CNR
ISMAR
ISTITUTO
DI SCIENZE
MARINE

Coupled Ocean–Acoustic Data assimilation with a neural network approach

Andrea Storto, CNR ISMAR, Rome, Italy
&
Paolo Oddo, NATO/STO CMRE, La Spezia, Italy
(+ many other contributions)

Motivation and outline

- Motivation: underwater acoustic characterization
- Motivation: acoustic measurements as an opportunity for recovering from poorly or under-sampled ocean areas (ideas from the 70s/80s), especially at the mesoscale (10-100km)
- Methods: the "underwater acoustic sound propagation observation operator" to investigate data-driven approaches in DA
- Results from idealized configurations
- Conclusions and discussions

Motivation

- Several biological, civil, industrial and military activities rely on the knowledge of the underwater environment, including the sound propagation characteristics, motivating in turn at least two scientific questions:
    - ***Is physical ocean data assimilation able to improve our underwater sound propagation simulations?***
    - ***Are sound propagation measurements able to improve our physical ocean knowledge?***

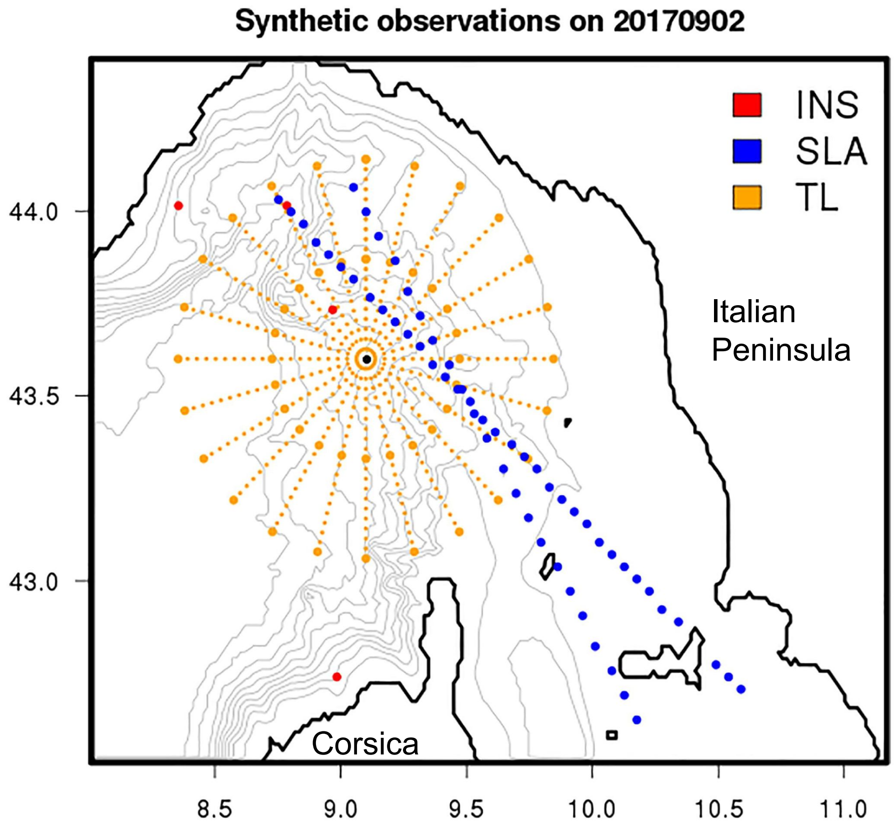
Motivation

- Several biological, civil, industrial and military activities rely on the knowledge of the underwater environment, including the sound propagation characteristics, motivating in turn at least two scientific questions:
  - ***Is physical ocean data assimilation able to improve our underwater sound propagation simulations?***
  - *Are sound propagation measurements able to improve our physical ocean knowledge?*

Experimental setup

Idealized configuration with one sound source, and a radial network of receivers

Realistic in-situ (Argo) and satellite (SLA) observational sampling, taken by CMEMS



Experimental setup

Idealized configuration with one sound source, and a radial network of receivers

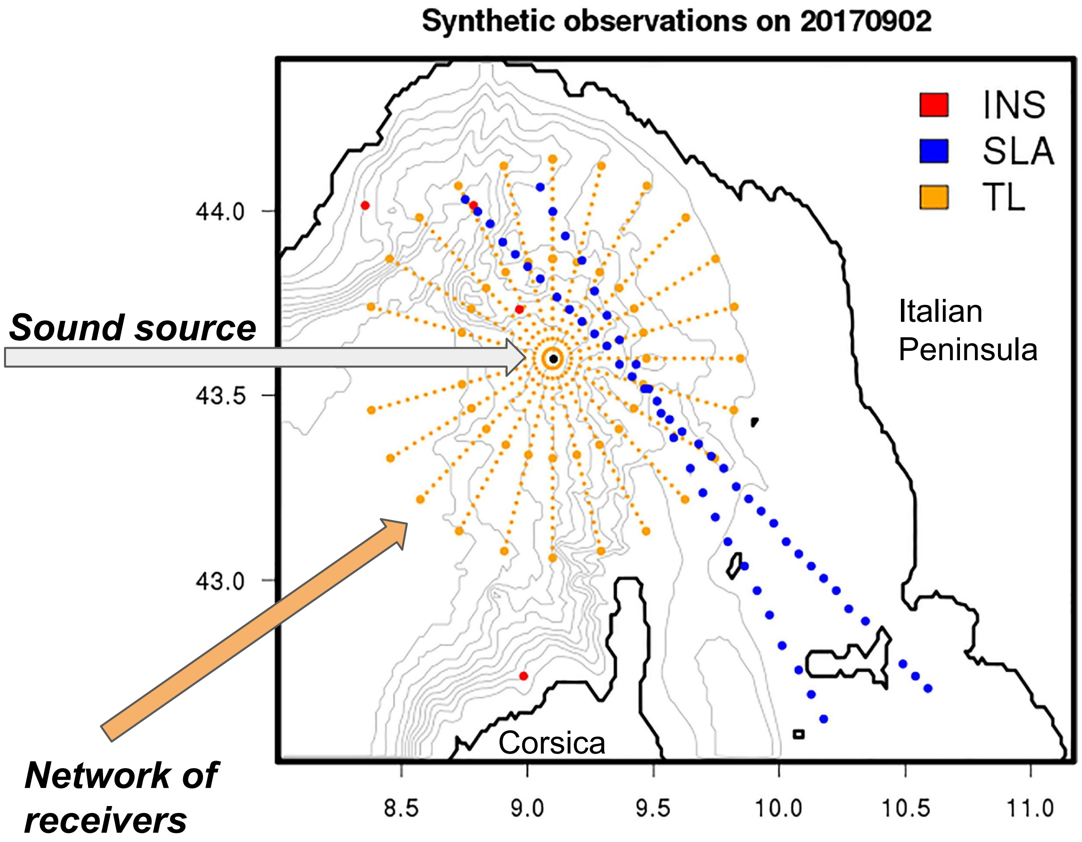
Realistic in-situ (Argo) and satellite (SLA) observational sampling, taken by CMEMS

Assessing the effect of the physical DA on the sound propagation at a distance of 30 and 60 km and at frequencies of

75 Hz (ship noise)

2.5 kHz (active sonar applications)

The acoustic prediction system is based on the Range-dependent Acoustic Model (RAM), a 2-D range-dependent acoustic model using the parabolic equation (PE) method



DA schemes used and compared

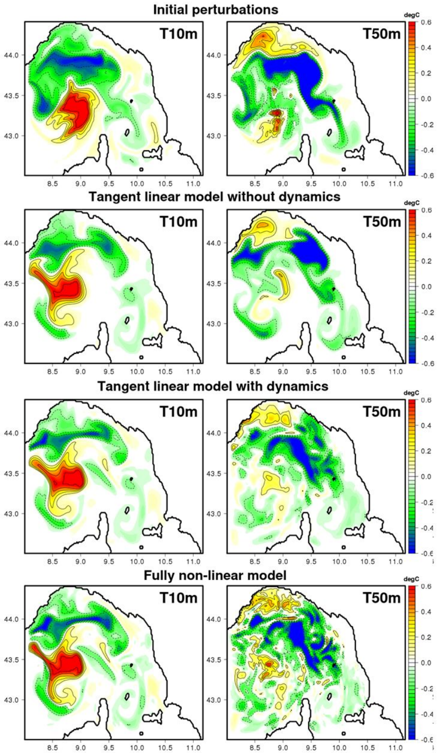
- **3DVAR**: classical 3DVAR formulation with control vector transformation, vertical multivariate EOFs and recursive filter on the horizontal

- **4DVAR**: simplified TL/AD where only T/S are propagated in time (i.e. $\partial M/\partial \mathbf{u} = 0$) and u/v/SSH are derived from the balance operators (**3.5DVAR!**). Switching the TL operator with the balance operator ($\mathbf{V} = \mathbf{M}\,\mathbf{V}_b\,\mathbf{V}_h\,\mathbf{V}_v \rightarrow \mathbf{V} = \mathbf{V}_b\,\mathbf{M}\,\mathbf{V}_h\,\mathbf{V}_v$). Roughly halves the cost with respect to a full 4DVAR, at the expenses of some accuracy.

- **HYBRID**: combining the stationary **B** (as in 3DVAR) with an ensemble-derived flow-dependent component. Note: also for the ensemble component, we use the same parametric definition as for the stationary component, namely the ensemble is used to estimate flow-dependent multivariate EOFs and horizontal correlation length-scales (it does not rely on sample covariance matrix! it does not need localization as the eigen-decomp. acts as a filter! it does not allow for anisotropies!)

DA schemes used and compared

4DVAR



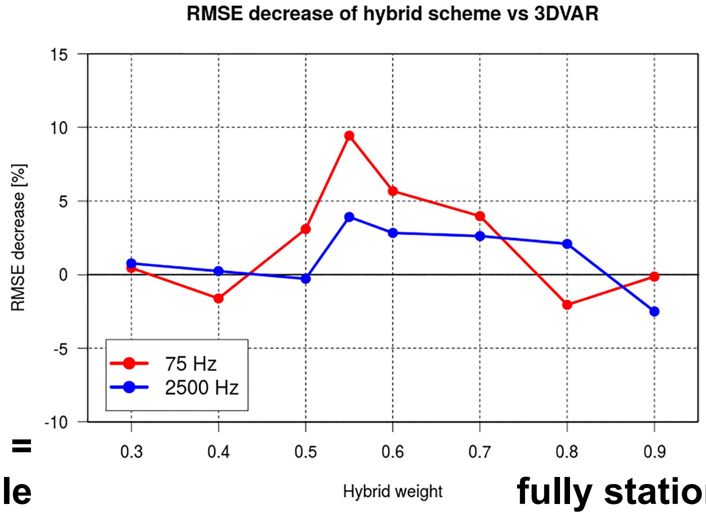
δx

Mδx (w/o dynamics)

Mδx (with dyn.)

$M(\mathbf{x}+\boldsymbol{\delta}\mathbf{x}) - M(\mathbf{x})$

HYBRID



0 = fully ensemble

1 = fully stationary

Results in acoustic space

Table 1. NRMSE for the Experiments Presented in the Text and the Physical and Acoustic Quantities Assessed

Experiment Variable		CTRL	3DVAR	4DVAR	HYBRID
Sound speed	**Depth (m)**				
	0–30	1.79 (2.0 m/s)	1.54 (13%)	1.48 (17%)	1.47 (18%)
	30–100	5.33 (1.0 m/s)	3.57 (33%)	2.71 (49%)	3.08 (42%)
	100–300	2.46 (0.4 m/s)	2.17 (12%)	2.08 (16%)	2.27 (8%)
	300–800	2.47 (0.4 m/s)	1.72 (30%)	1.79 (27%)	1.71 (31%)
Transmission loss (Hz)	**Range (km)**				
75	30	3.24 (2.6 dB)	1.91 (41%)	1.82 (44%)	1.76 (46%)
	60	4.52 (3.6 dB)	3.75 (17%)	3.41 (24%)	3.42 (24%)
2,500	30	5.04 (10.3 dB)	4.97 (2%)	4.65 (8%)	4.51 (11%)
	60	7.56 (15.8 dB)	6.45 (15%)	6.39 (15%)	6.15 (19%)

Motivation

- Several biological, civil, industrial and military activities rely on the knowledge of the underwater environment, including the sound propagation characteristics, motivating in turn at least two scientific questions:
  - *Is physical ocean data assimilation able to improve our underwater sound propagation simulations?*
  - ***Are sound propagation measurements able to improve our physical ocean knowledge?***

Motivation

Sound propagation path, time of arrival and geometry at arrival (angles) depend on the underlying sound speed fields (some analogy with GPS Zenith Total (Slant) Delay, or GPS Radio Occultation).

Two possible technological approaches, which lead to different inversion problems :

1. ***Measure time/angle of arrival at the receiver in a classical Ocean Acoustic Tomography (OAT) formulation to infer sound speed (and then T/S) along the propagation path***

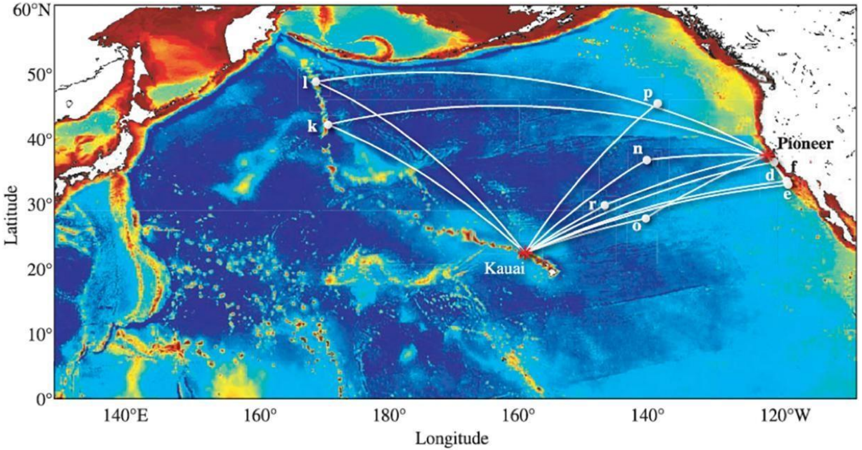
2. ***Measure Transmission Loss at the receiver to infer sound speed (and then T/S) along the propagation cross-section***

Motivation

1. *Measure time/angle of arrival at the receiver in a classical Ocean Acoustic Tomography (OAT) formulation to infer sound speed (T/S) along the propagation path*

Pros: Relatively well-posed, analytical obs operator (and not much non-linear), straight forward to implement

Cons: Technological difficult requirement for very precise measurements: feasible only for very long ranges; typically relies on "background propagation path" (e.g. from an eigenray tracing model like Bellhop) and on correcting the mean temperature profile



From Munk's pioneering ideas

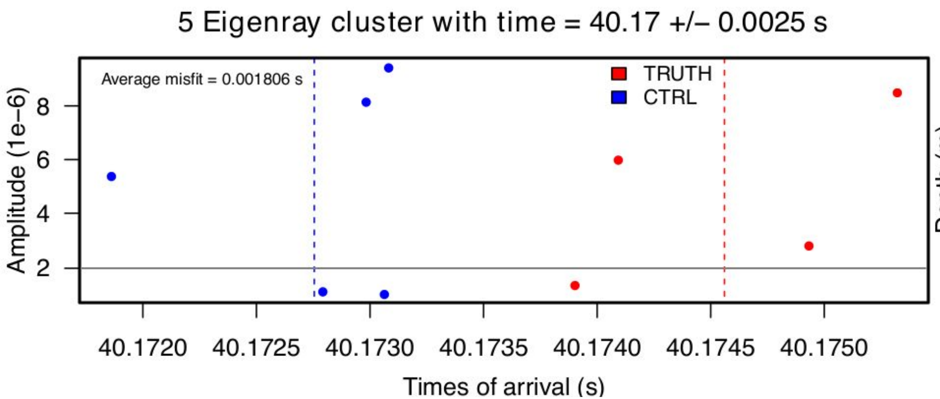
Howe BM, Miksis-Olds J, Rehm E, Sagen H, Worcester PF and Haralabus G (2019) Observing the Oceans Acoustically. Front. Mar. Sci. 6:426. doi: 10.3389/fmars.2019.00426

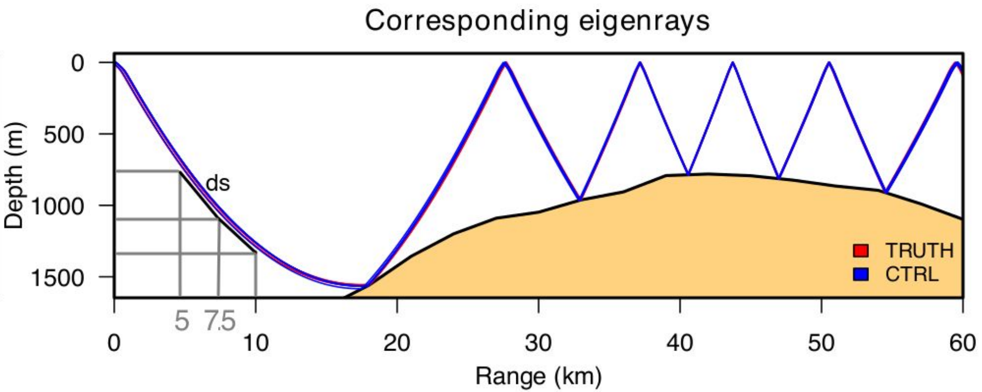
Motivation

1. ***Measure time/angle of arrival at the receiver in a classical Ocean Acoustic Tomography (OAT) formulation to infer sound speed (T/S) along the propagation path***

Pros: Relatively well-posed, analytical obs operator (and not much non-linear), straight forward to implement

Cons: Technological difficult requirement for very precise measurements: feasible only for very long ranges; typically relies on "background propagation path" (e.g. from an eigenray tracing model like Bellhop) and on correcting the mean temperature profile

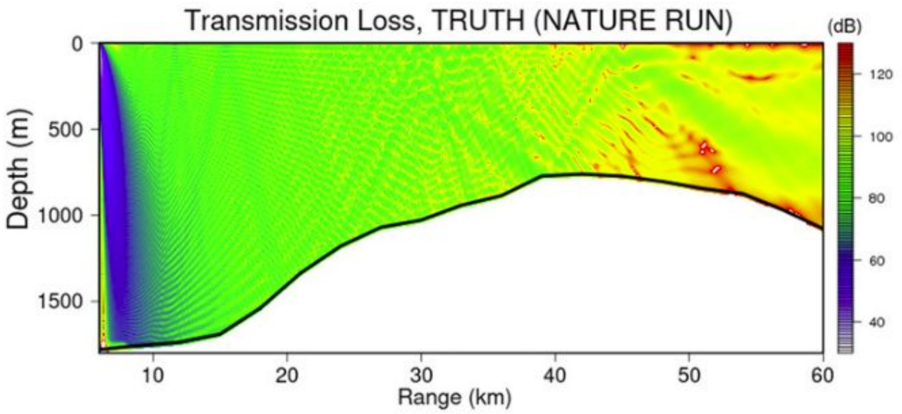


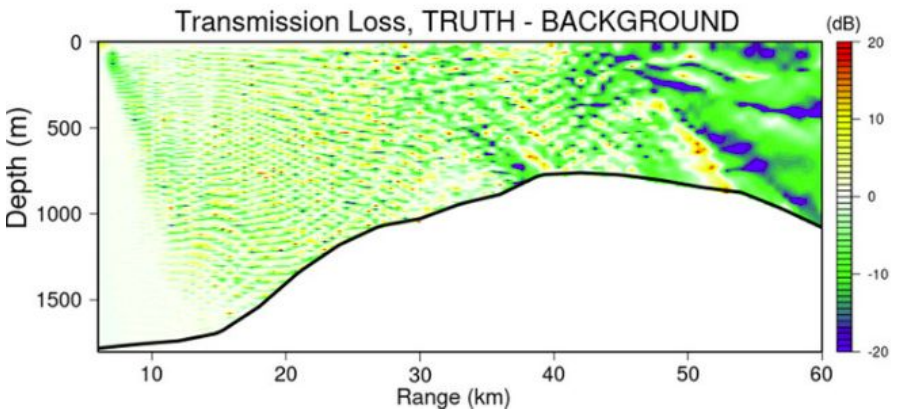


2. Measure Transmission Loss at the receiver to infer sound speed (T/S) along the propagation cross-section

Pros: Technologically more appealing for short ranges

Cons: Worse-posed, complex obs operator (and **strongly non-linear:** questionable validity for TL on ranges > 10 km), not much explored in literature

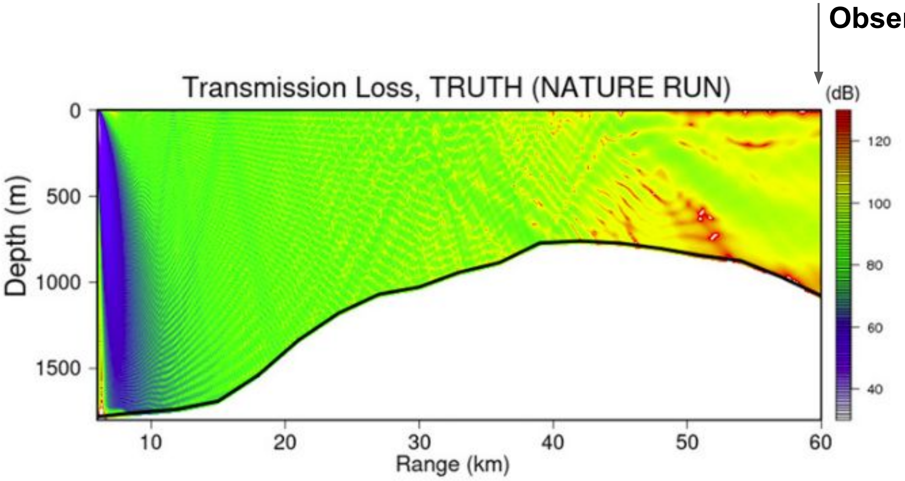


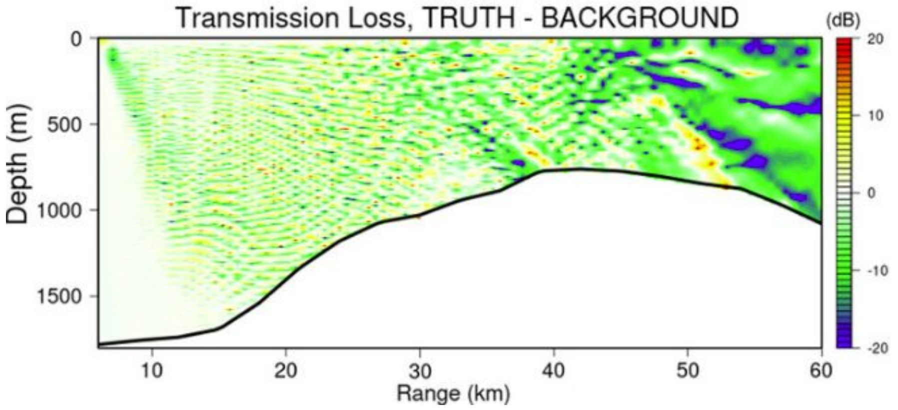


2. *Measure Transmission Loss at the receiver to infer sound speed (T/S) along the propagation cross-section*

Pros: Technologically more appealing for short ranges

Cons: Worse-posed, complex obs operator (and **strongly non-linear:** questionable validity for TL on ranges > 10 km), not much explored in literature

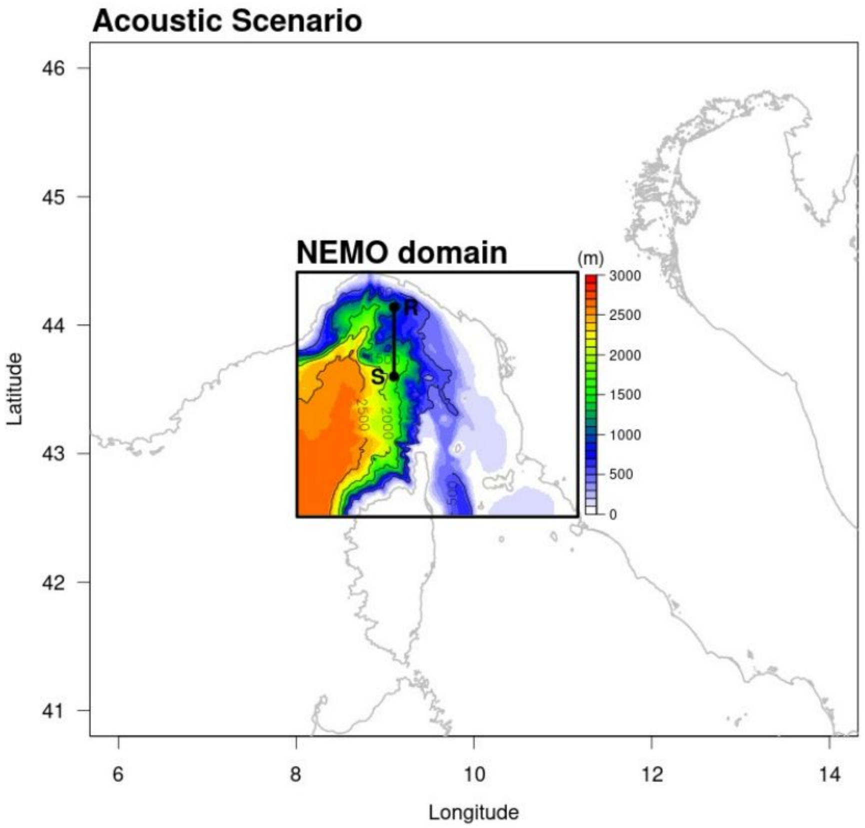




Outline

Assimilate TL data relative to a 60 km propagation path over the Ligurian Sea (western Mediterranean Sea) at a frequency of 75 Hz (typical of ship noise).

We consider a hydrophone tower with 18 receivers (upper 200m).



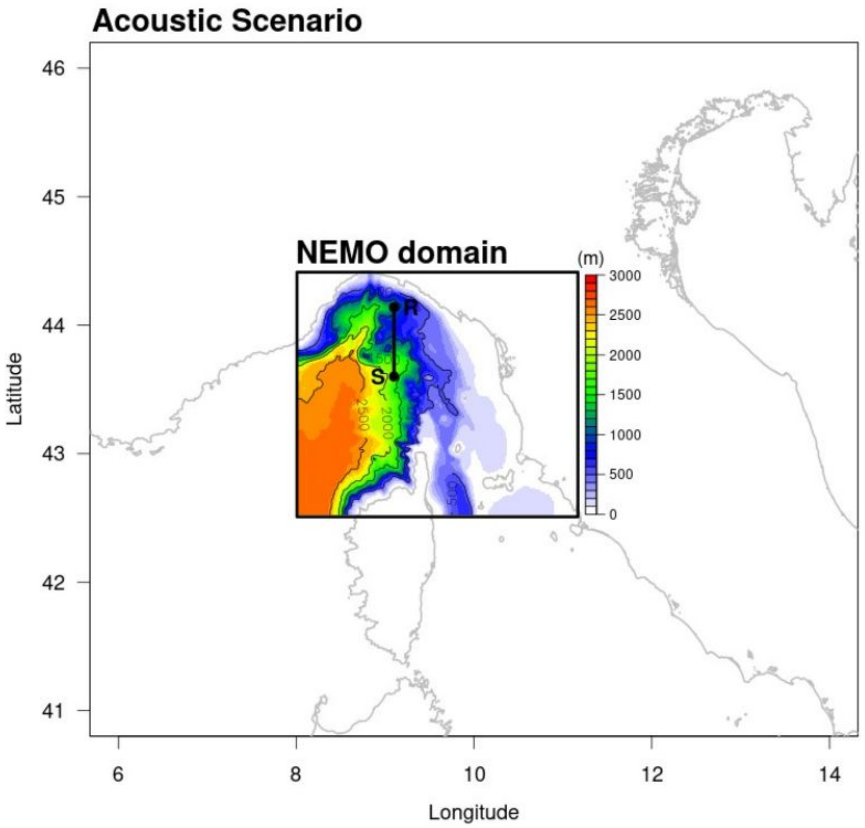
Outline

Assimilate TL data relative to a 60 km propagation path over the Ligurian Sea (western Mediterranean Sea) at a frequency of 75 Hz (typical of ship noise).

We consider a hydrophone tower with 18 receivers (upper 200m).

Use of data-driven algorithms:

- To fully replace DA (e.g. Deep DA)
- To replace parts of a DA scheme (QC, BC, OO, BAL, TL/AD, etc.)



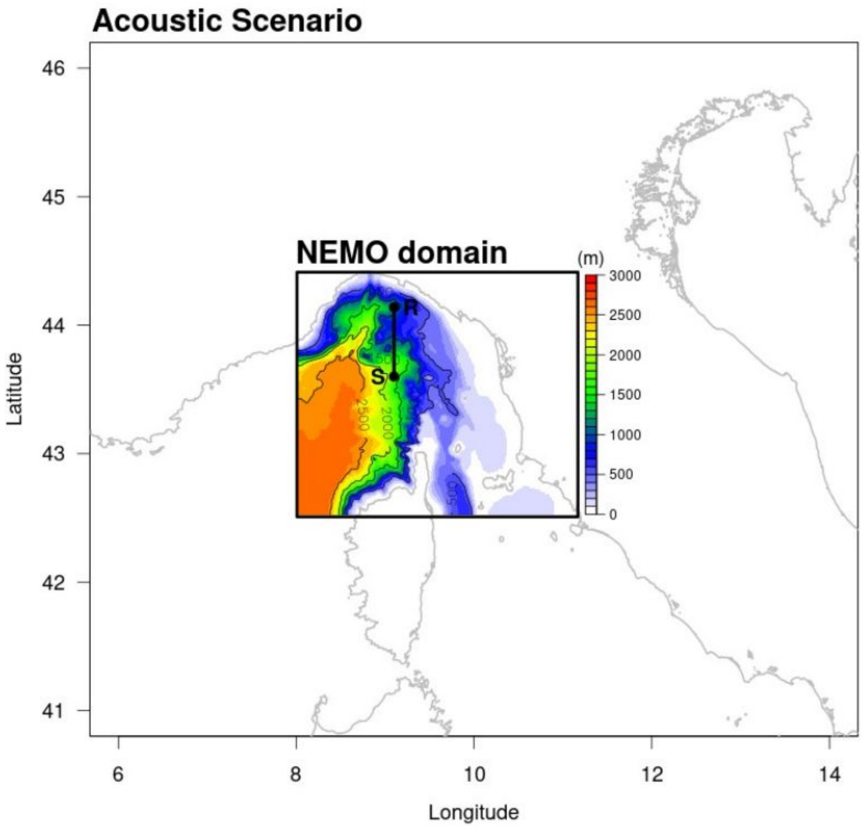
Outline

Assimilate TL data relative to a 60 km propagation path over the Ligurian Sea (western Mediterranean Sea) at a frequency of 75 Hz (typical of ship noise).

We consider a hydrophone tower with 18 receivers (upper 200m).

Use of data-driven algorithms:

- To fully replace DA (e.g. Deep DA)
- To replace parts of a DA scheme (QC, BC, OO, BAL, TL/AD, etc.)



Methods

Observation operator: $\mathbf{y}^{TL} = H^{AC}(\mathbf{x}) + \boldsymbol{\varepsilon}$ $\quad H^{AC}(\mathbf{x}) \equiv \mathrm{RAM}$

Tangent-linear approximation: $H^{AC}(\mathbf{x}) - H^{AC}(\mathbf{x}^b) \cong \mathbf{H}^{AC}(\mathbf{x} - \mathbf{x}^b)$

x: Cross-section of Temperature (2D) **y**: profile of transmission loss

Canonical Correlations (CCA)

Find the modes of (co)variability that maximize the cross correlation between different sets of variables (the input, T, and the output, TL, data of the observation operator).

CCA relies on a linear transformation, therefore its TL/AD version is straight forward.

versus

Neural Networks (NN)

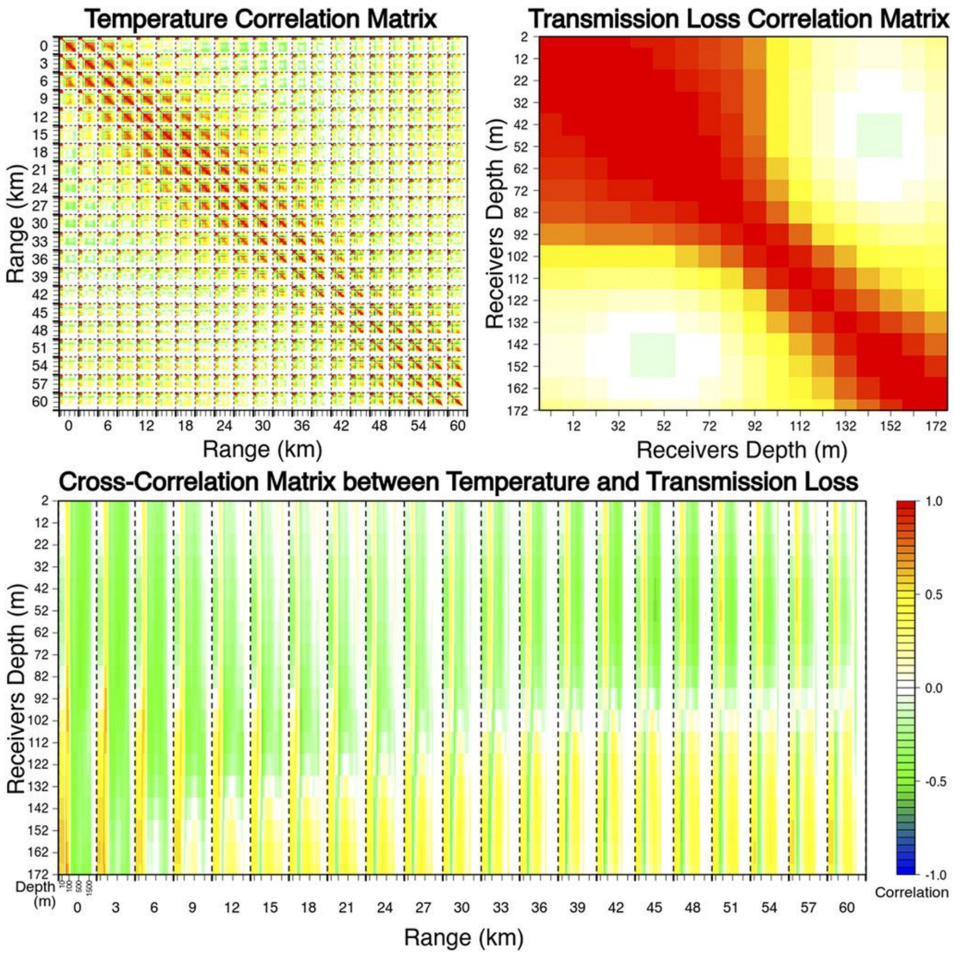
Approximate non-linear functions through connecting neurons across different layers.

NNs are non-linear, therefore their use in variational schemes shall consider some sort of linearization.

Correlation matrix

T-TL Correlation Matrix

The Correlation matrix in fact underlies directly the relationship between the input and the output used in the CCA-based observation operator



Fitting to test data

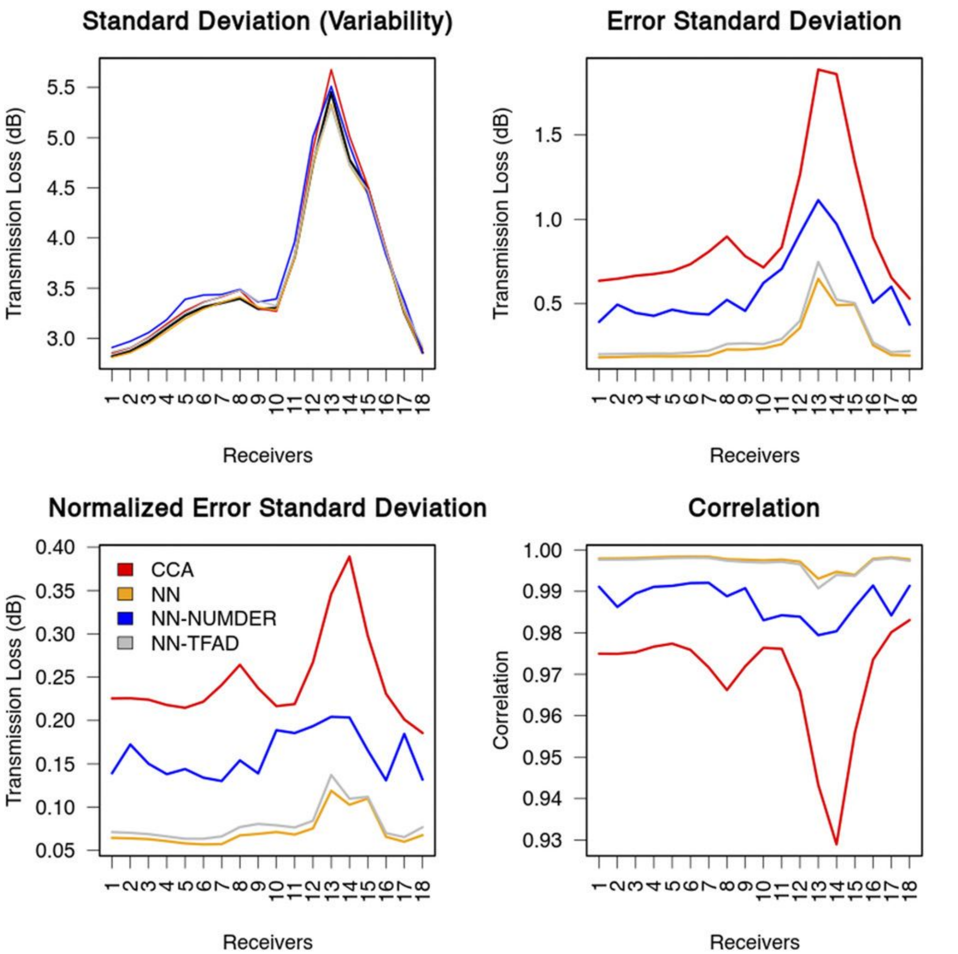
Training dataset

A ~ 3000-member ensemble of temperature cross-sections (stochastic physics + multiple times), to each of them the RAM propagation model is coupled to provide pairs of **T-TL realizations**

80% is used for training
20% is used for test (independent verification)

NN configuration
ReLU activation
3 layers; 128 neurons; 128 batches;
5000 epochs

- **NUMDER**: Richardson extrapolation
- **TFAD**: Tensorflow Reverse-Mode Automatic Differentiation

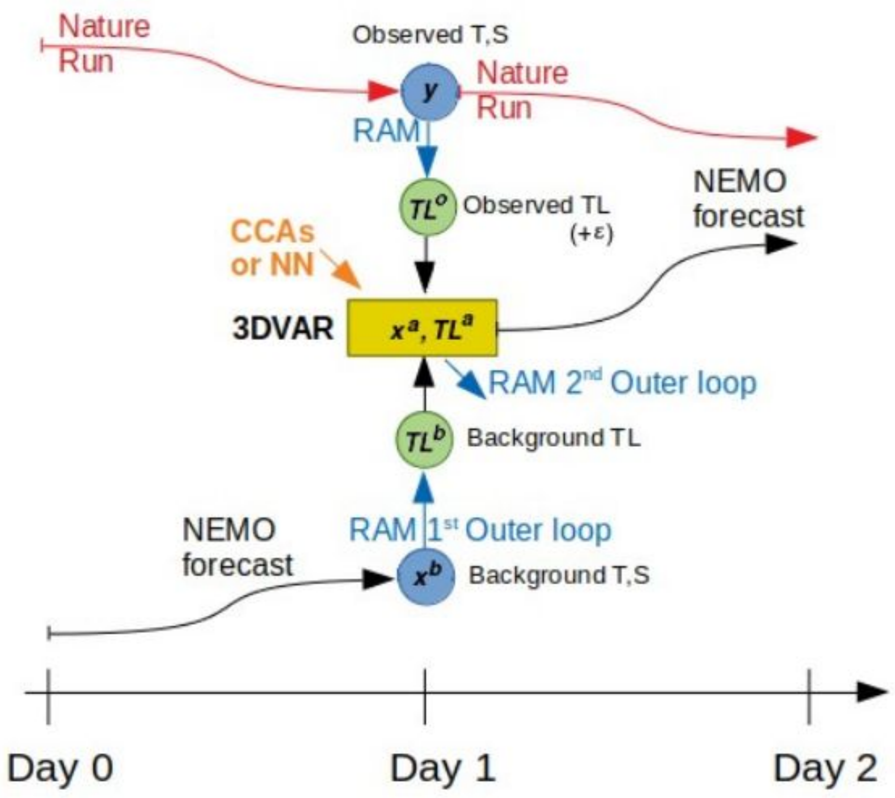


Coupled oceanic–acoustic OSSEs

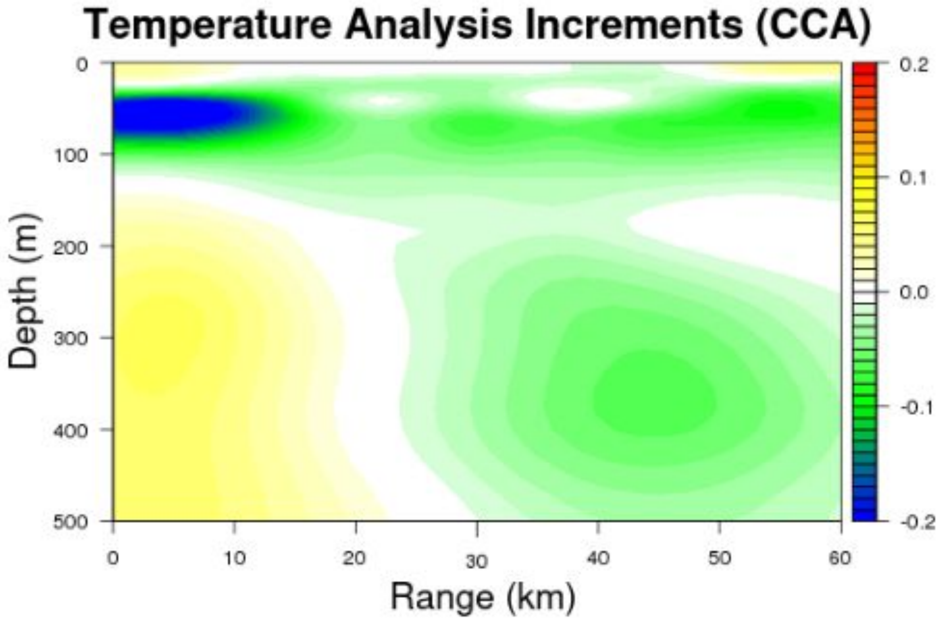
OSSE configuration

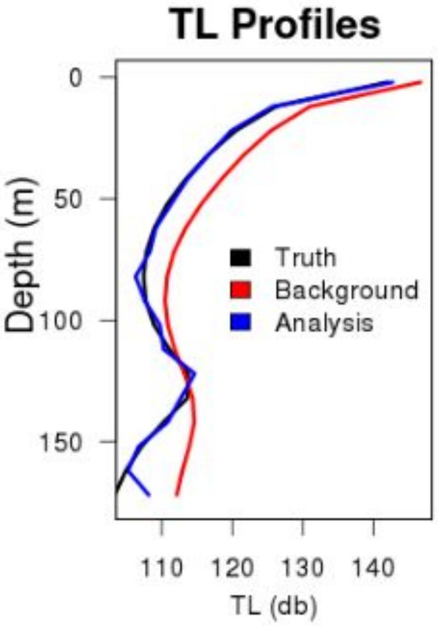
OSSE for the coupled ocean-acoustic system relies on running RAM on the nature run to extract TL observations, which are subsequently assimilated through either the CCA or the NN observation operators.

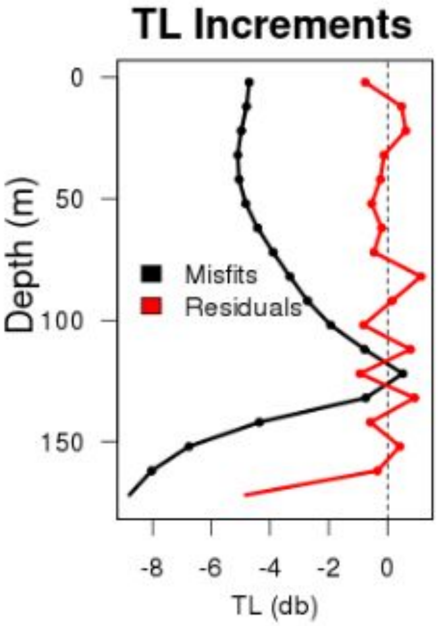
Multiple outer loops may be embedded to refine the linearization (in case of the NN observation operator).



The inversion problem

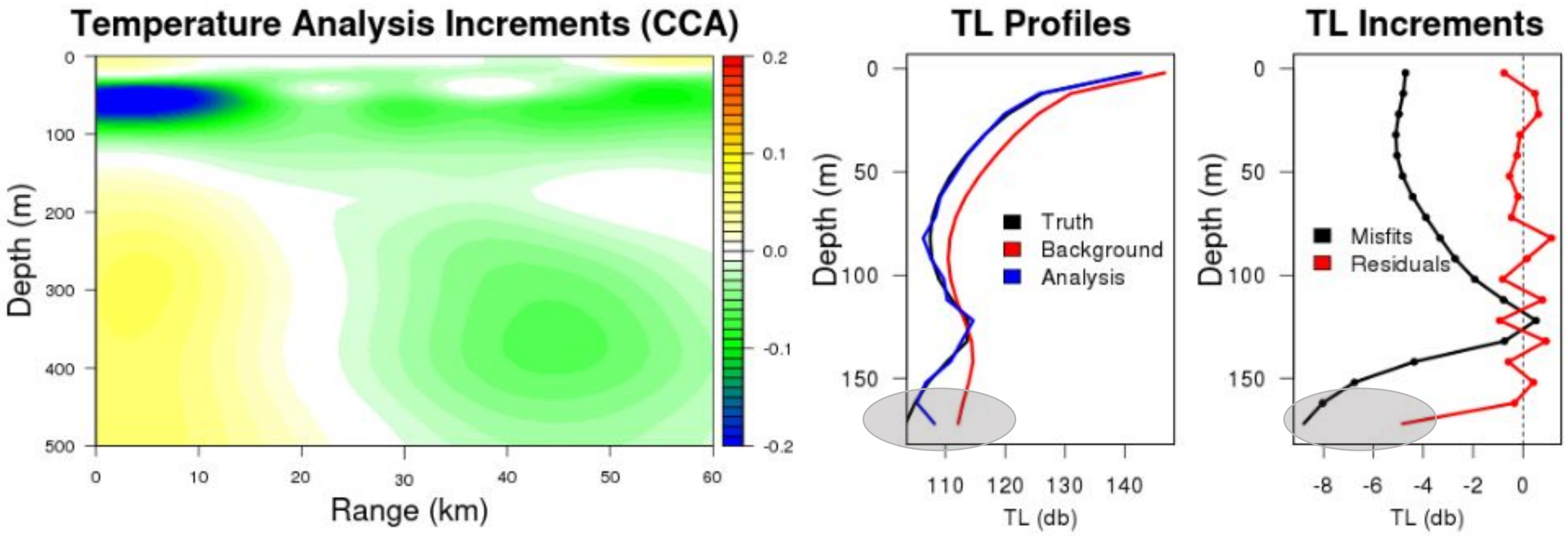






The inversion relies on the joint effect of the AD obs operator and vertical EOFs

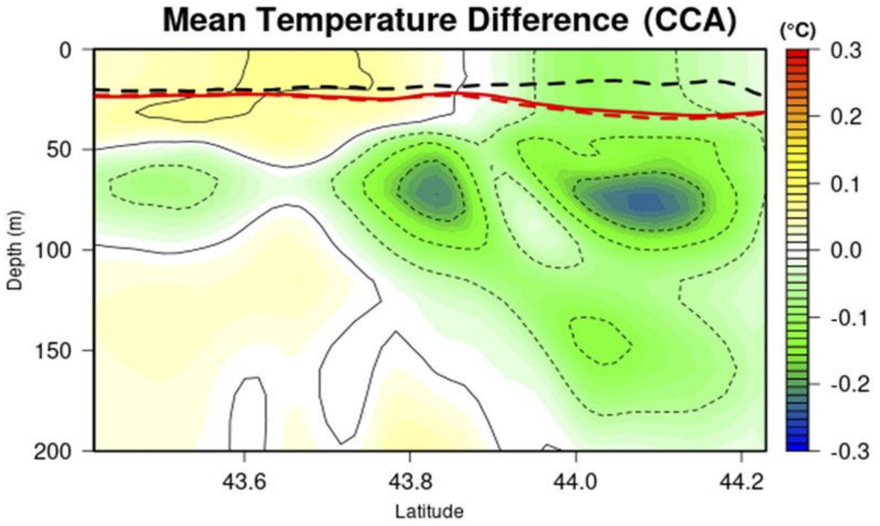
The inversion problem

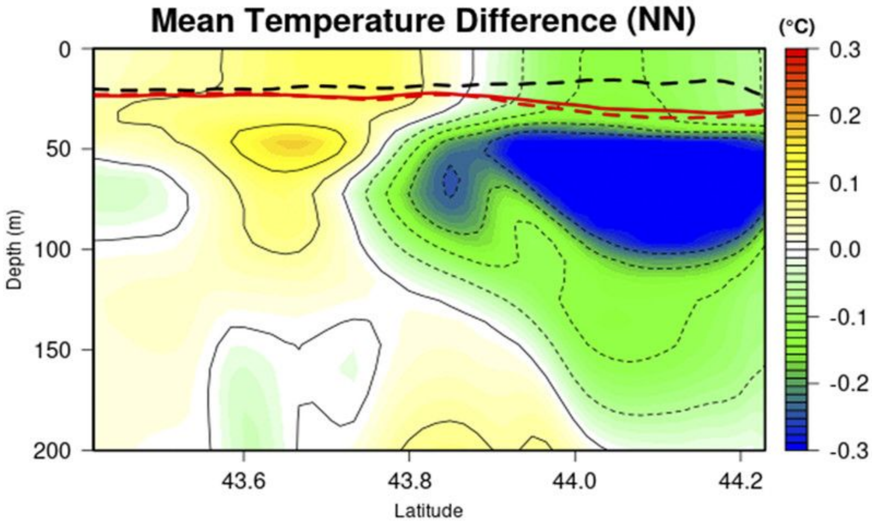


The inversion relies on the joint effect of the AD obs operator and vertical EOFs

Background quality check acts to exclude some observations

Mean temperature differences

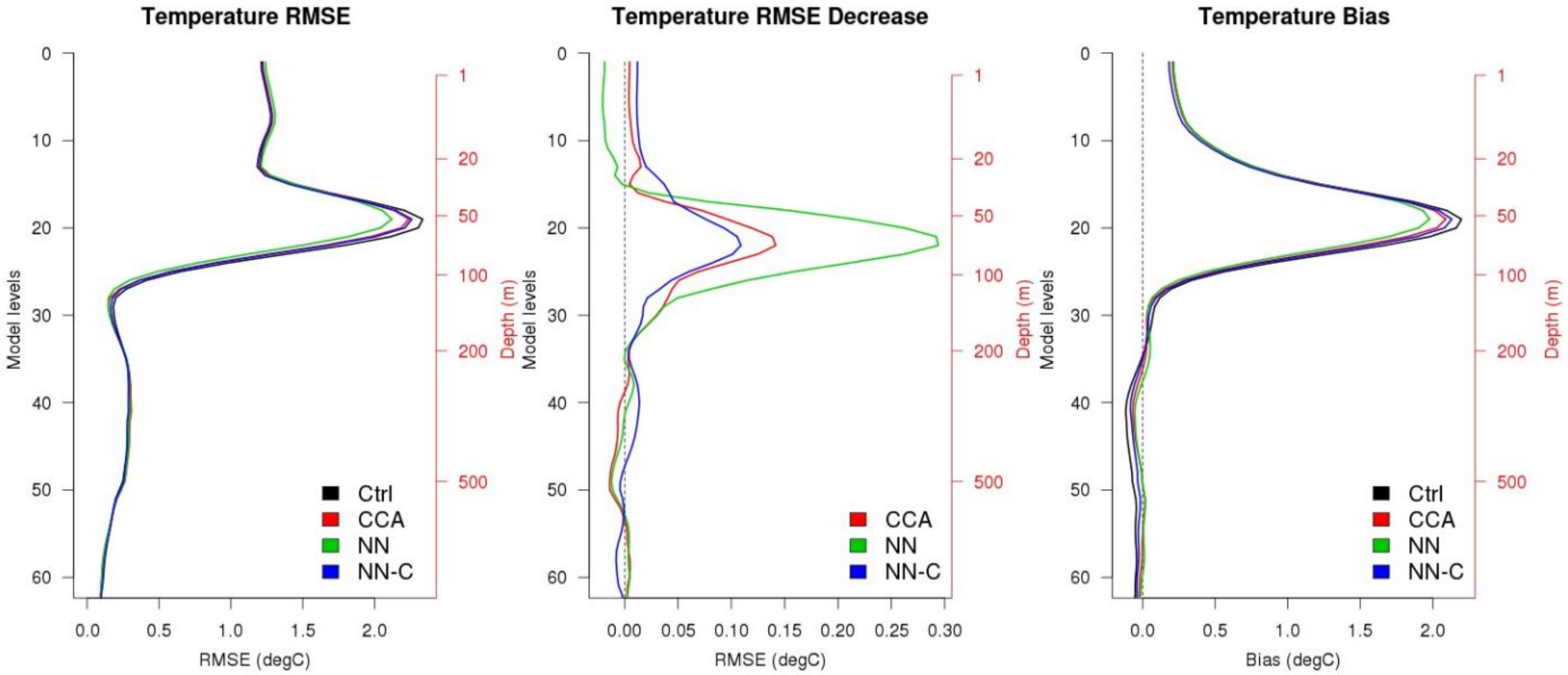




Comparable average increments in terms of spatial patterns across the section

NN is able to discriminate more clearly which areas to spread the increments to

Forecast skill scores



***Ctrl**: NO DA* ***CCA**: CCA OO* ***NN**: NN OO* ***NN-C**: NN OO linearized around Climatology*

CNR ISMAR ISTITUTO DI SCIENZE MARINE

Conclusions & Discussion

Methodological

- Whenever DA approximates a relationship through some sort of regression (observation operators, balance operators, TL/AD operators), then it is worth considering data-driven NN as a possible technique.
- Strongly non-linear functions can greatly benefit from NN compared to traditional methods
- Off-line or sequential use: straight-forward, also in VAR schemes where linearization can be given by the automatic differentiation tools
- On-line coupling: need probably more robust/flexible libraries than those available now (e.g. ModernFortran) or need to adopt other specific approaches (e.g. *SmartSIM* orchestrator*)

Technological

- Acoustic environmental characterization is, in general, significantly affected by physical data assimilation and its degree of sophistication
- Although quite ill-posed, inverting Transmission Loss measurements may be promising as complementary observing networks for operational oceanographic applications (e.g. focus on the mesoscale)

CNR ISMAR
ISTITUTO DI SCIENZE MARINE

Contact: andrea.storto@cnr.it

Thank you for the attention,

Questions?

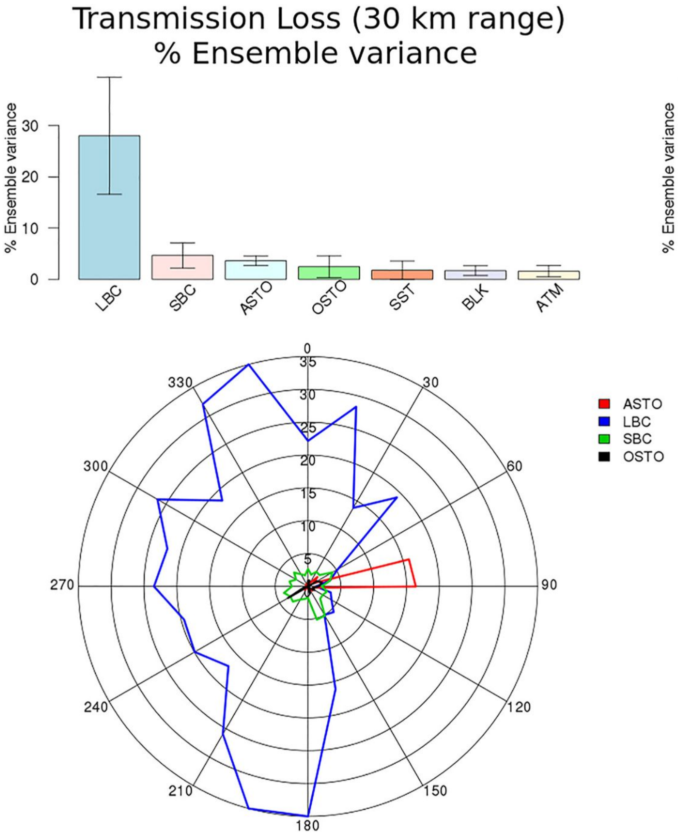
Most of the material presented here was taken from:

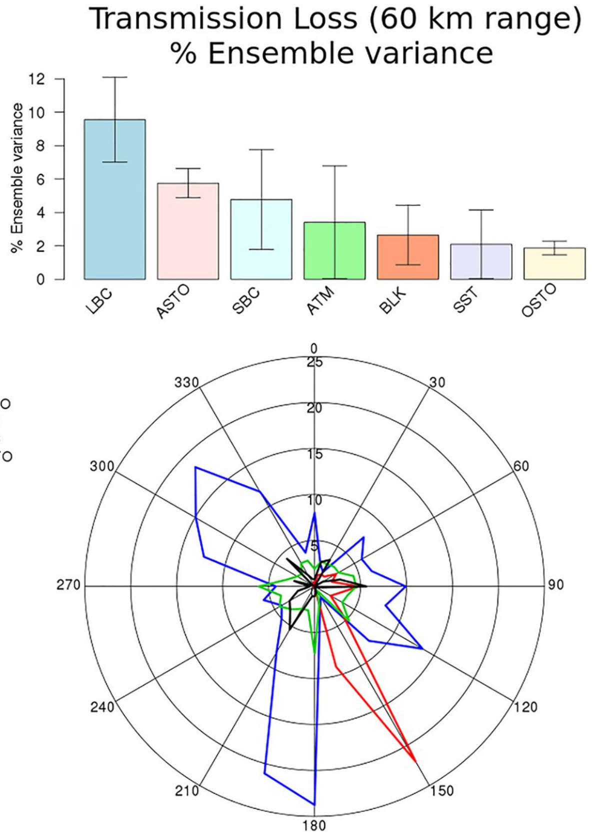
- Storto, A., Falchetti, S., Oddo, P., Jiang, Y.-M., & Tesei, A. (2020). Assessing the impact of different ocean analysis schemes on oceanic and underwater acoustic predictions. Journal of Geophysical Research: Oceans, 125, e2019JC015636. https://doi.org/10.1029/2019JC015636
- Storto, A., De Magistris, G., Falchetti, S., & Oddo, P. (2021). A Neural Network-Based Observation Operator for Coupled Ocean-Acoustic Variational Data Assimilation, Monthly Weather Review, 149(6), 1967-1985, DOI: https://doi.org/10.1175/MWR-D-20-0320.1

We do have 2 postdoc vacancies at CNR ISMAR (Rome) to work on coupled DA and optimal model bias correction (deadline: 5/OCT)

Extra – Slides

Impact of uncertainty on sound speed propagation

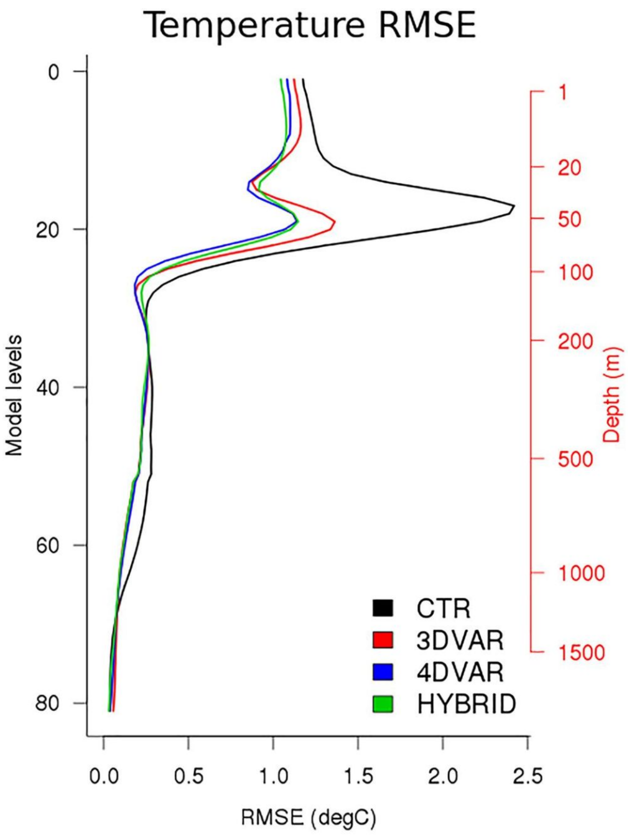


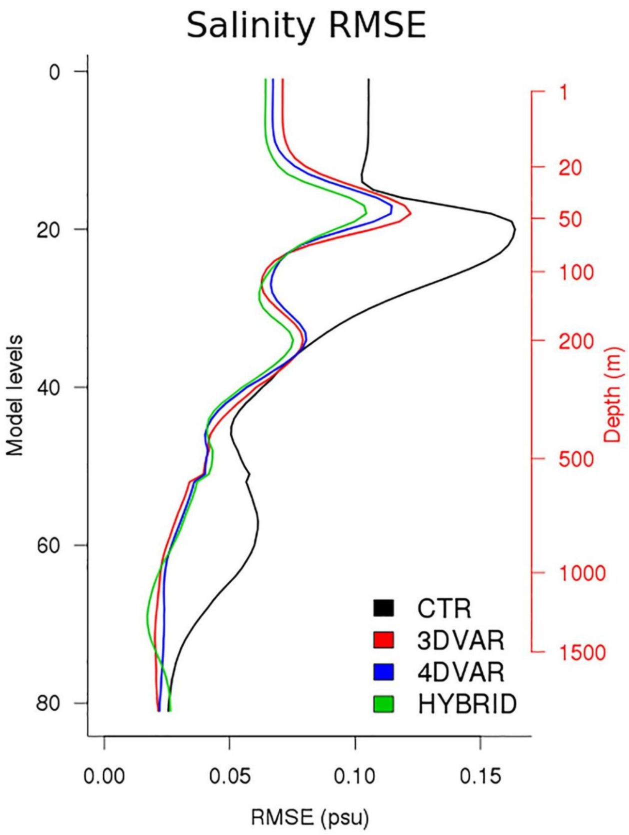


A large multi-perturbation ensemble helps understand the sensitivity of the underwater sound propagation to the model uncertainties

(through ensemble spread diagnostics and clustering)

Results in physical space





At 1-day forecast:

Similar improvement when 4DVAR and HYBRID are used