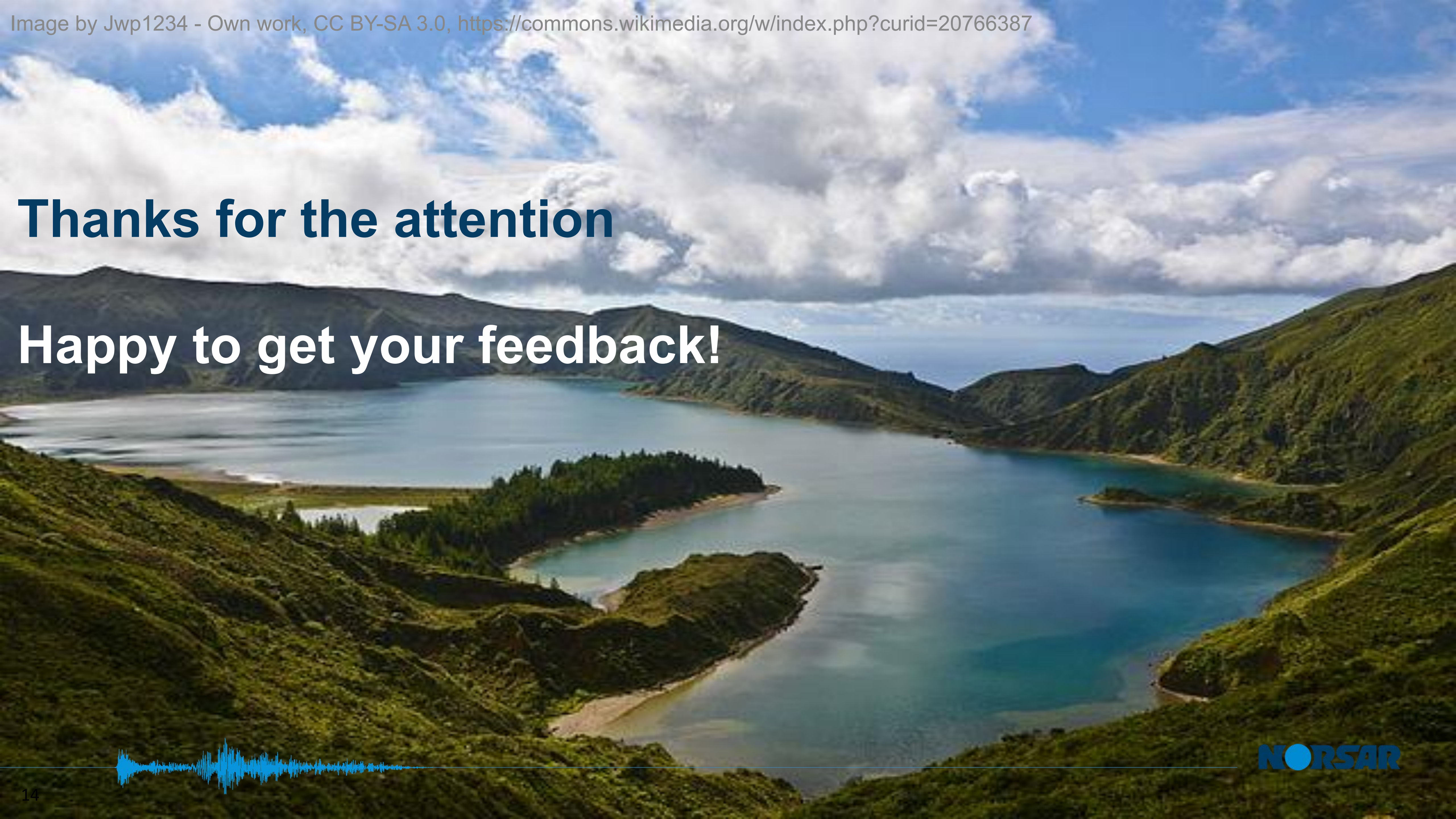
Funding making this work possible

- NORSAR internal research funding
- Research Council of Norway FRIPRO/FRINATEK basic research contract 274377:
  Middle Atmosphere Dynamics: Exploiting Infrasound Using a Multidisciplinary Approach at High Latitudes (MADEIRA)

Credit where credit is due for hands-on coding & analyses

- Edouard Forestier
- Quentin Brissaud
- Antoine Turquet

Thank you Claus Hetzer & the ncpaprop team for the open PE code!



Thanks for the attention

Happy to get your feedback!

Extra slides →

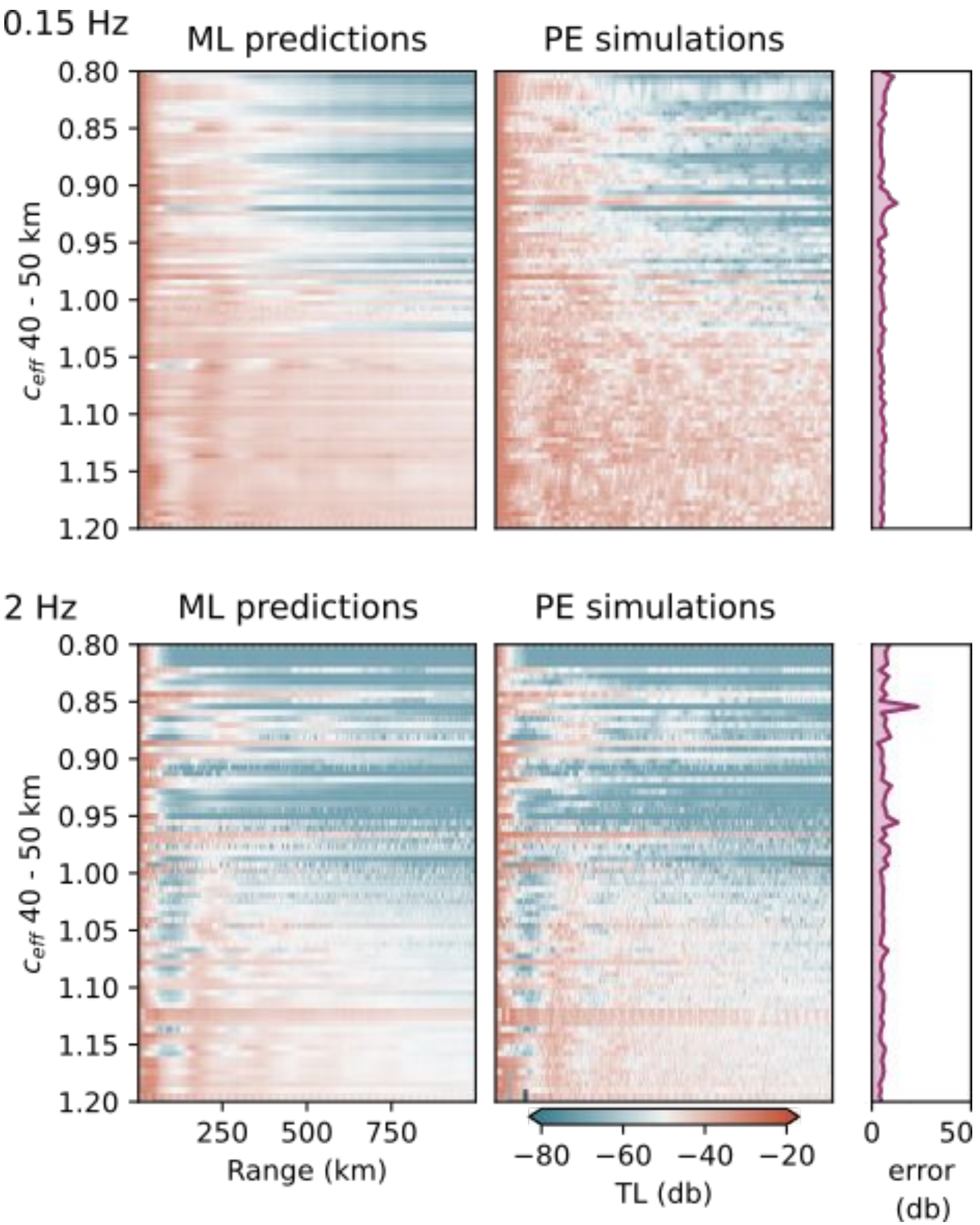
Gated Recurrent Units, GRUs

- "Compute a bad TL" & improve, reading the wind profile range-by-range
- GRU computes a 4 000 km TL with the wind profile at range 0
- Then: update the 4 000 km TL, looking at wind profile at range 1, and so on

Resulting model

ML captures main features:

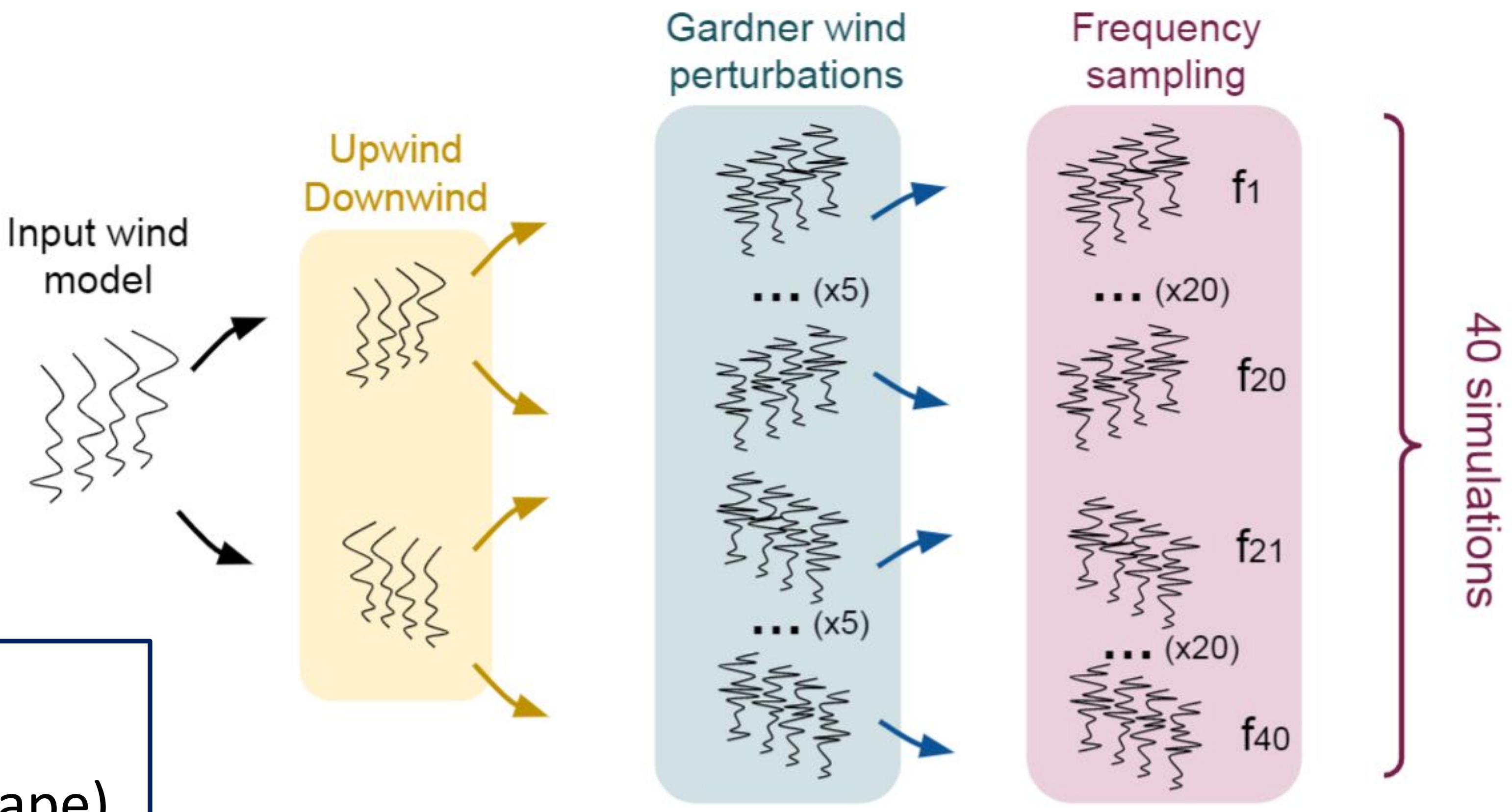
- Multiple stratospheric shadow zones
- Tropospheric & thermospheric phases
- Low vs. high effective sound speed ratio
- Error within ~ 5 dB



Goal

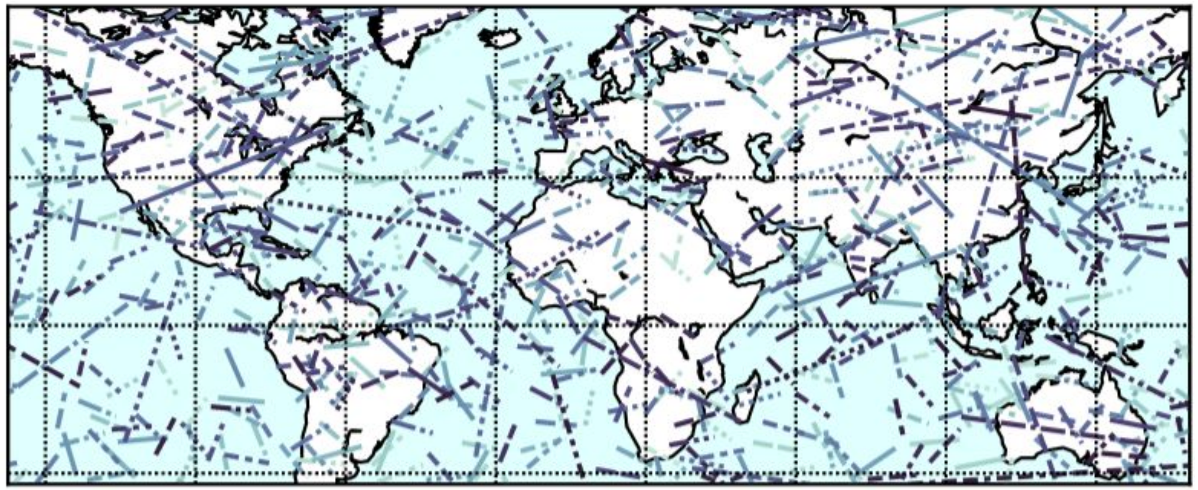
Fast infrasound amplitude predictor

⇒ Transmission loss for any range-dependent atmospheric model



Ground-truth dataset

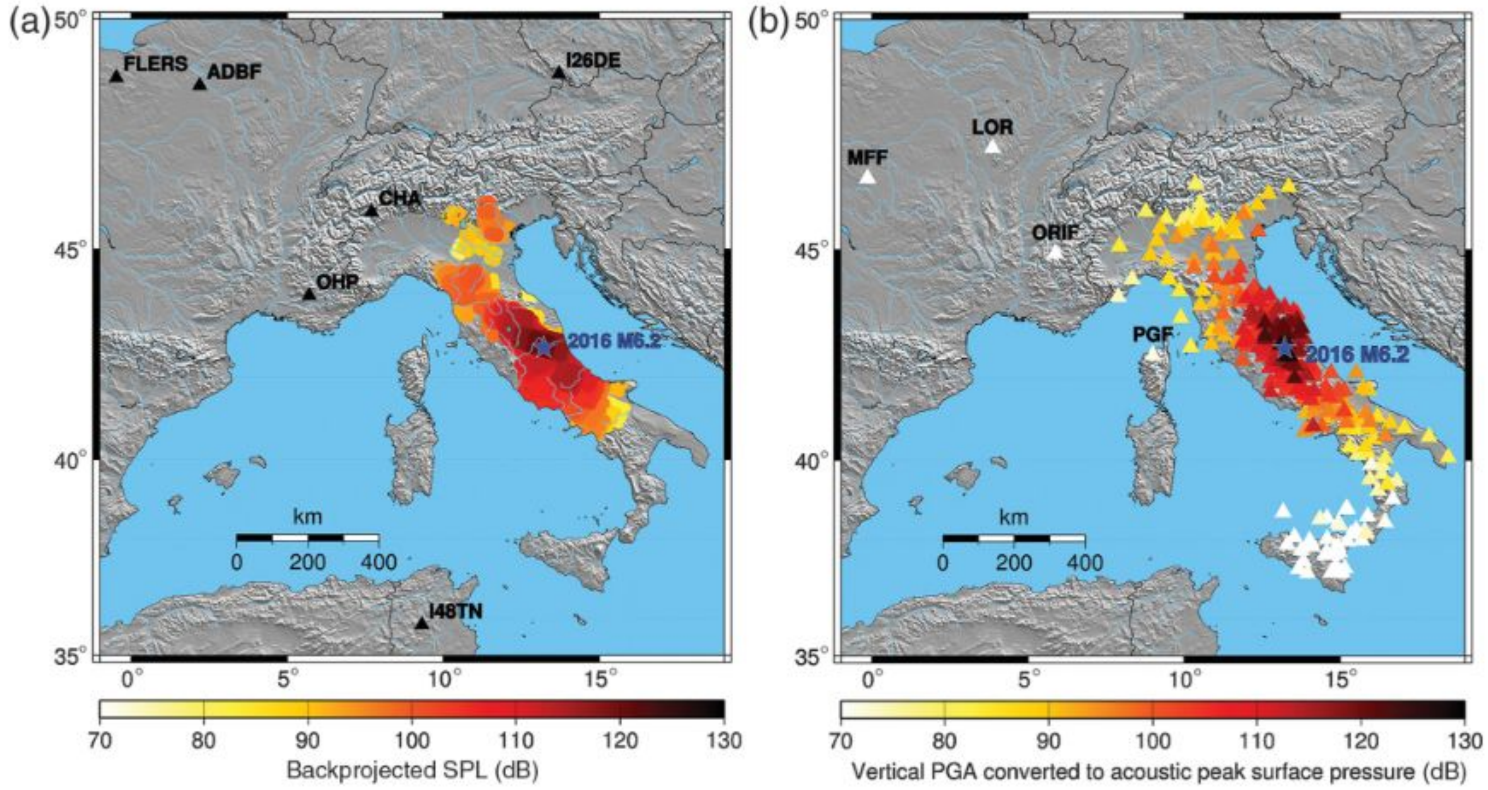
- Massive PE simulations (NCPA ePape)
- Range-dependent:
  ERA5 & NRLMSIS-00/HWM14
- Randomization:
  - Slice locations
  - Time



Infrasound to retrieve source parameters

Infrasound excited by surface sources can travel large distances & 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.

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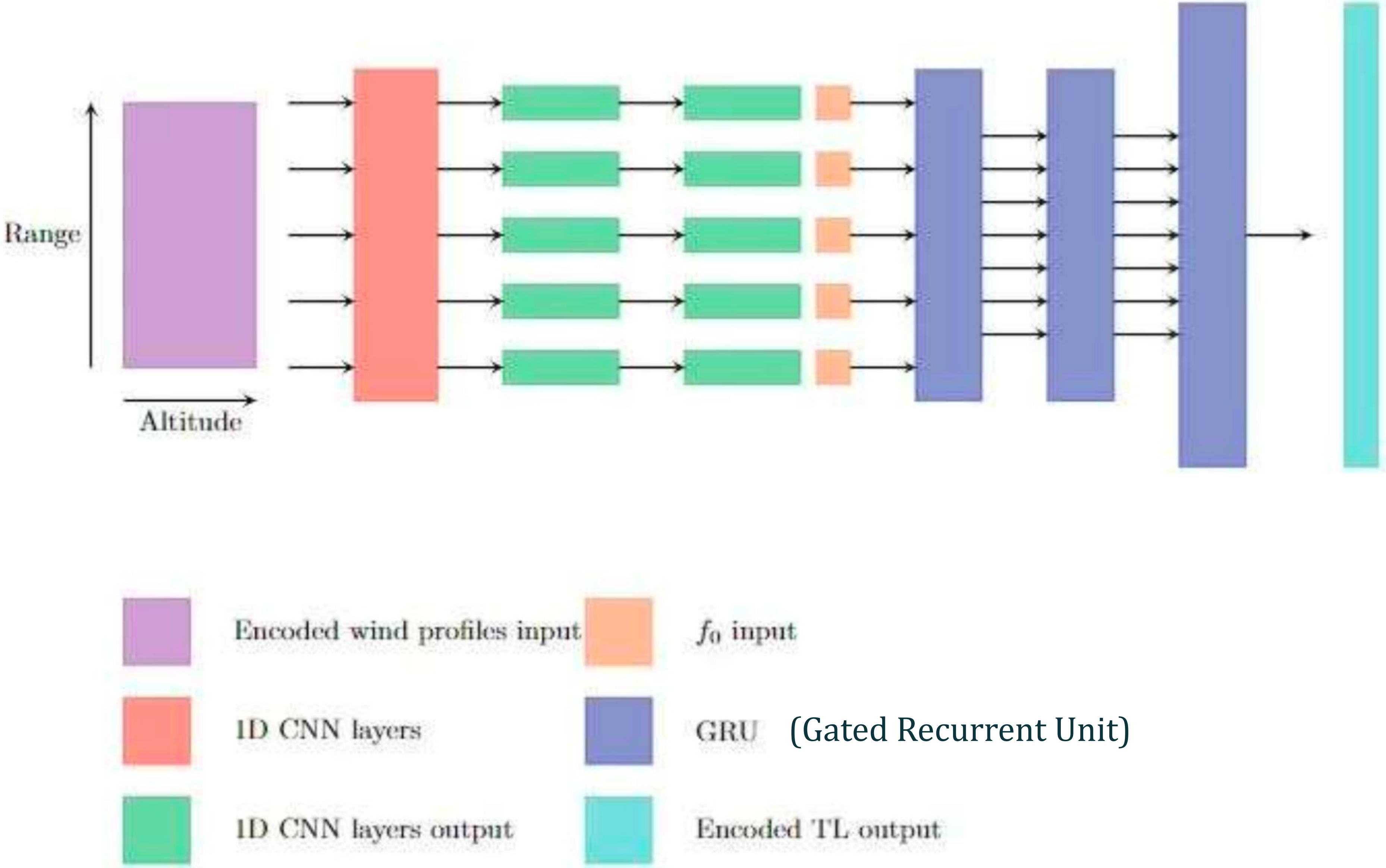
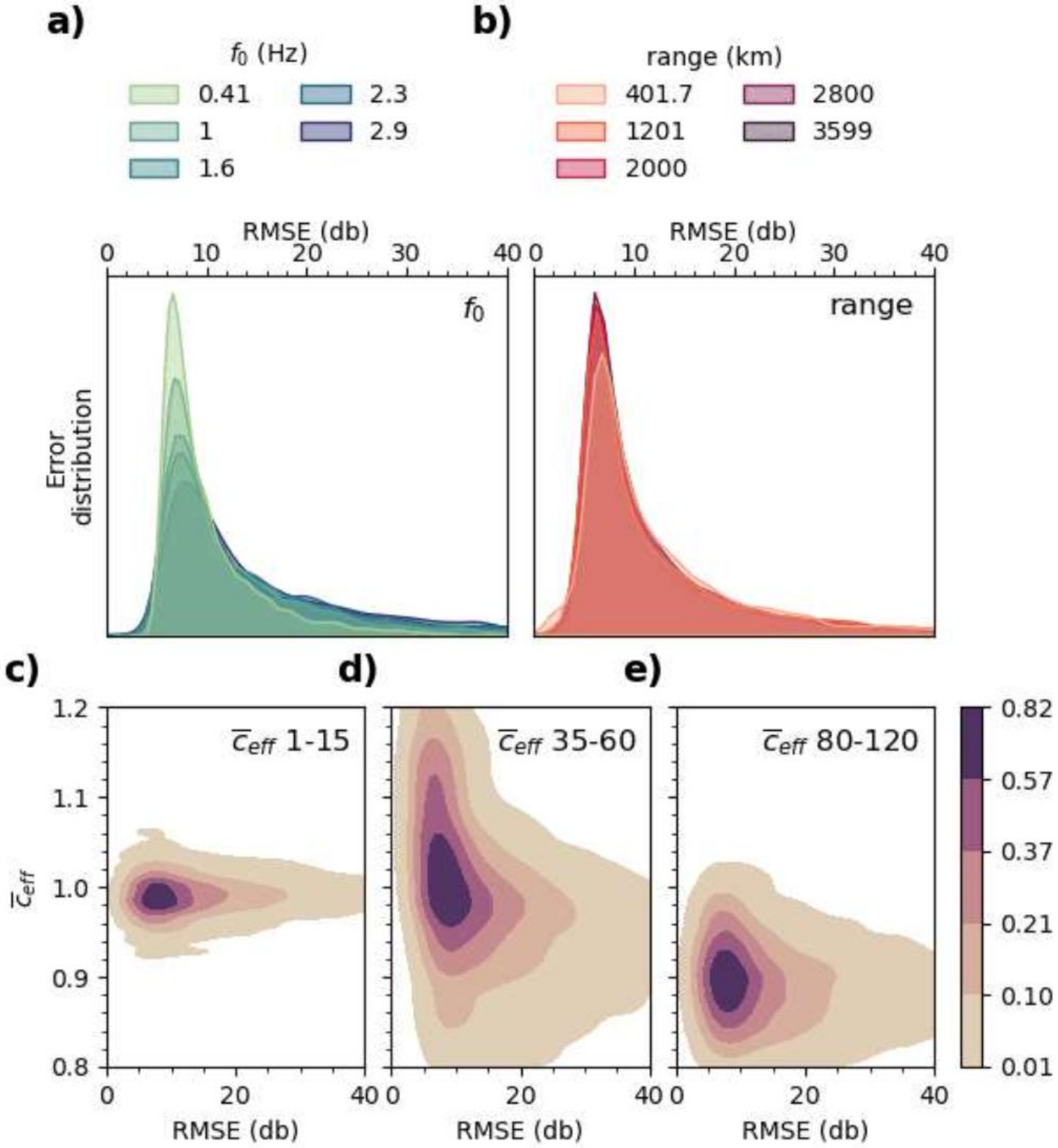
Brissaud, Q., Näsholm, S. P., Turquet, A., & Le Pichon, A. (2023). Predicting infrasound transmission loss using deep learning. *Geophysical Journal International*, *232*(1), 274-286.

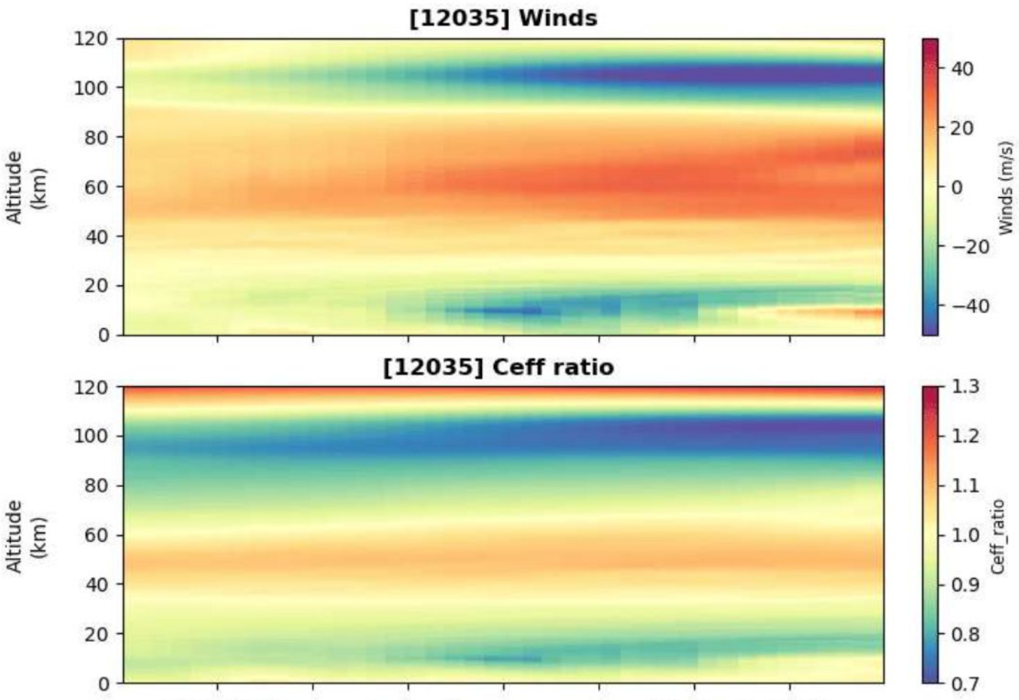
RNN

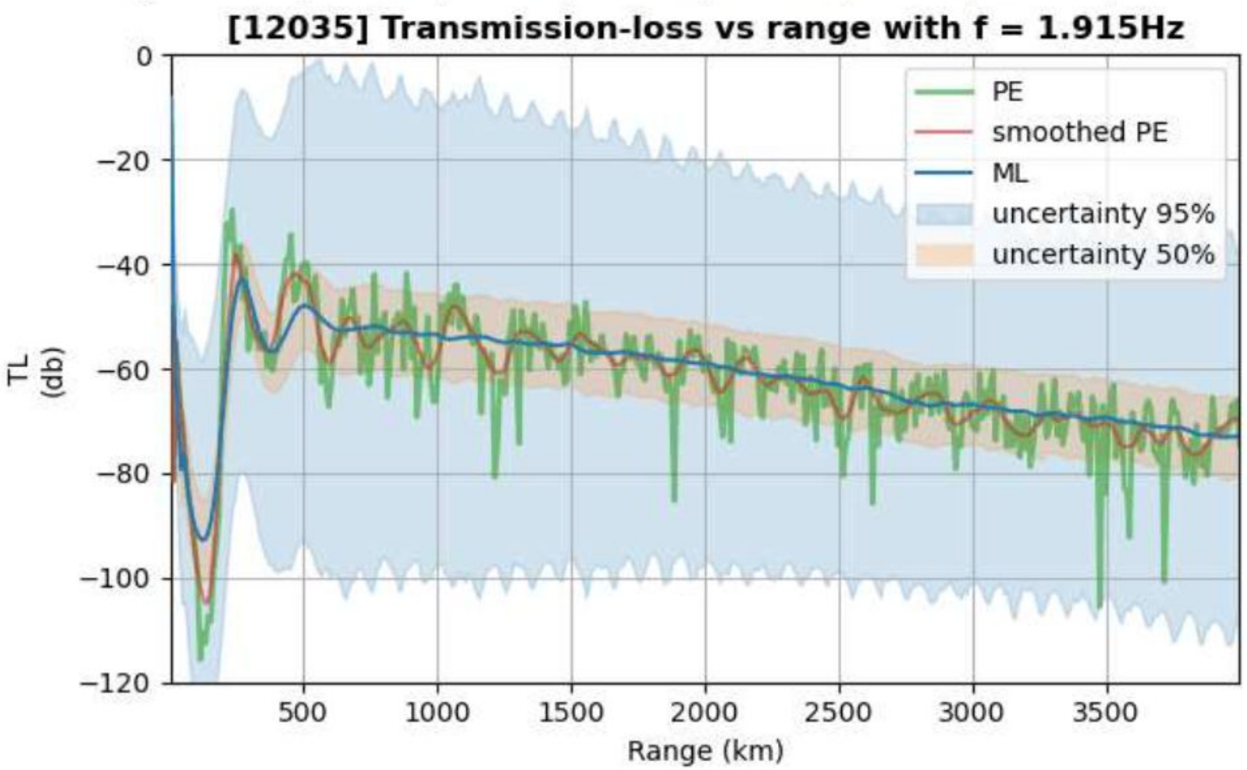

Range
Altitude
Encoded wind profiles input
f_0 input
1D CNN layers
GRU (Gated Recurrent Unit)
1D CNN layers output
Encoded TL output

Errors RNN


a)
b)
f_0 (Hz)
0.41
2.3
1
2.9
1.6
range (km)
401.7
2800
1201
3599
2000
RMSE (db)
Error distribution
f_0
range
c)
d)
e)
$\overline{c}_{eff}$ 1-15
$\overline{c}_{eff}$ 35-60
$\overline{c}_{eff}$ 80-120
$\overline{c}_{eff}$
0.82
0.57
0.37
0.21
0.10
0.01
RMSE (db)

Without stacked GRUs





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Without stacked GRUs