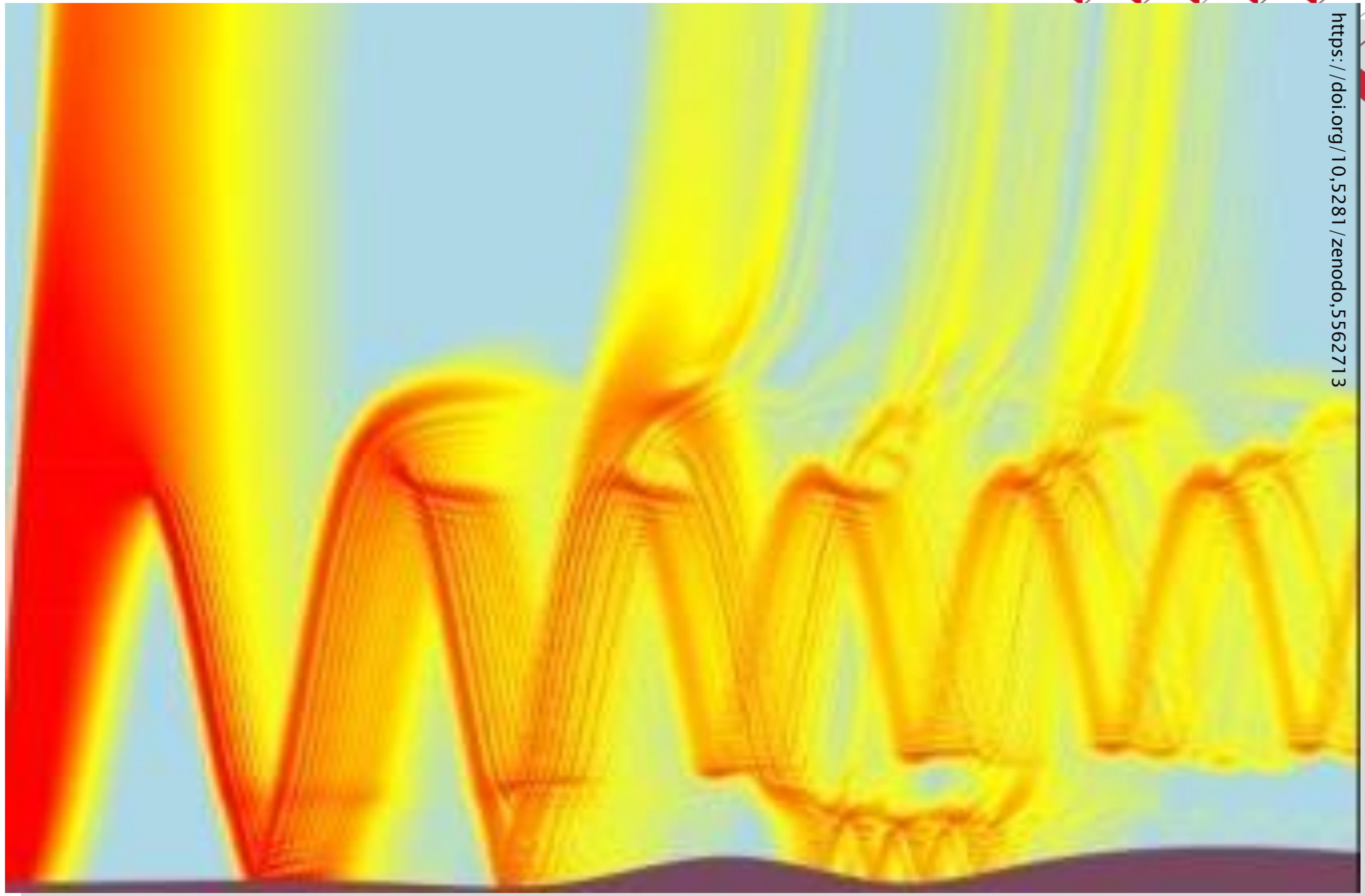
Deep learning methods for modeling infrasound transmission loss in the middle atmosphere



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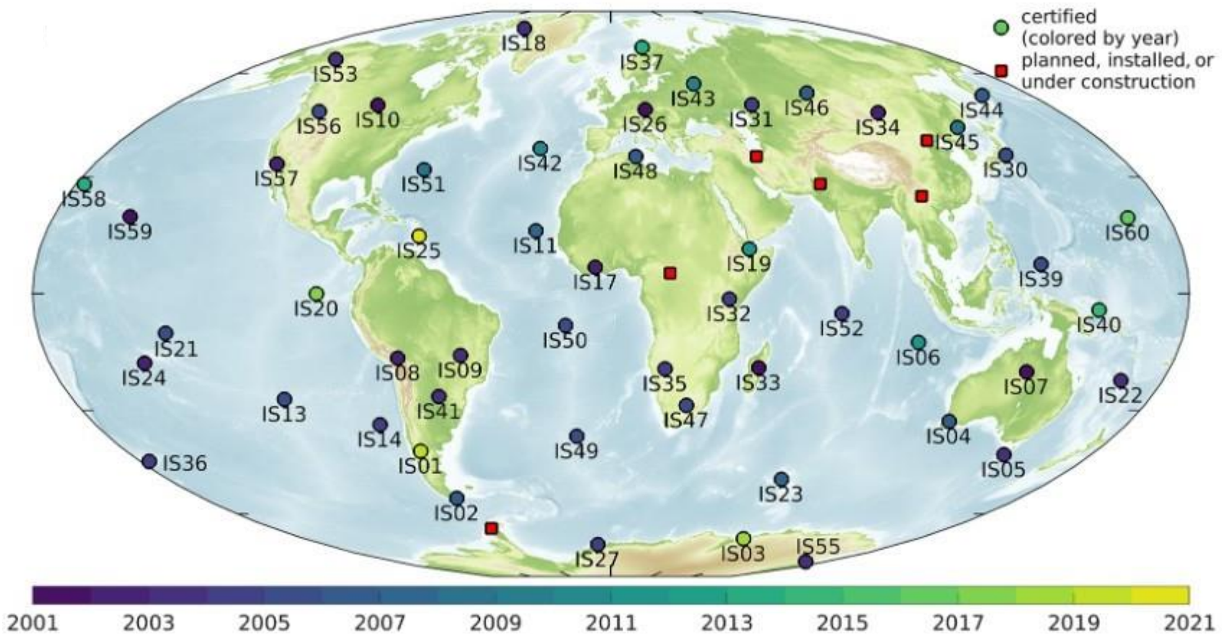
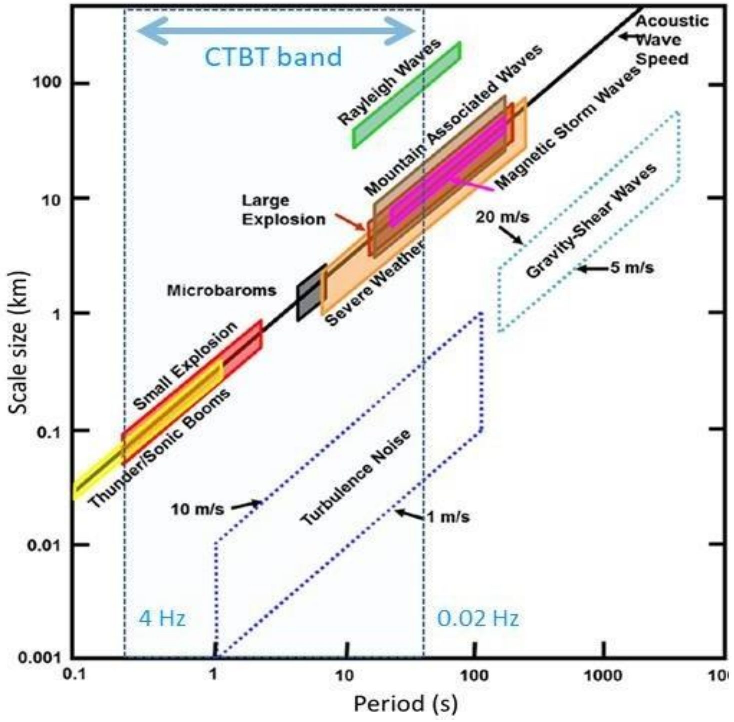
Context: CTBT

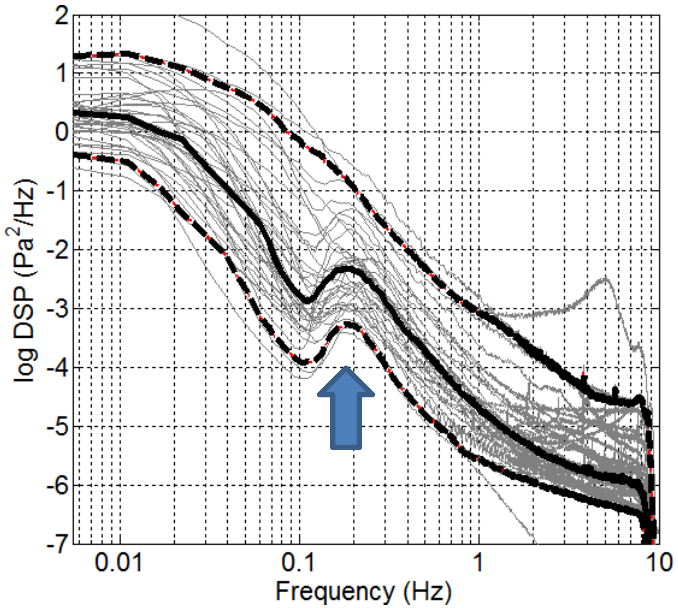
- International Monitoring System (IMS) under the Comprehensive Nuclear Test Ban Treaty (CTBT)
- infrasound stations uniformly distributed around the globe to detect, characterize and locate 1kt nuclear explosions
- Many sources; natural (volcanoes, earthquakes, etc.) or artificial (turbines, explosions, etc.)



Overview of the IMS infrasound network
(Hupe et al. 2021)



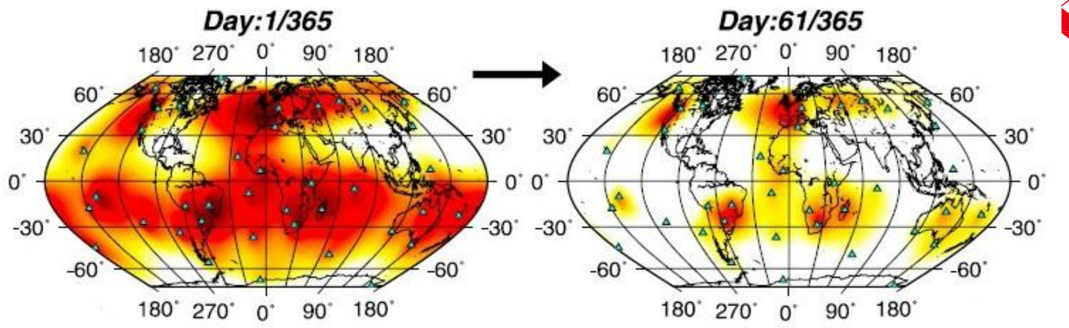
Silber et al. 2014



Wind / turbulence
microbarom peak
Brown et al., 2014

Motivations

- Assess IMS detection capabilities: requires near-real-time modeling of infrasound transmission losses (TLs)
- Existing full wave propagation modeling tools (used to model TLs): costly
- *Brissaud et al. 2023*: deep learning algorithm to model TLs up to 1,000 km in near-real-time

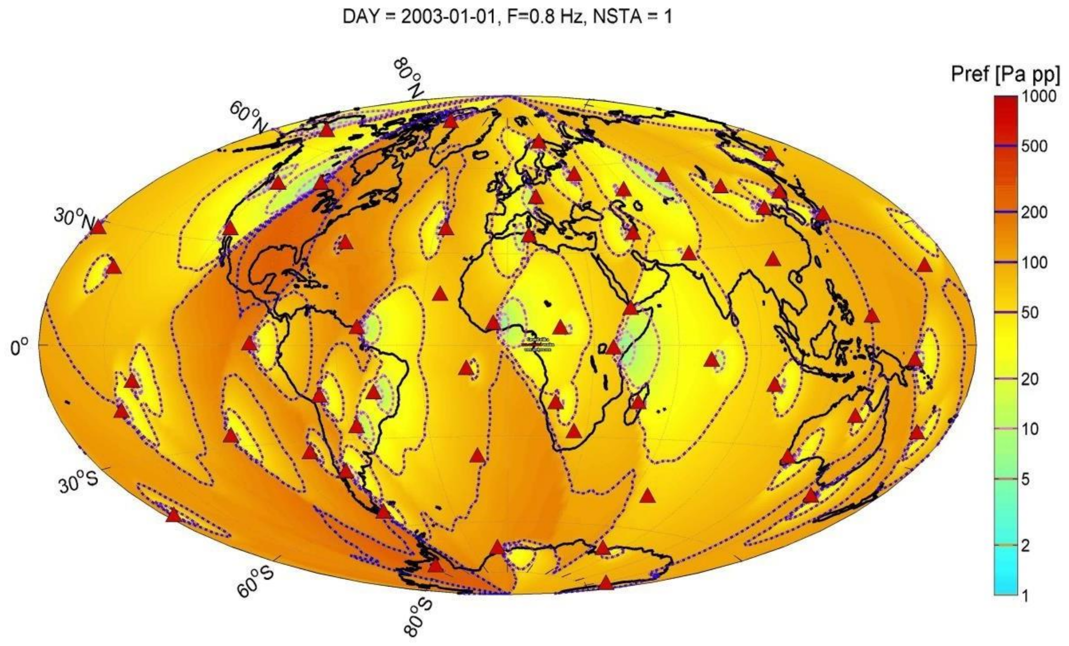


Detection capability of IMS: highly variable in space and time (90 % detection probability) (*Green et al. 2010*)

Objectives

- accurate + near-real-time modeling of TLs up to 4,000 km;
- quantify associated uncertainties;
- account for the multiple atmospheric range-dependent wave guides.
- draw IMS detectability maps in near real-time

using deep learning



IMS capacity of detection map at 0,2 Hz

Method

From realistic 2D range-dependent atmospheric slices…

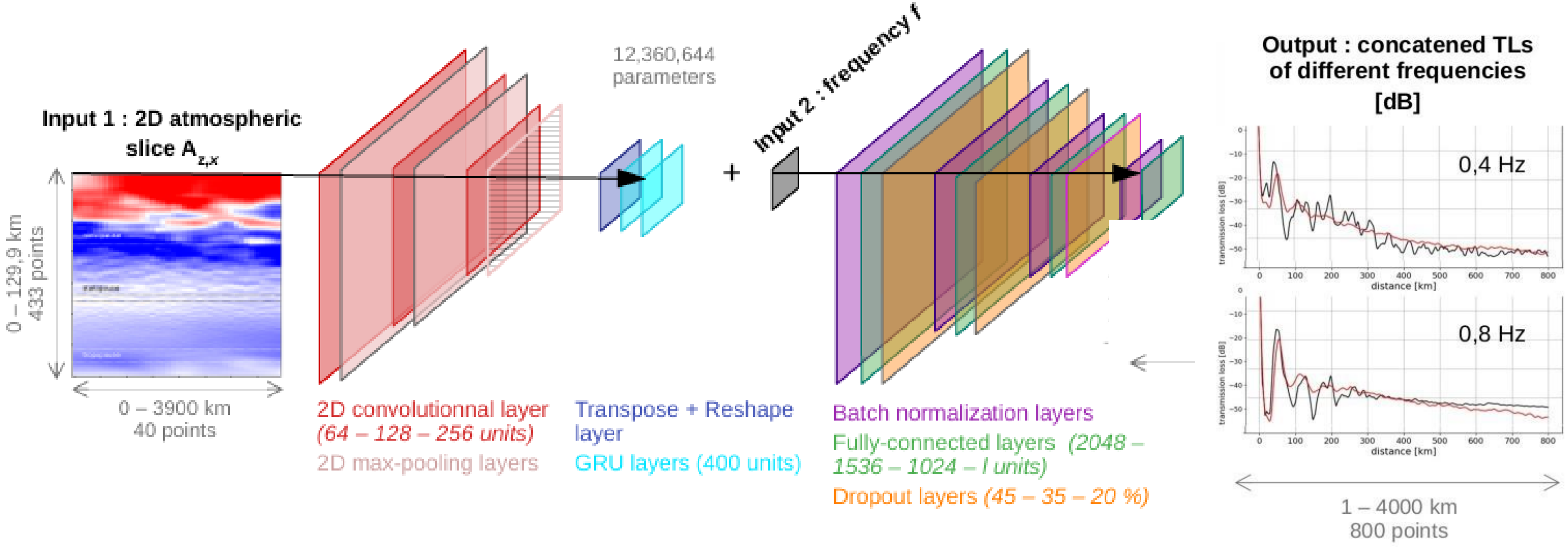
… using a Convolutional Recurrent Neural Network

… estimate in near-real-time ground-level TLs up to 4,000 km at ≠ frequencies

inputs

method

outputs



Inputs: atmospheric slices

- **Realistic range-dependent 2D atmospheric slices at a global scale**

- Mean atmospheric conditions

  x ∈ [0; 4,000] km distance;

  z ∈ [0; 130] km altitude;

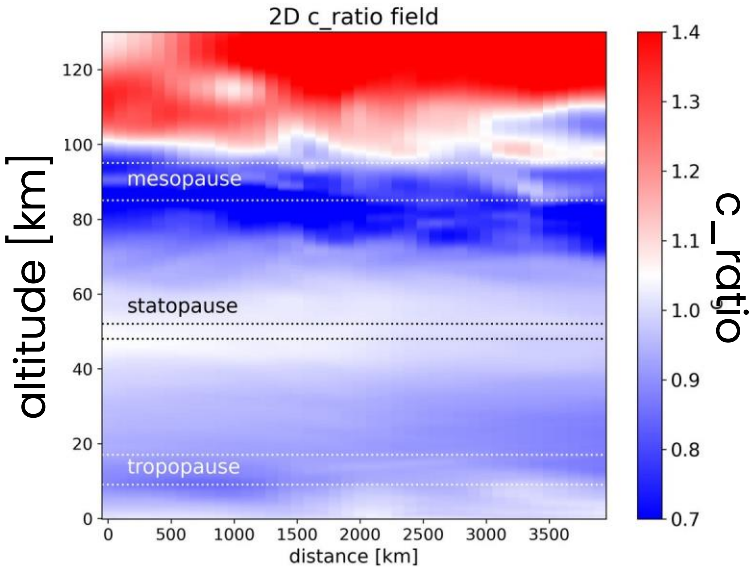
  vertical tempertaures + horizontal windspeeds extracted using the Whole Atmosphere Community Climate Model (*Gettelman et al. 2019*).

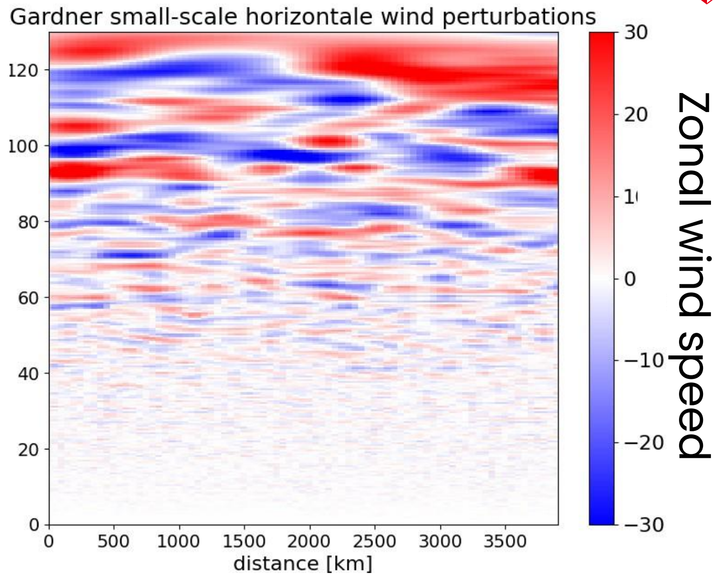
- Small scale variations

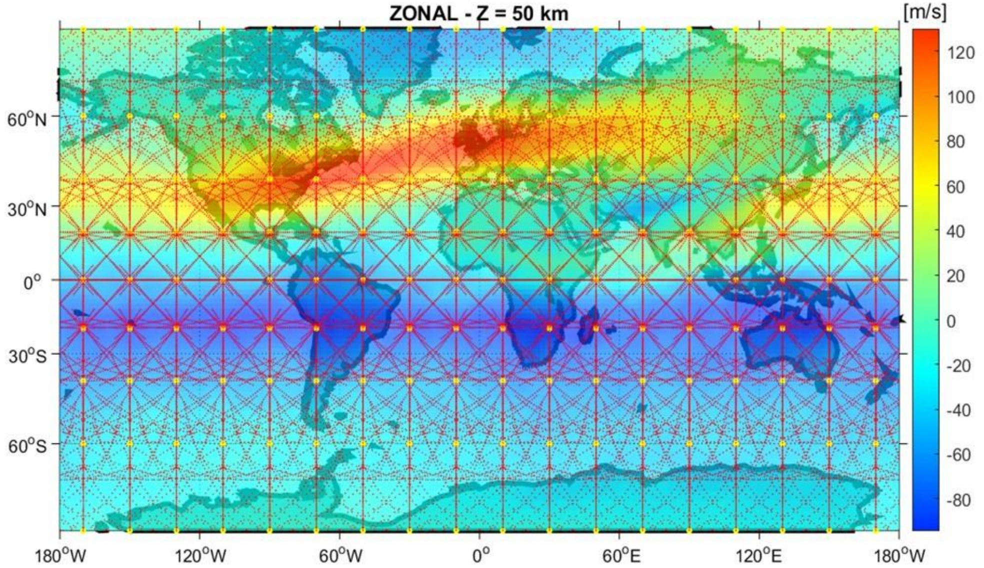
  partly due to gravity waves;

  small-scale windspeed perturbations (*Gardner et al. 1993*)

Atmospheric slice + small scale variations







162 sampling points (15/01/2021)

+ 8 directions

+ 2 azimuths of projection

+ 10 Gardner model realizations

= 25,920 input slices

Output: transmission losses

- **Ground-level infrasound TLs**
  - x ∈ [0; 4,000] km distance
  - Atmospheric absorption coefficients (*Sutherland et al. 2004*)
  - Parabolic equation (PE) solver (*Waxler et al. 2021*)
  - 5 frequencies: 0.1, 0.2, 0.4, 0.8 and 1.6 Hz.

→ 25,920 slices x 5 = 129,600 simulations

Equation of acoustic wave propagation in the atmosphere

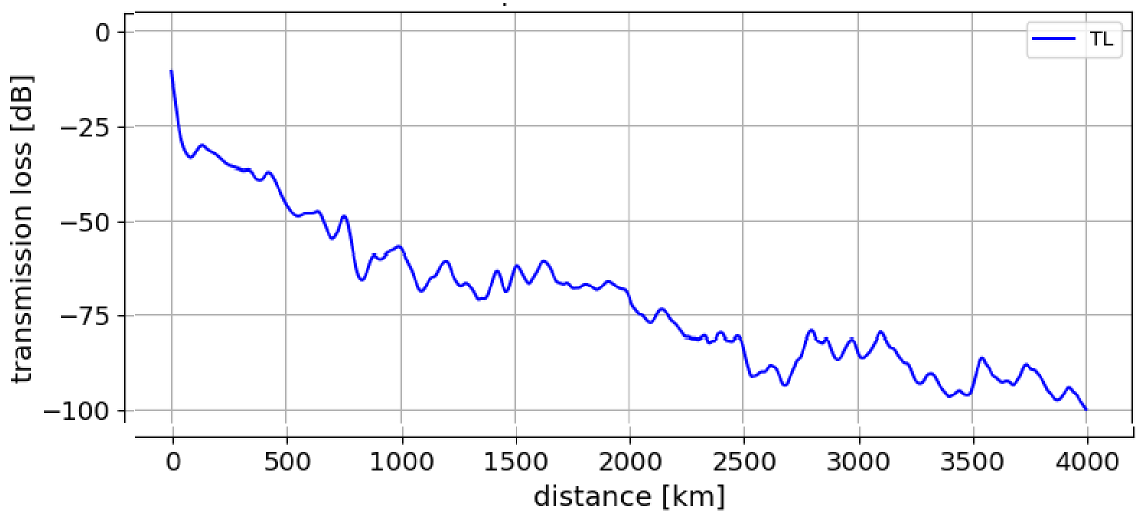
↓ *Parabolic Equation method*

Amplitude of long-range **pressure** generated by a unit point source at a reference distance of 1 km

↓ *modulus + logarithmic scale*

Transmission loss in dB

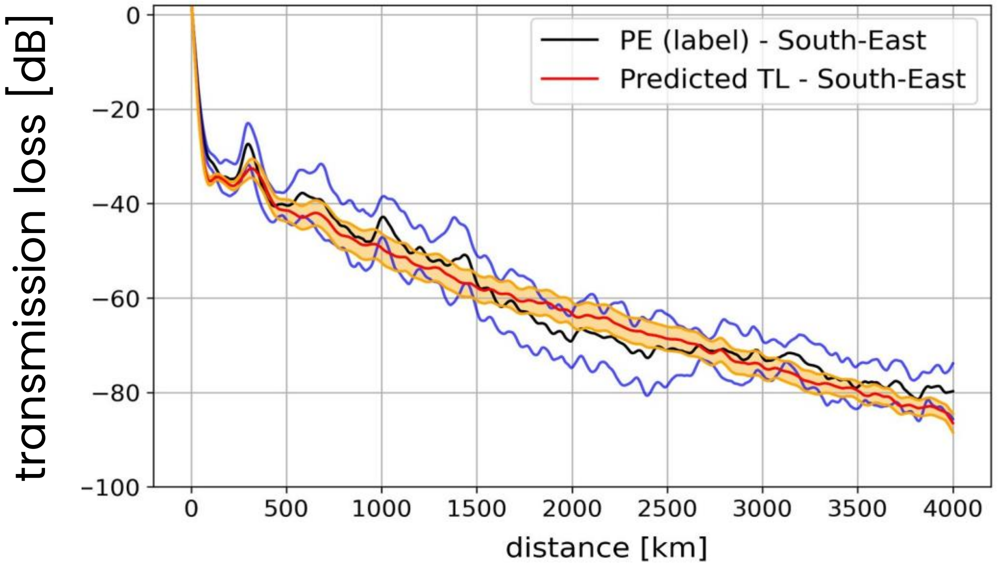
PE simulation at 0.2 Hz



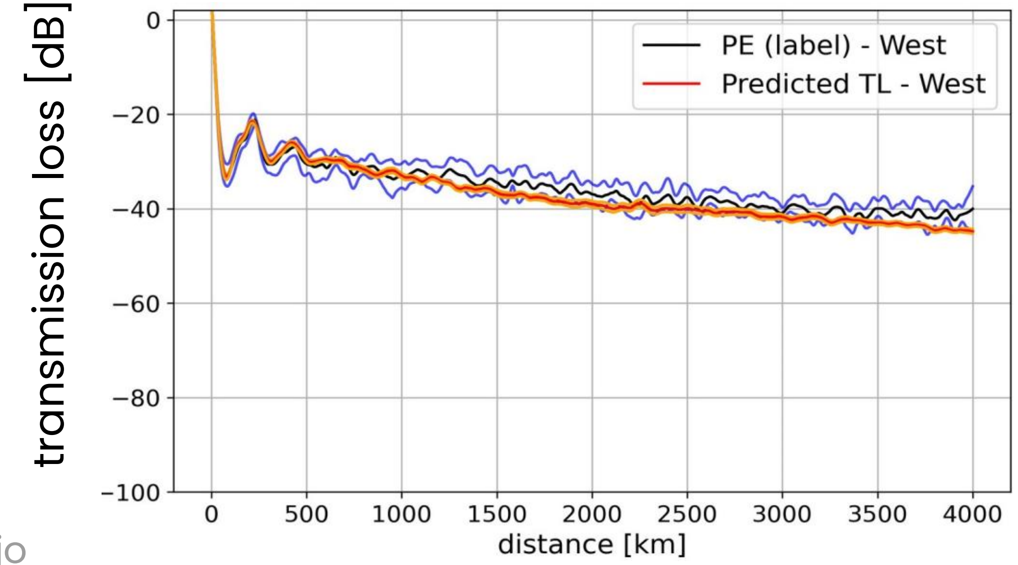
Results: training + testing performances

- **Training process**
  - On A100 GPU
  - convergence of the model after 30 iterations (~ 7s / iteration)

- **Test performances**
  - Good estimation of mean attenuation + asymptotic behavior over 4,000 km
  - Small-scale variations not fully recovered
  - Robust in all initial atmospheric scenarios



Predicted TLs / expected PE
0.2 Hz
No stratospheric duct



Predicted TLs / expected PE
1.2 Hz
Stratospheric duct

Results: error metrics

- Mean Relative Absolute Error (**MRAE**): difference in %

  median of 7.5 % over 4,000 km;

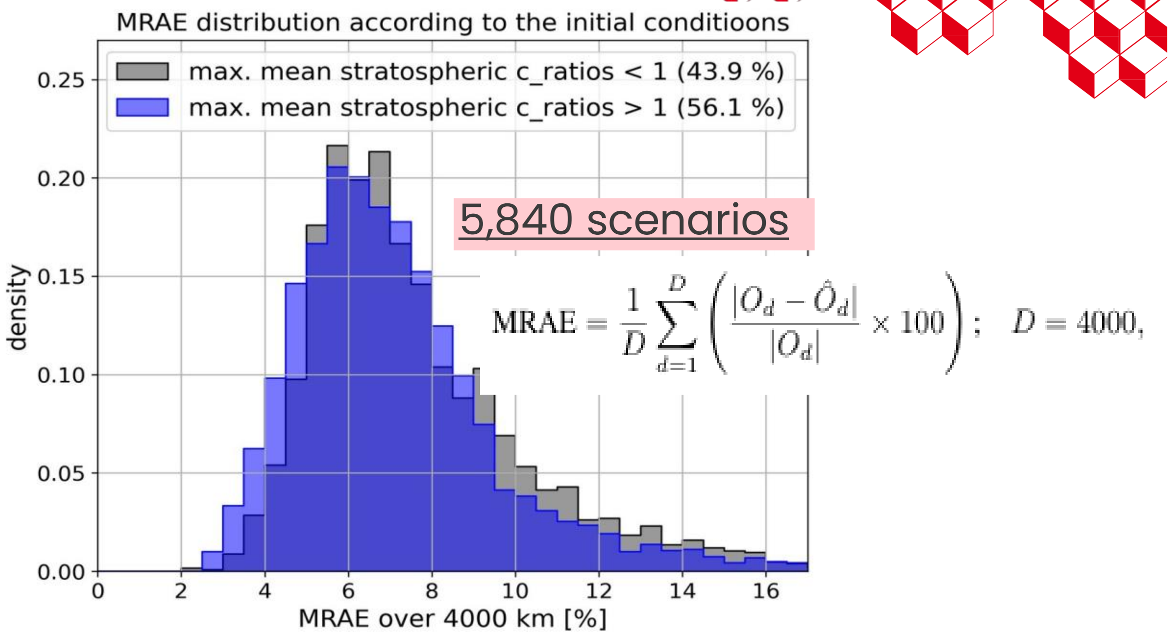
  > 15 % generally below 200 km distance.

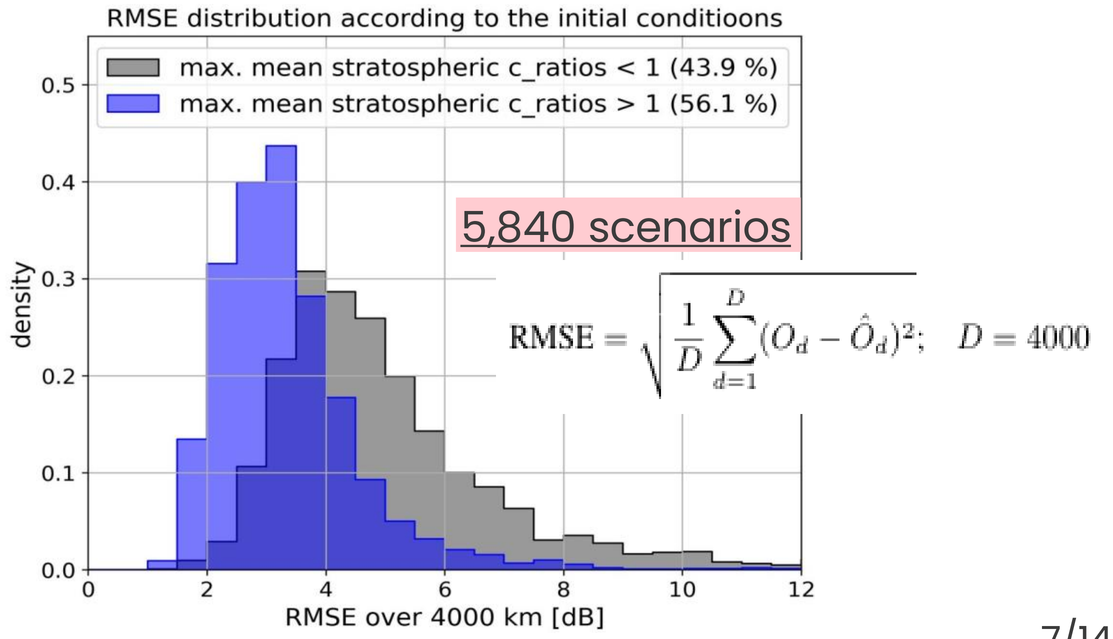
- Root Mean Squared Error (**RMSE**): difference in dB

  median of 4 dB over 4,000 km;

  higher mean RMSE of ~1 dB for scenarios without stratospheric wave duct.

→ consistent with *Brissaud et al. 2023*: mean RMSE of 5 dB regardless of the initial conditions over 1,000 km



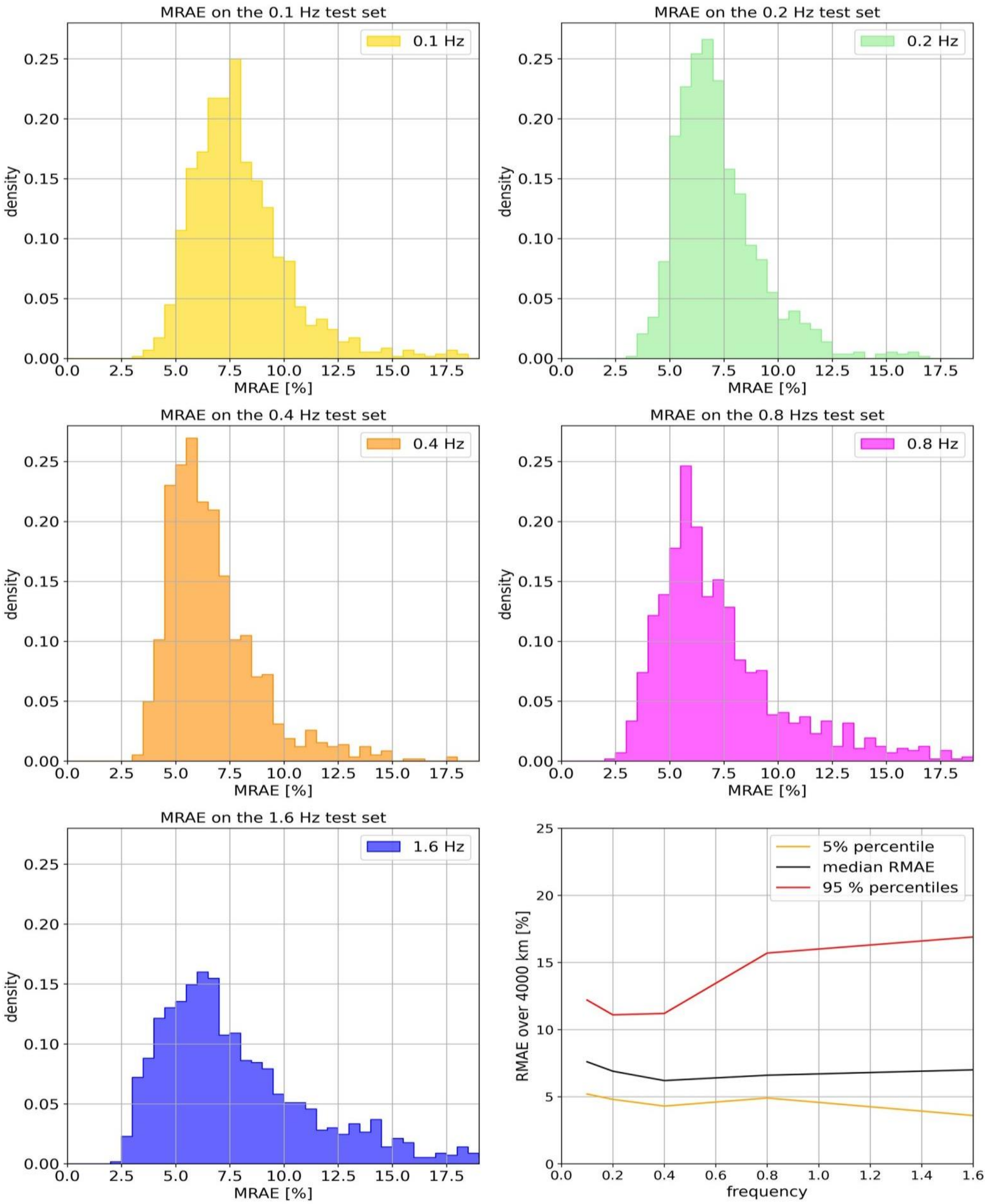


Results: « frequency effect »

- Degradation of performance with increasing frequencies

    identical median of 7,5 % RMAE for the 5 frequencies;

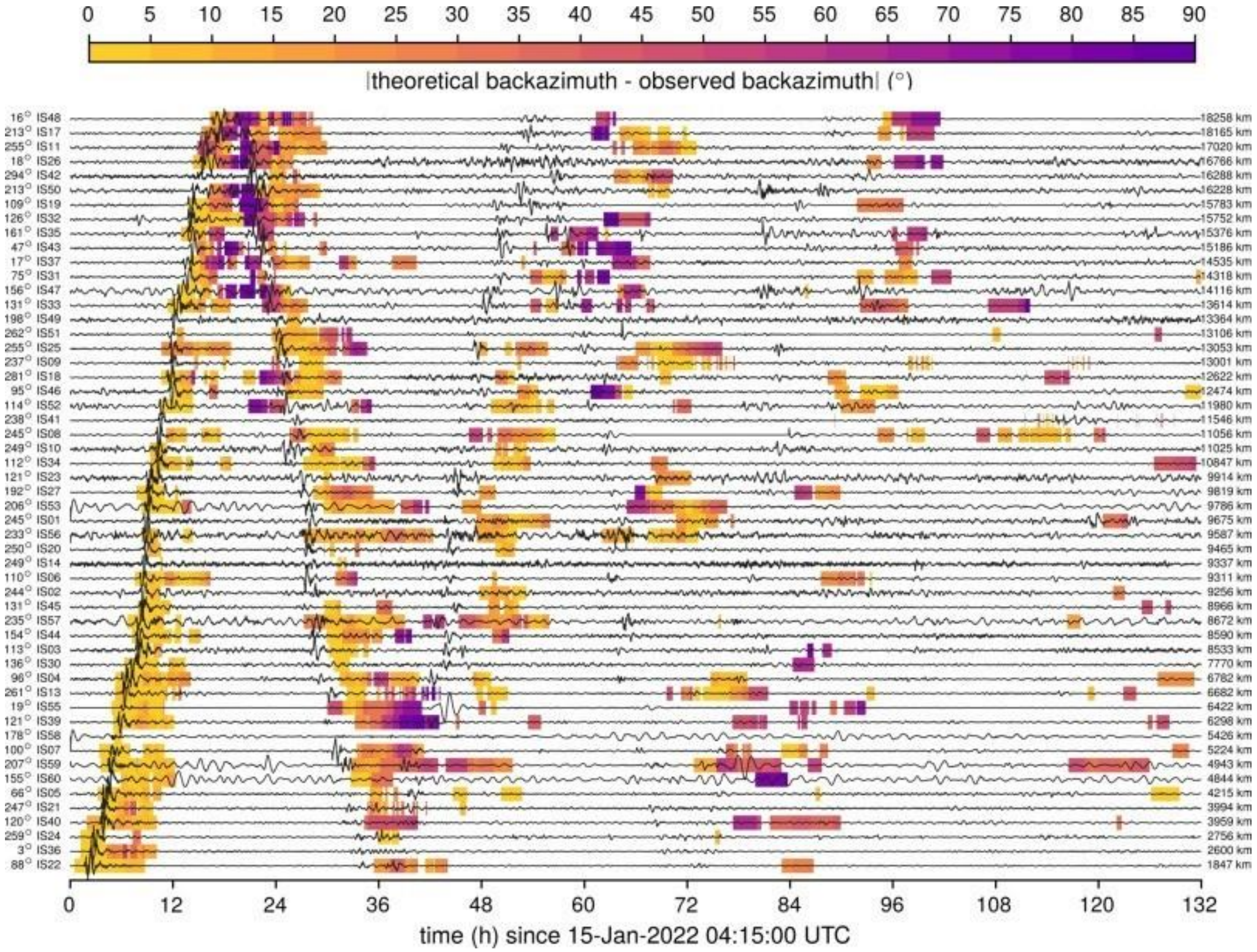
    higher 95 % percentile for higher frequencies.



Results: generalization performances

- Generalization set : atmospheric slices around the Tonga Volcano (01/15/22)
  → different from the training slices

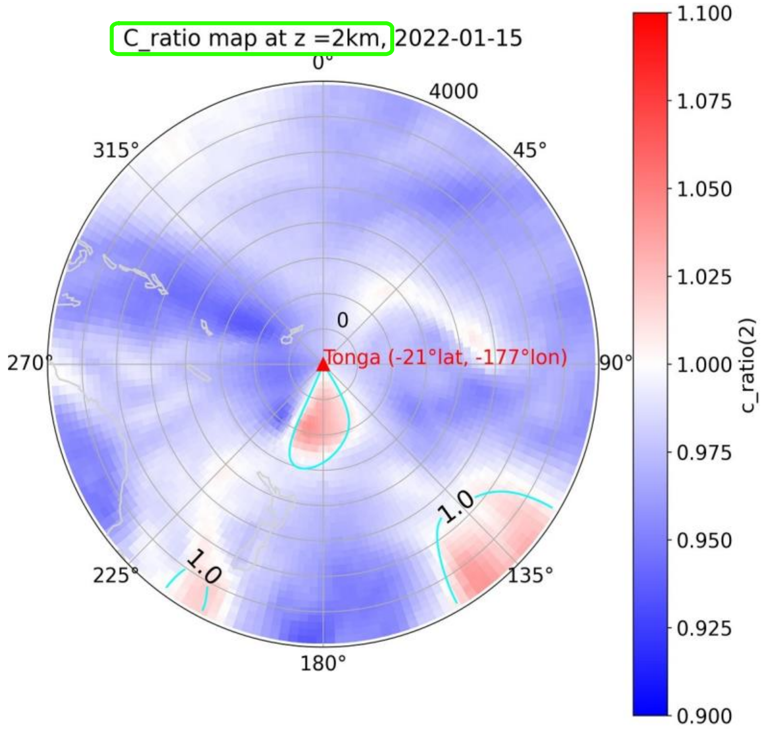
- Estimate attenuation maps around the volcano, obtained almost instantaneously (~ 0,05 s / prediction)

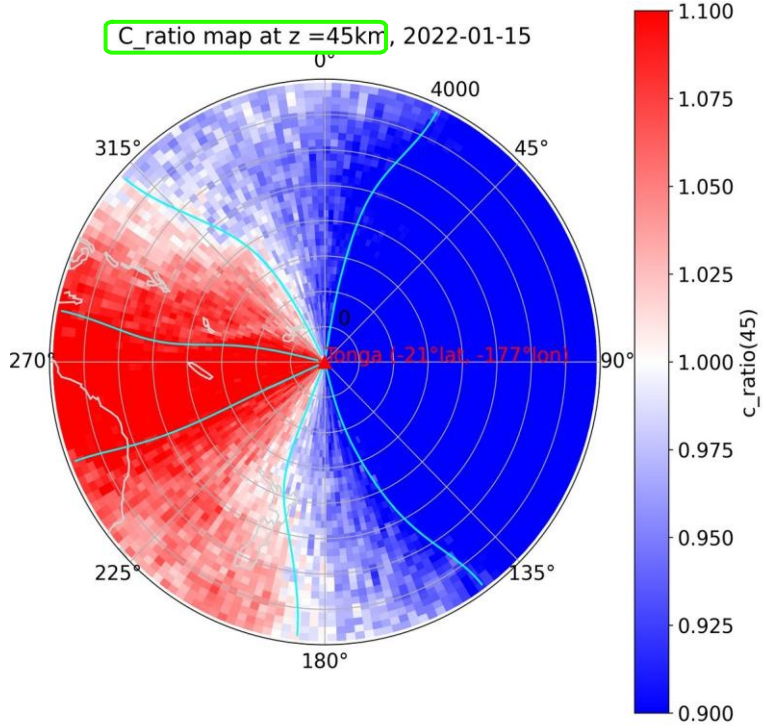


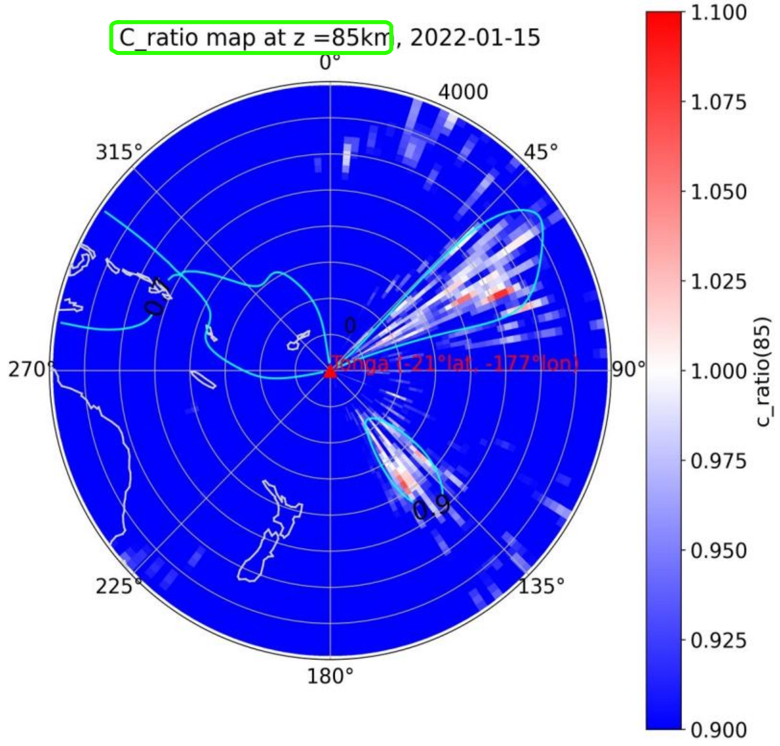
Infrasound detection on the entire surveillance network (*Vergoz et al. 2022*)

Results: generalization inputs

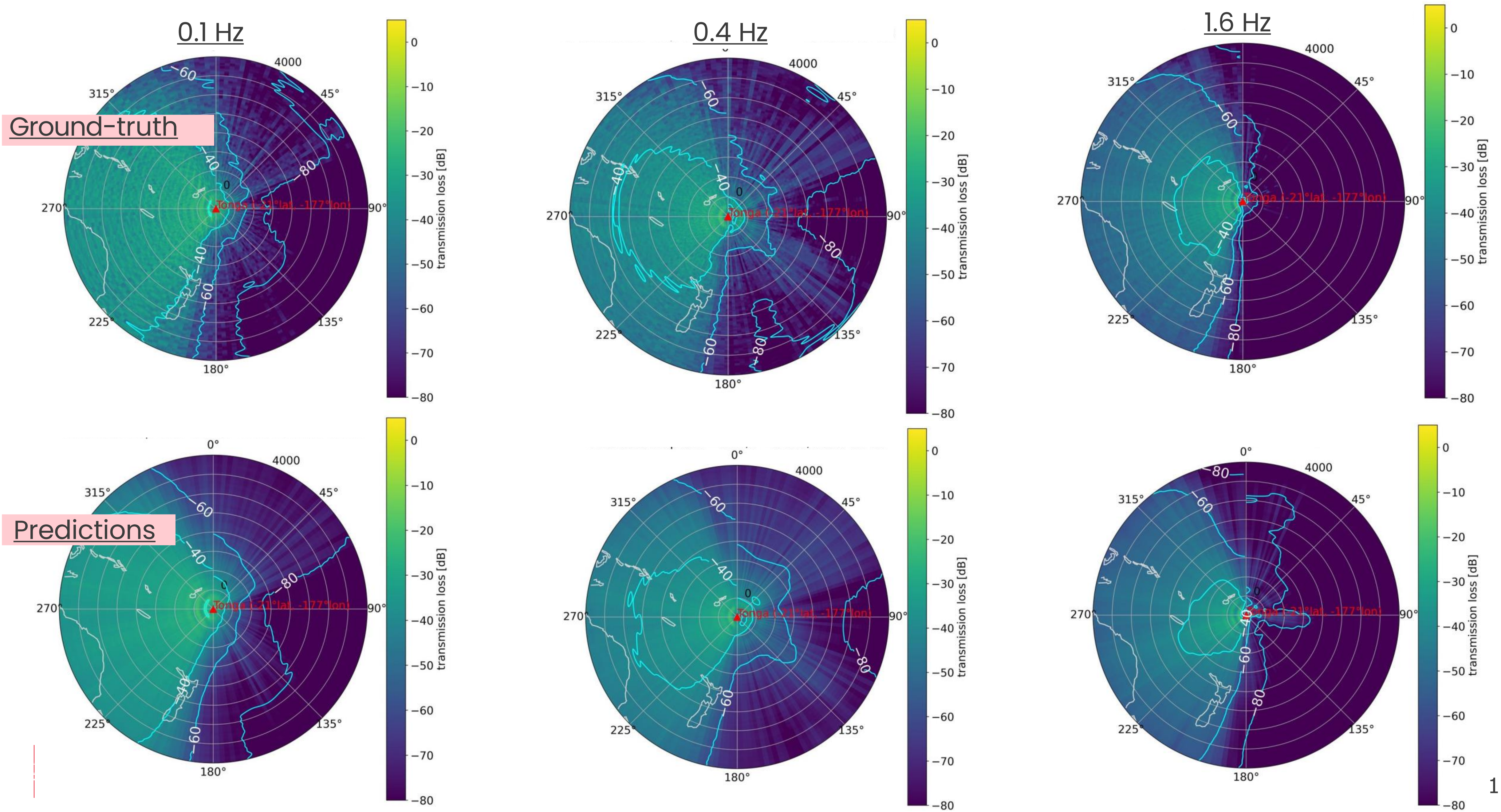
Atmospheric conditions that day





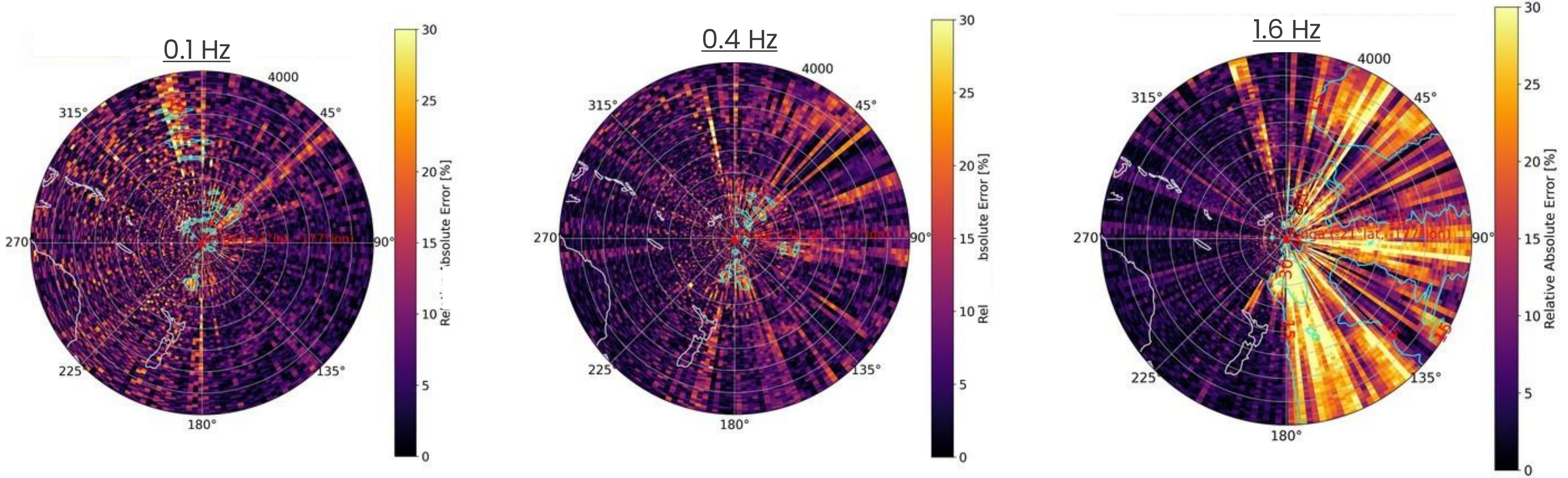


Results: generalization



Results: generalization errors

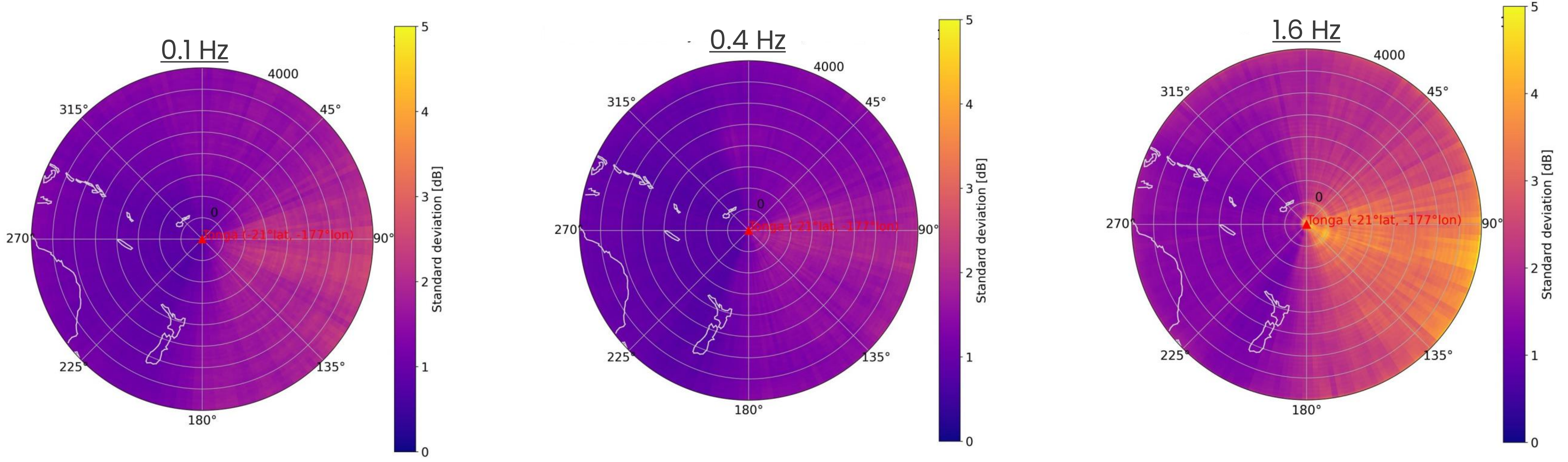
Point-by-point Relative Absolute Error (%) between predictions / expected TLs



$$\mathrm{RAE} = \frac{|\mathrm{label}_d - \mathrm{pred}_d|}{\mathrm{label}_d} \times 100 \quad ; \quad d \in [1, 4000]$$

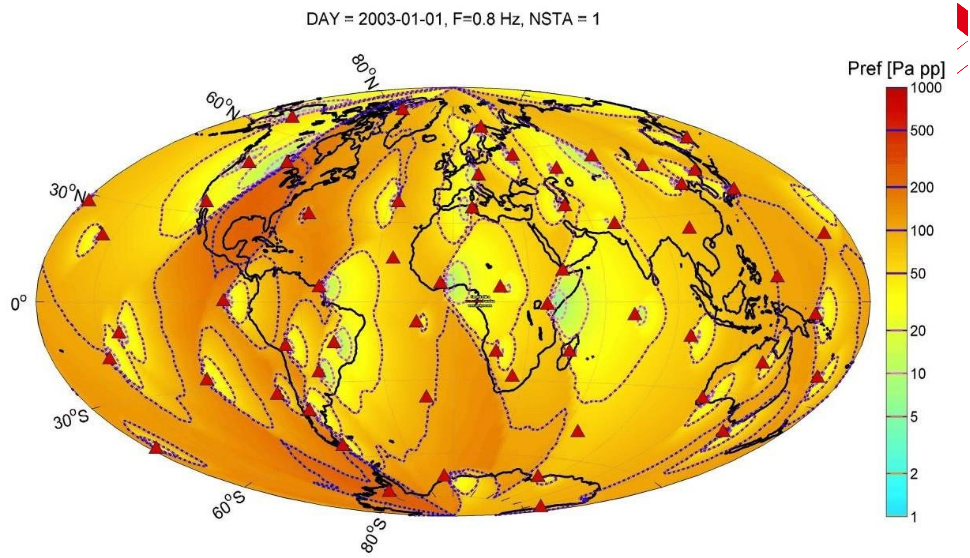
Results: generalization uncertainty

Model + data uncertainty associated with predictions *(Gawlikowski et al. 2023)*



Summary / perspectives

- 1st surrogate deep learning model mapping 2D realistic atmospheric
- slices with ground-level TLs at ≠ frequencies Confidence levels: model + data uncertainty
- Promising results using global dataset (WACCM, winter time): testing ≈ 7,5 % and generalization ≈ 10 % of MRAE over 4000 km
- Ongoing evaluation on reference events (global and regional scales)



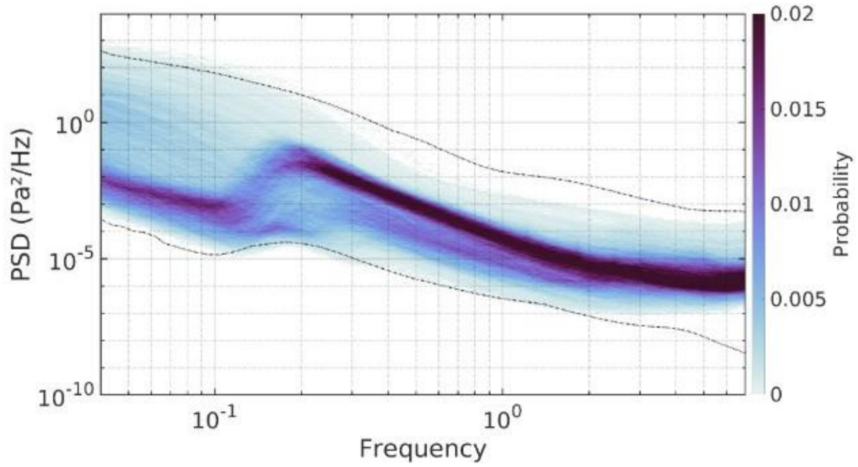
IMS capacity of detection map at 0,2 Hz

- **Perspectives**
  - Enlarge training dataset: spatial / time coverage
  - Ensemble Prediction System (Integrated Forecasting System)
  - Global detection capability maps using measured station noise
  - Develop **Transformer** architectures (*Vaswani et al. 2017*):

    improve the encoding of atmospheric and propagation conditions capture;

    more effectively complex range-dependent features;

    recover small scale atmospheric variations.



PSD probability density at IS37 infrasound station

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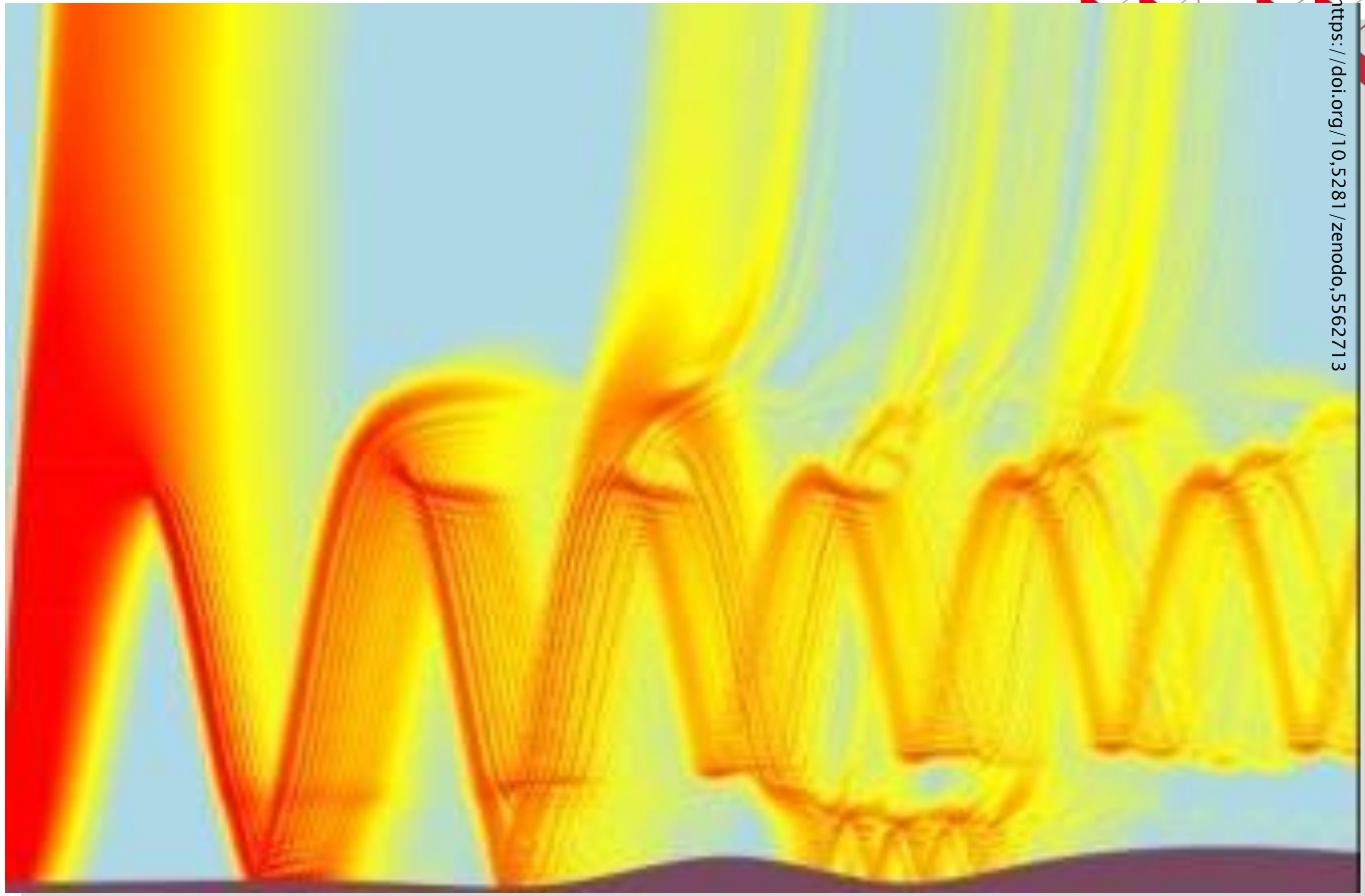
Thank you for your attention !



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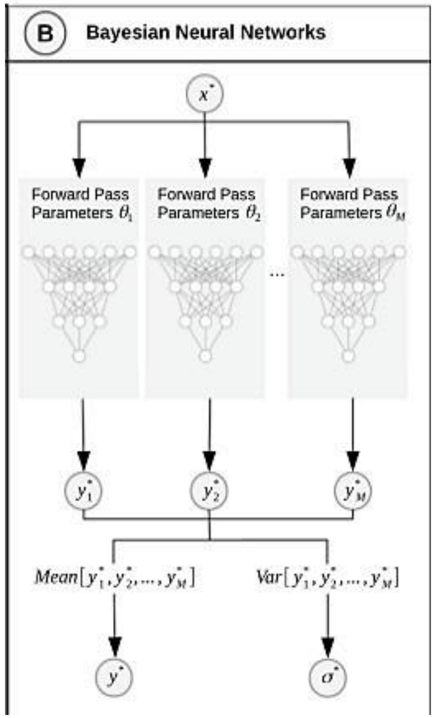
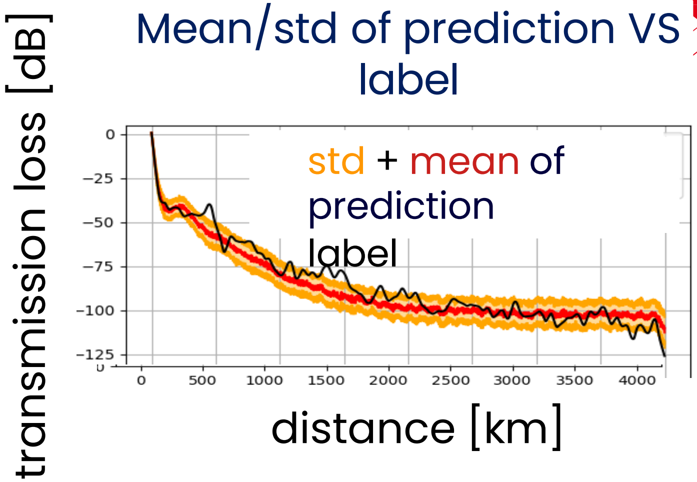
uncertainty + sensitivity

- **Model uncertainty : Bayesian method (Monte-Carlo Dropout)**
  - Make dropout layers active during training + predicting stages
  - Make the model no more deterministic but stocastic
  - m TLs predictions realized from each test-data → mean and std (= uncertainty) computed

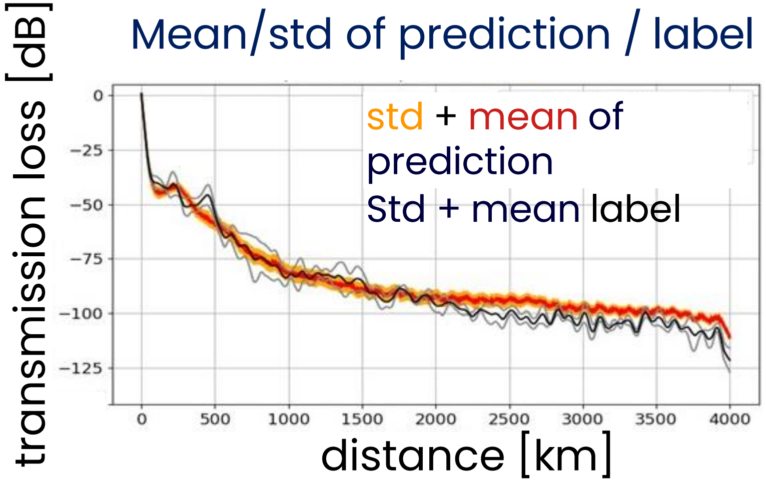


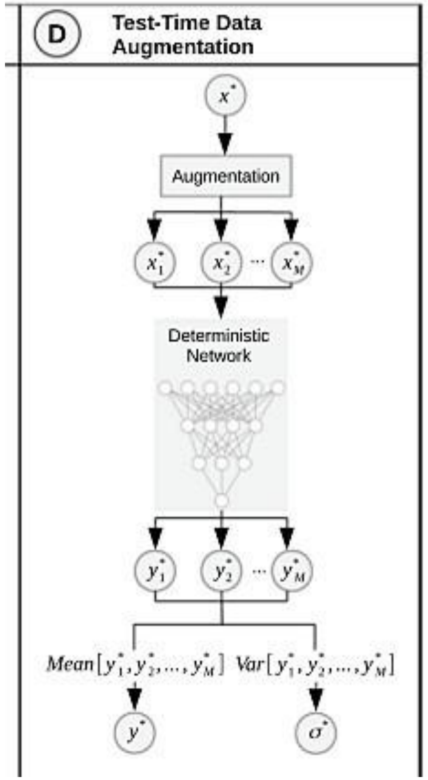
Mean/std of prediction VS label



- **Data sensitivity : Test-Time Augmentation**
  - Each test-data is augmented in m versions using ≠ Gardner realizations
  - Prediction of m TLs → mean and std computed + compared to mean and std of expected labels

Mean/std of prediction / label





Gawlikowski et al. 2023

Training set VS generalization set