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Towards a tool to assess and update atmospheric specifications in the middle atmosphere using microbarom observations.

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INTRODUCTION AND MAIN RESULTS


Photo credit: Christian Palmer

- Development of a **microbarom observation operator**.
- Proof of concept for **diagnostics of NWP models' relative performances** in the middle atmosphere *Letournel et al. 2024, doi:10.1029/2024JD042034*
- **Fully differentiated processing chain for data assimilation** using automatic differentiation and a ML propagation meta model
- **Towards first experiments of data assimilation** using synthetical observations.

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Context

Infrasound monitoring activities to assess compliance with the CTBT require good knowledge of the Middle Atmosphere (MA, 20-120 km), for source localization and characterization.

Numerical weather prediction (NWP) models, which feed National Data Centres are significantly biased in the middle atmosphere (e.g. Le Pichon et al. 2015).

Reason for this is the lack of operational wind measurements in the MA above 30 km as well as the relatively low top (~80 km) and sponge layers (> 30 km) of the NWP models.

Objectives

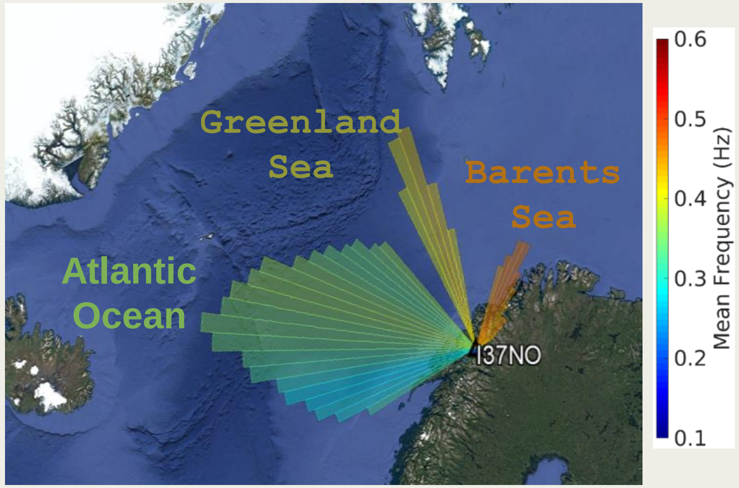
Using oceanic infrasound (microbaroms) to probe the MA and improve atmospheric specification, developing :

- **Diagnostic tool to assess relative performances of atmospheric products** (simulation outputs), guiding the choice of best atmospheric specification
- **Data assimilation using a differentiable observation operator** to update atmospheric specifications

For past/current efforts using microbaroms or other sources, see e.g.: Donn & Rind, 1972; Assink et al., 2019; Vanderbecken et al. 2021; Vorobeva et al. 2024; Amezcua et al. 2024

Data and Tools

Data: IMS station IS37 (year 2021)



Array processing: MultiChannel Maximum-Likelihood (MCML, Poste et al. 2023)
→ adapted to the 360° observations of microbaroms

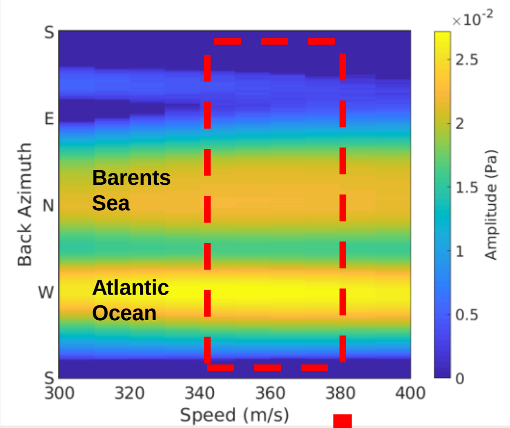
Source model AtmospheRic InfRasound by Ocean Waves, (ARROW): Acoustic intensity (W.m^{-2}.Hz^{-1}), every 3 hours, on a 0.5°x0.5°grid, 22 freq. bands from 0.08 Hz to 0.6 Hz.

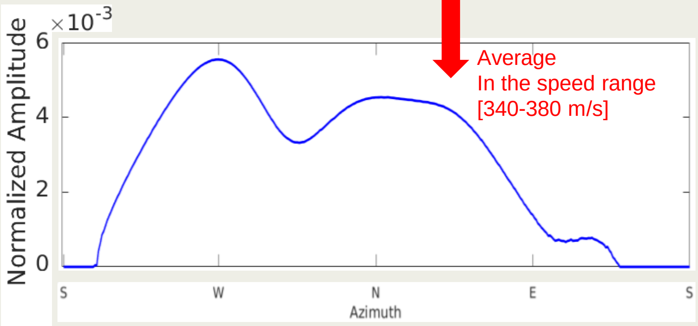
Propagation simulations:

- Parabolic Equation, PE (NCPAprop, Waxler et al., 2021)
- Parameterized transmission loss (Le Pichon et al. 2012)
- CRNN predictions of transmission loss (Cameijo et al. 2025)

Adapting the array processing

- MCML estimates $(\theta, v, s^2, \sigma^2)$ through a likelihood function maximization. (where s is signal, σ is noise)
- We adapt it to microbarom observations: s^2 is derived over the complete (θ, v) grid.





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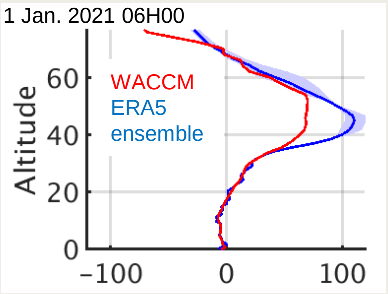
Atmospheric specifications

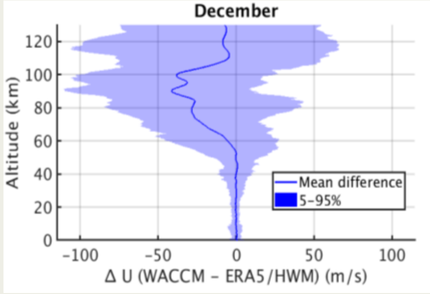
- **WACCM**, NCAR's forecast product, version 6, up to ~130 km. (Gettelman et al. 2019) → Hight-top model product
- **ERA5**, ECMWF's re-analysis, cy41r2, up to ~80 km (Hersbach et al. 2020)

  + HWM-14/NRLMSISE-00, up to ~130 km (Drob et al. 2015; Picone et al. 2002)

  → Approach often used in IS community



Zonal wind at IS37 (m/s)

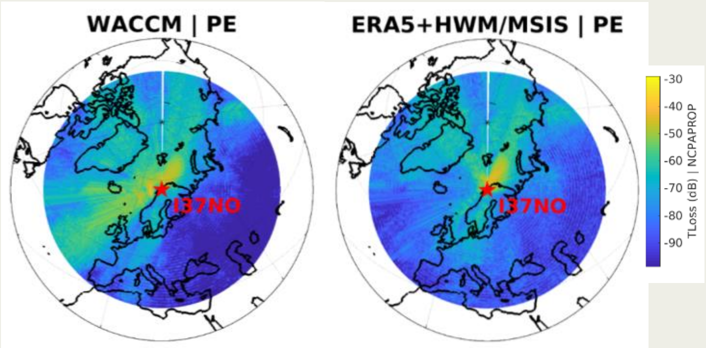


Key message :

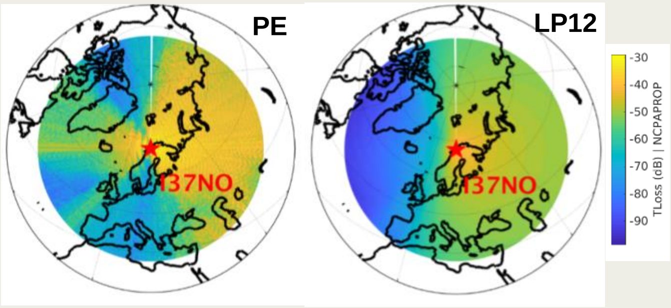
- We aim at **assessing the relative performances of different models instead of that of ensemble members for a given model** (as in Vanderbecken et al. 2021, who used vocanic infrasound and Meteo-France ARPEGE ensemble.)

Propagation

Effect of atmospheric specification on PE transmission loss (TLoss)



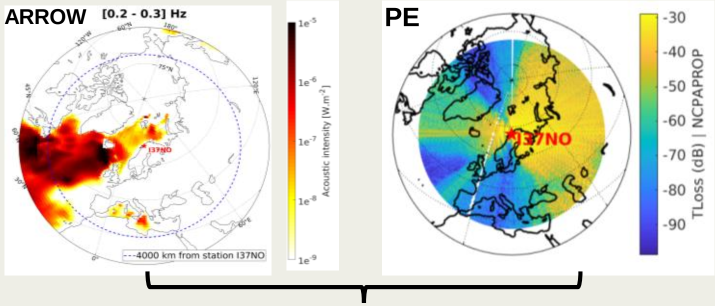
Effect of propagation model on TLoss



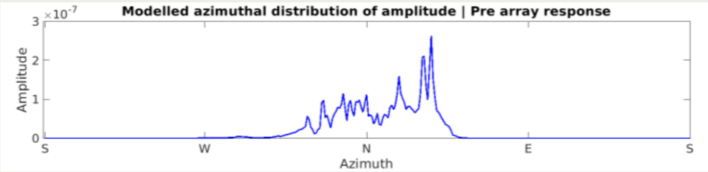
Key messages :

- Differences caused by the propagation method (PE or Le Pichon et al. 2012, LP12) appeared to be larger than differences induced by the use of difference specifications
- **Explicit PE simulations are necessary to assess model relative performances**

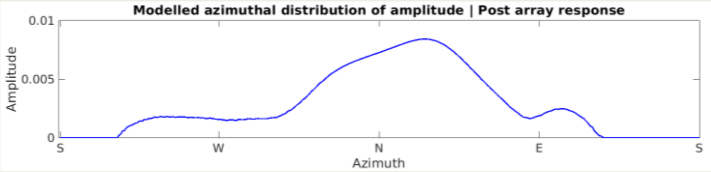
Simulating the observation



Simulated microbarom distribution at IS37 (De Carlo et al. 2021)



goes through our MCML processing:
→ accounting for the response of the antenna and for that of the algorithm



Key messages :

- **An observation operator was developped.**
- A metric is used to compare observed azimuthal distributions to simulated ones: the circular optimal transport metric based on the Wasserstein distance (Flamary et al. 2021)

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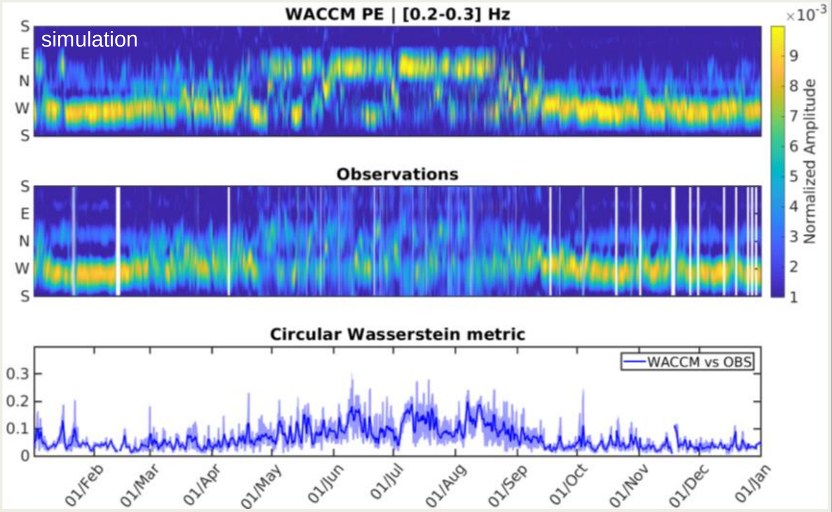
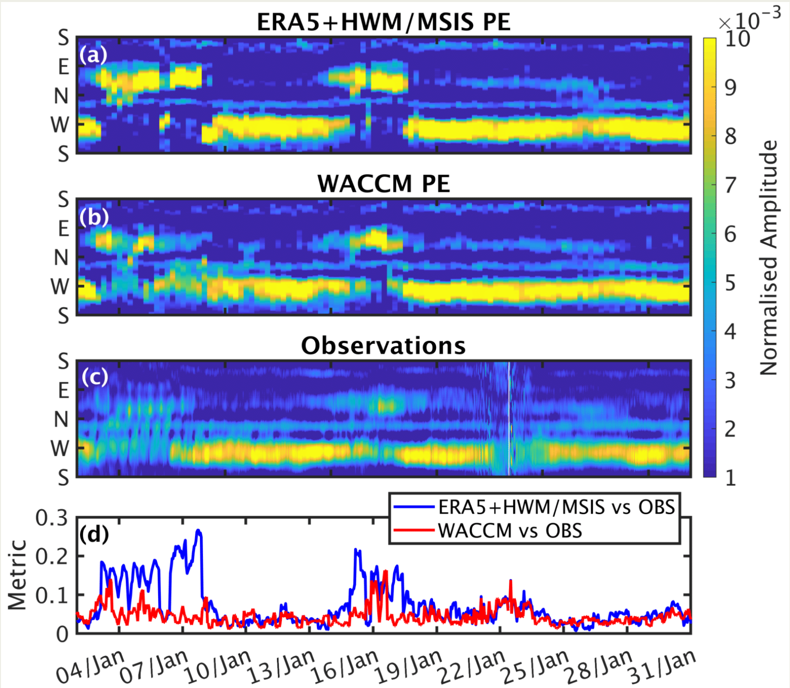
Full year of microbarom simulation at IS37



- The polar vortex leads to observations of microbaroms mainly from the West (Atlantic Ocean) Model performs better in the winter (low metric).
- We simulate the sidelobes induced by the array/algorithm response (North and South-East).
- Simulations overestimate amplitudes when changes in the main direction of arrivals occur, e.g.:

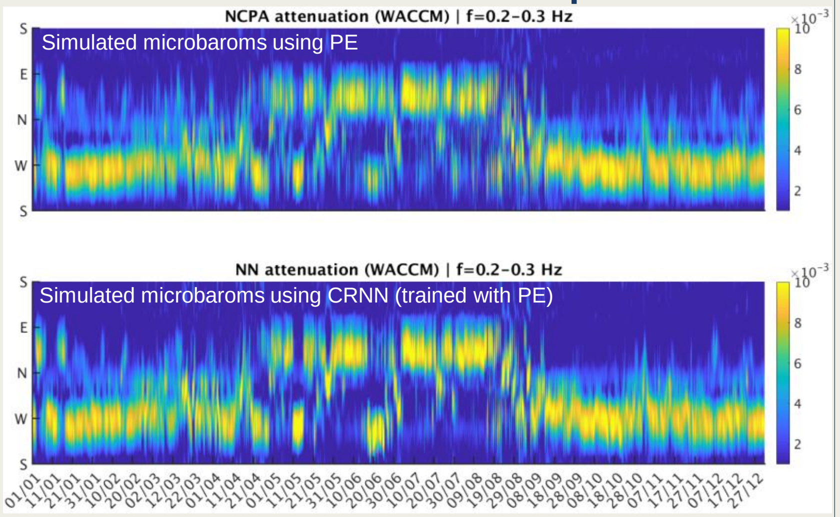
 - During sudden stratospheric warming (SSW), in Jan.
 - During the winter-to-summer stratospheric winds transition period

Metric-based assessment of atmospheric specifications



- The metric allows systematic comparison of atmospheric specifications (the lower the better).
- **Two periods stand out where WACCM outperforms ERA5+HWM/MSIS (during SSW)**
- First inversion (>~4 Jan 2021) is related to mesospheric guiding best simulated with WACCM
- Second inversion (>~16 Jan 2021) is related to stratospheric guiding best simulated with WACCM

Introducing a CRNN to achieve a fully differentiable observation operator



- PE simulation software is not differentiable as such and not adapted to Data assimilation process.
- CRNN trained on PE outputs and developed by Cameijo et al. 2025 proves to be robust wrt explicit PE simulations for simulating transmission losses.
- CRNN is autodifferentiable with python/tensorflow.
- **We now have a robust, quick and differentiable method to model the infrasound propagation**

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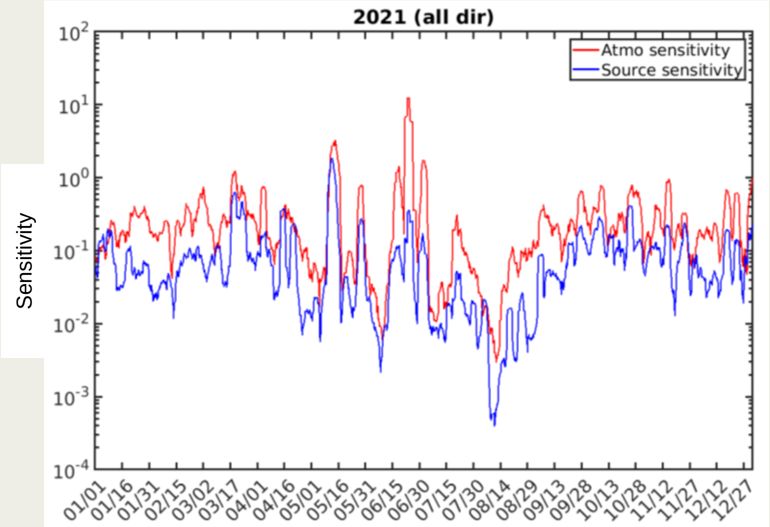
Automatic differentiation of the observation operator: application



- The validation of the full observation operator leads to **an error of 2% between tensorflow's automatic differentiation and finite differences derivation.**
- We estimate atmospheric model and source errors, respectively, using differences between successive forecast (Polavarapu et al. 2005).
- Using the gradient of the observation operator derived with tensorflow **we validate the hypothesis of greater sensitivity of the observation operator to the atmosphere than to the source.**

Conclusion and Perspectives

- Robust **microbarom processing chain** and proof of concept for deriving **diagnostics of NWP models relative performances** in the middle atmosphere. **(Letournel et al. 2024)**
- Fully **differentiated processing chain** for data assimilation thanks to tensorflow's **automatic differentiation** and a **ML propagation meta model.**
- Formalization of the data assimilation scheme :
  - Use of EOFs on atmospheric fields
  - Background (prior) error covariance matrix
  - Observation error covariance matrix

  ➔ **Towards a first proof of concept for microbarom assimilation (ongoing tests)**

See paper on the proof of concept for diagnostics:

Letournel, P., Listowski, C., Bocquet, M., Le Pichon, A.,& Farchi, A. (2024). *Journal of Geophysical Research: Atmospheres*, 129,e2024JD042034. https://doi.org/10.1029/2024JD042034

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