Deep learning surrogate model for near real-time estimation of ground-level infrasound transmission loss

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INTRODUCTION AND MAIN RESULTS

We present a Convolutional Recurrent Neural Network emulating parabolic equation-based solver to predict infrasound transmission loss in near real-time. The predictions are associated with model and data-related uncertainties, and can be interpreted using AI explainability tools. Our method can be used for operational assessment of infrasound event detection capability at a global scale.

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Context

International Monitoring System (IMS) stations provide a worldwide coverage of infrasound sources (Christie & Campus, 2009).

IMS designed to detect atmospheric nuclear explosions with a minimum yield of 1 kiloton of TNT equivalent (Marty et al., 2019) to monitor compliance with the Comprehensive Nuclear-Test-Ban Treaty.

To achieve this, new advanced processing methods (e.g., for wavefront parameters estimation or source location) leveraging deep learning algorithms are being developed (Bishop et al., 2022; Albert & Linville, 2020).

Motivations

Accurate modelling of infrasound TL is essential to:

- Interpret IMS stations measurements
- Assess IMS detection thresholds and optimize its design to monitor sources worldwide (Green et al., 2010, Le Pichon et al., 2012, Vergoz et al., SnT 2025 Session O4.1)
- Help infer atmospheric properties (e.g., winds or temperatures) at altitudes where measurements are scarce (Assink et al., 2012; Smets & Evers, 2014; Vera Rodriguez et al., 2020; Blixtet al., 2019; Amezcua et al., 2024; Letournel et al., 2024).

Challenges

State-of-the-art modelling tools (finite-difference, spectral element, normal modes or parabolic equation methods; de Groot-Hedlin et al., 2011; Brissaud et al., 2016; Waxler et al., 2021; Martire et al., 2022):

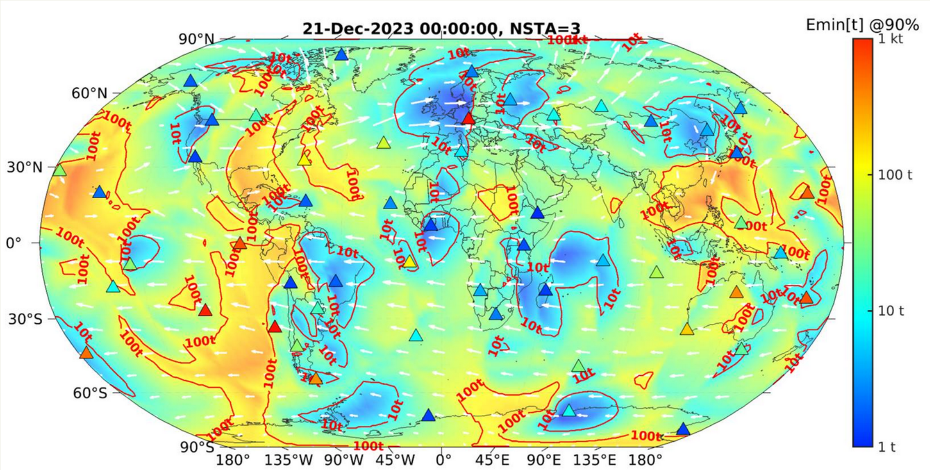
- Accurate
- ✗ High computational costs.

Le Pichon et al., 2012's semi-empirical expression:

- Fast
- ✗ The complexity of infrasound propagation is oversimplified.

Brissaud et al., 2023's Convolutional Neural Network:

- Fast and acccurate
- ✗ Propagation range of 1,000 km limiting when performing global-scale Tls simulations
- ✗ Uses interpolated atmospheric models leading to incomplete representation of the propagation medium.



IMS infrasound detection capability map (0.2 Hz)

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Inputs: 2D realistic atmospheric slices

- Horizontal wind speed + temperature extracted using the Whole Atmosphere Community Climate Model (Gettelman et al., 2019)
- Range-dependent small-scale disturbances (Gardner et al., 1993)

Method

Supervised **Convolutional Recurrent Neural Network** (Cameijo et al., 2025)

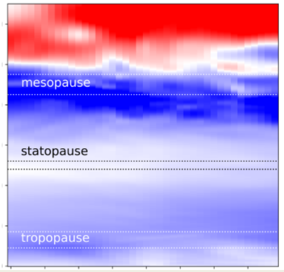
- Fast and accurate
- Capture spatially + range-dependent features embedded in inputs
- Propagation range up to 4,000 km
- Evaluated on unseen atmospheric conditions, seasons, & frequencies
- Epistemic + data uncertainties (Gawlikowski et al., 2023)
- Interpretability tools available.

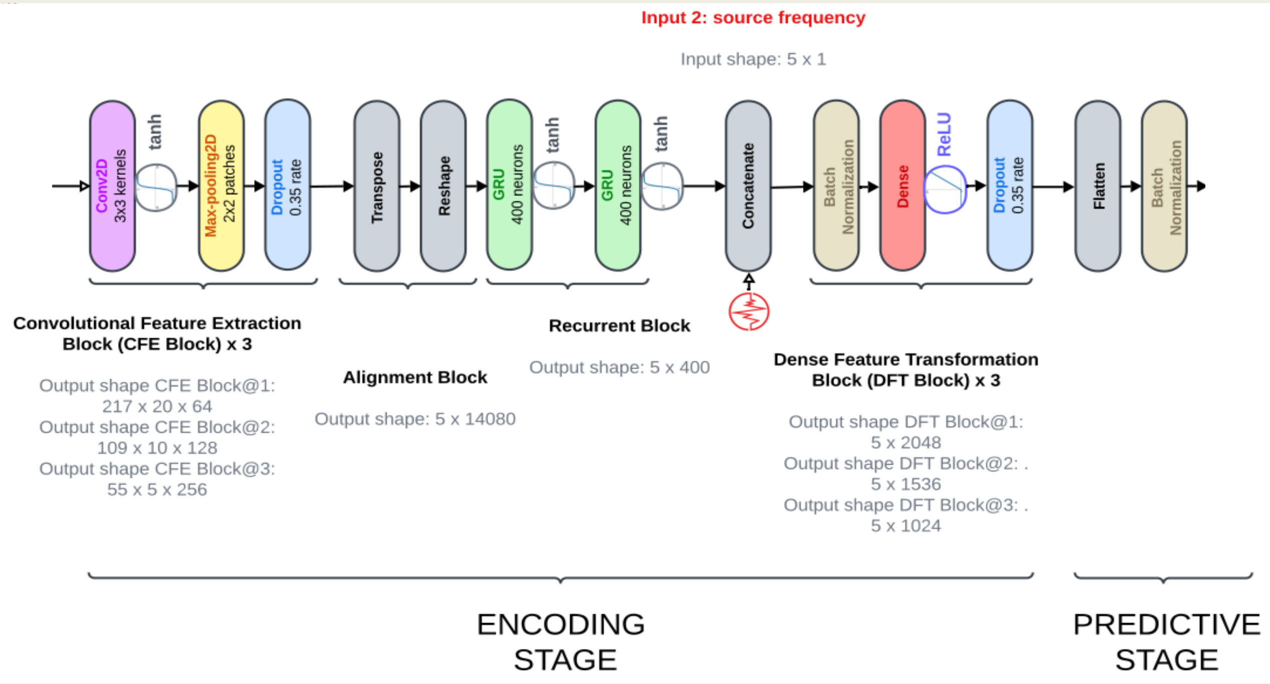
Outputs: 1D ground-level TLs

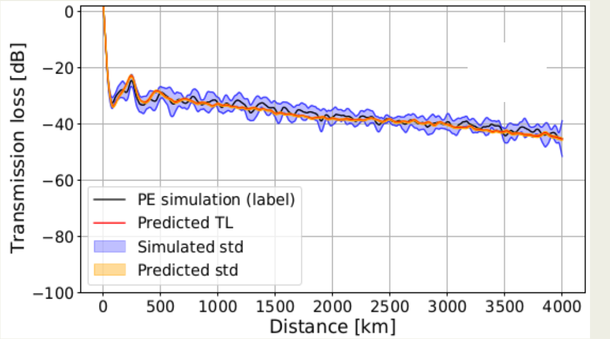
- Computed using atmospheric absorption coefficients (Sutherland & Bass, 2004) and parabolic equation-based solver (Waxler et al., 2021)
- 5 frequencies: 0.1, 0.2, 0.4, 0.8, 1.6 Hz

Input 1: 2D atmospheric slice Az,x

Input shape:
1 x 433 x 40







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Training

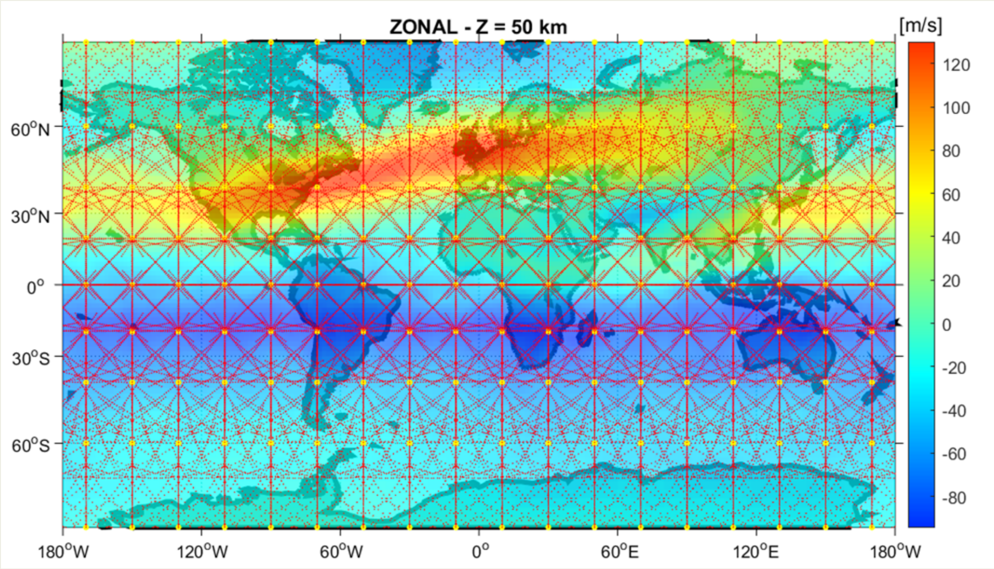
Earth sampled with 162 points on January and August 2021.

Atmospheric slices collected along 8 directions and 2 azimuths + perturbed by 10 small-scale disturbance fields.

Simulations at 5 frequencies.

=> 77,760 scenarios.

Extraction points, January 2021



Testing (global scale)

6,000 unseen atmospheric conditions (≠ locations)

- ~ 7% average error
- Good estimation including in case of abrupt change in propagation regime
- Robustness in the presence/absence of stratospheric wave guides
- ✗ High-frequency variability not fully captured

Generalization (regional scale)

Unseen atmsopheric conditions (≠ locations, dates, & frequencies)

- ~ 9% error around the Hunga Tonga volcano (eruption on January 2022; Vergoz et al., 2022)
- ~ 10% error around Beirut (explosion on August 2020; Pigler et al., 2021)
- ~ 11% error around the Hukkakero military site (explosions every summer; Gibbons et al., 2018)

Perspectives

- Create a more complete dataset (more sampling points & dates)
- Develop more advanced algorithms (Transformer; Vaswani et al., 2017)
- Use explainability methods to interpret predictions (ablation tests, gradient-based visualization tools; Selvaraju et al., 2016)
- Enfore causality when predicting TLs, such as in physical modeling tools