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WOC 3D Ocean currents retrieval

Bruno Buongiorno Nardelli, Daniele Ciani

WorldOceanCirculation

esa

Improve our knowledge of the 3D transport and environmental conditions and that are known to potentially affect key biological and ecological processes in the upper ocean

Develop new products to explore of the potential impact of long term oceanic variability on the population dynamics of different fish species.

The main interest is to:

- investigate the role of frontal meanders and eddies in the and dispersal of larvae of selected species (keeping in mind the possibility of diel vertical migrations from the surface down to few hundreds meters)
- assess the vertical exchanges at the base of the euphotic layer and their potential impact on primary productivity

Objectives

Theme 2 WOC-NATL3D

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→New product to be tested by intermediate users active in fishery advisory bodies (e.g. ICCAT, ICES) working groups and projects to achieve maximum impact in support of sustainable fishery.

SOCIB	Diego Alvarez	Spain	http://www.socib.eu/
DTU Aqua	Patrizio Mariani	Denmark	https://www.aqua.dtu.dk/english

Technical University of Denmark

DTU

SOCIB Balearic Islands Coastal Observing and Forecasting System

Theme 2 session tomorrow

Improve our knowledge of the 3D transport and environmental conditions and that are known to potentially affect key biological and ecological processes in the upper ocean

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WOC-NATL3D: 3D quasi-geostrophic ocean currents (u,v,w) reconstruction covering the upper layer (0-1500 m)

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Copernicus-OMEGA3D:
-mesoscale "permitting" resolution
-reduced accuracy at the surface

Weekly 1/4°x1/4° (global)
3D multilinear regression (CMEMS-ARMOR3D)
surface geostrophic currents (AVISO)
Atmospheric fluxes (ERA-interim)

→

WOC-NATL3D:
-mesoscale "resolving" resolution
-more accurate surface Ekman currents

Daily, 1/10°x1/10° (regional)
3D neural network model (WOC-LSTM3D)
improved surface geostrophic currents (WOC-NATL2D)
Atmospheric fluxes (ERA5)
Empirical Ekman current shear (Copernicus)

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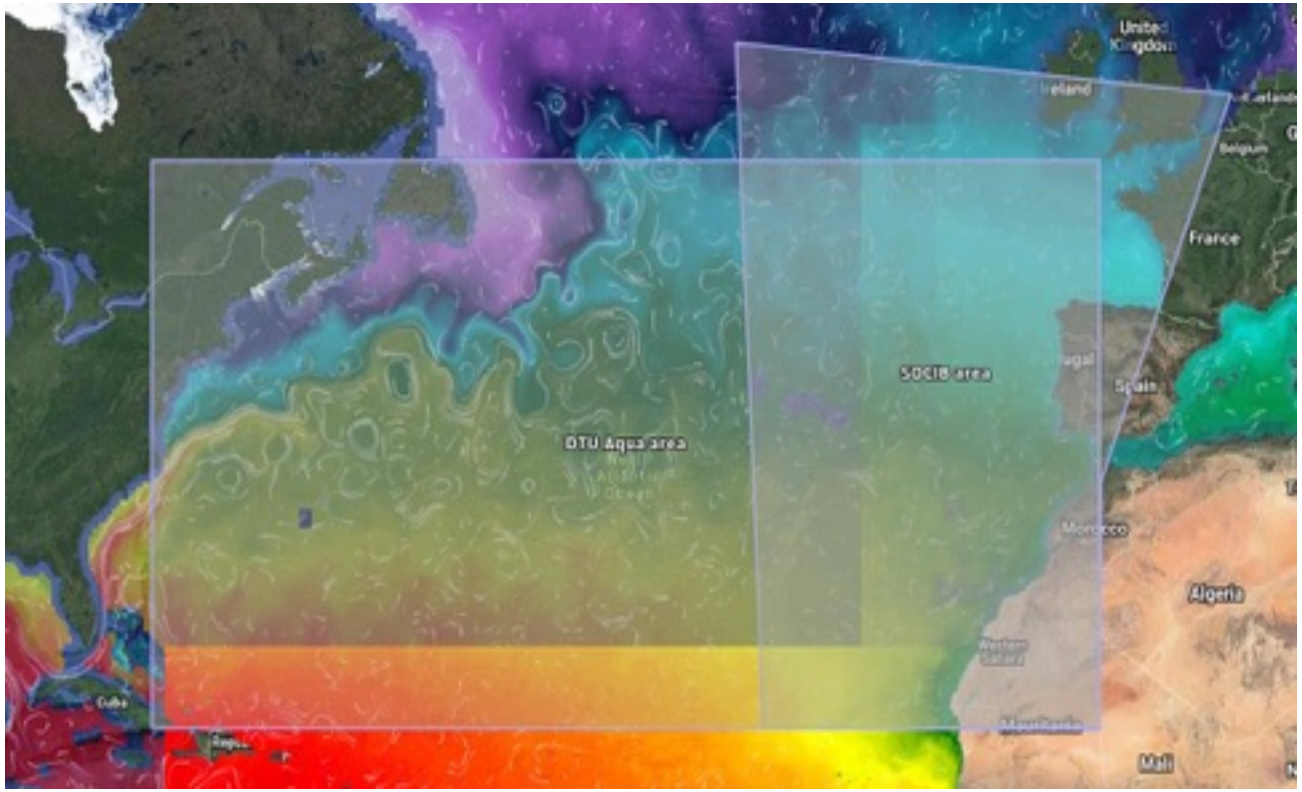
Study area

- **Sargasso Sea and Gulf Stream area** (Sargasso is the only location where the threatened European and American eels reproduce, Dekker, 2019).

- **Eastern Boundary Upwelling Systems** along the African and Iberian coasts →several species relevant for both local communities and commercial exploitation (Kämpf and Chapman, 2016)

The entire domain is ground for extremely relevant fishery activities, and identified as a key area within international conventions for the conservation of fishing resources (e.g. for tuna and tuna-like fishes, within ICCAT - International Commission for the Conservation of Atlantic Tunas)



WOC-NATL3D product development and processing steps
daily 3D (0-1500 m) quasi-geostrophic ocean currents (u,v,w), at mesoscale-resolving spatial resolution (1/10°x1/10°), over a wide section of the central/North Atlantic Ocean (20°N-50°N, 76°W-6°W). It covers ten years (2010-2019)

Three steps:

1. **Collect/develop high resolution surface data**

- Sea Surface Temperature (SST)
- Sea Surface Salinity (SSS)
- Absolute Dynamic Topography (ADT)

2. Retrieve ocean 3D hydrographic structure from combined surface data and in situ vertical profiles

- multivariate Empirical Orthogonal Function reconstruction
- Long-Short Term Memory Network

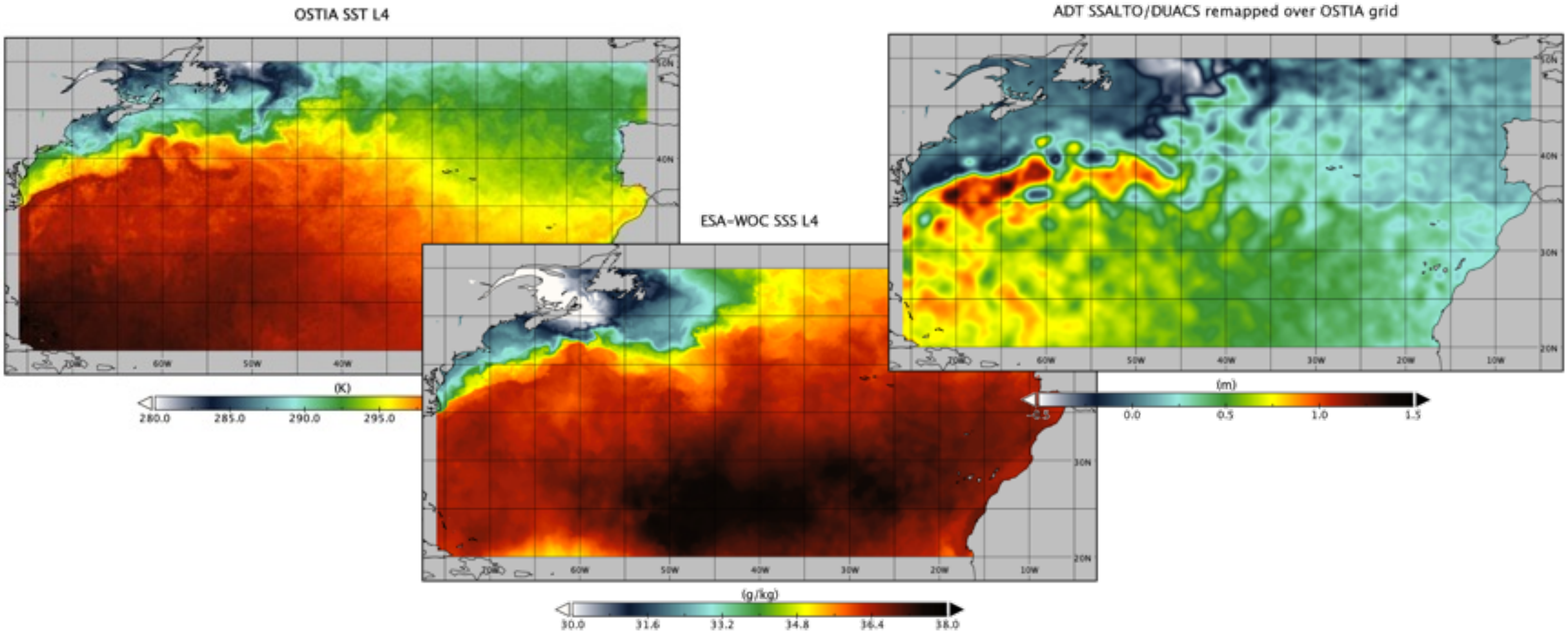
3. Solve diabatic Quasi-Geostrophic Omega equation including surface forcings

- adapt Copernicus Marine Service OMEGA3D processing chain to NATL3D domain/resolution
- improve forcings

Surface data

All reconstruction techniques tested here project the anomalies of **sea surface temperature (SST), sea surface salinity (SSS) and adjusted absolute dynamic topography (ADT)** at depth based on information extracted from T, S, and steric height anomaly profiles (all anomalies are computed vs climatologies)

High resolution surface data:
Sea Surface Temperature (SST) → OSTIA (UK Metoffice)
ESA-WOC Sea Surface Salinity (SSS)→***new ESA-WOC daily product at 1/10°***
Absolute Dynamic Topography (ADT) →***new ESA-WOC product: NATL2D***



Input vertical data

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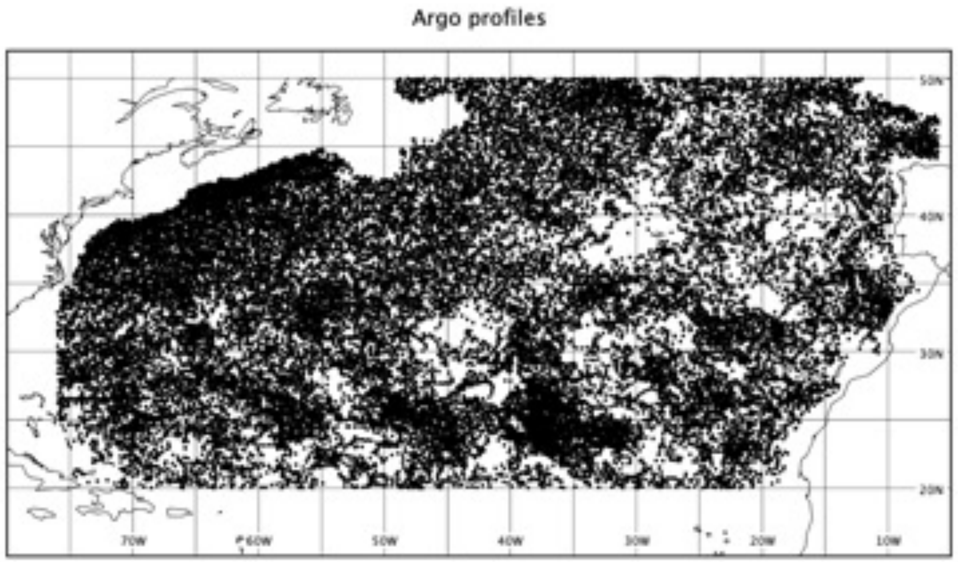
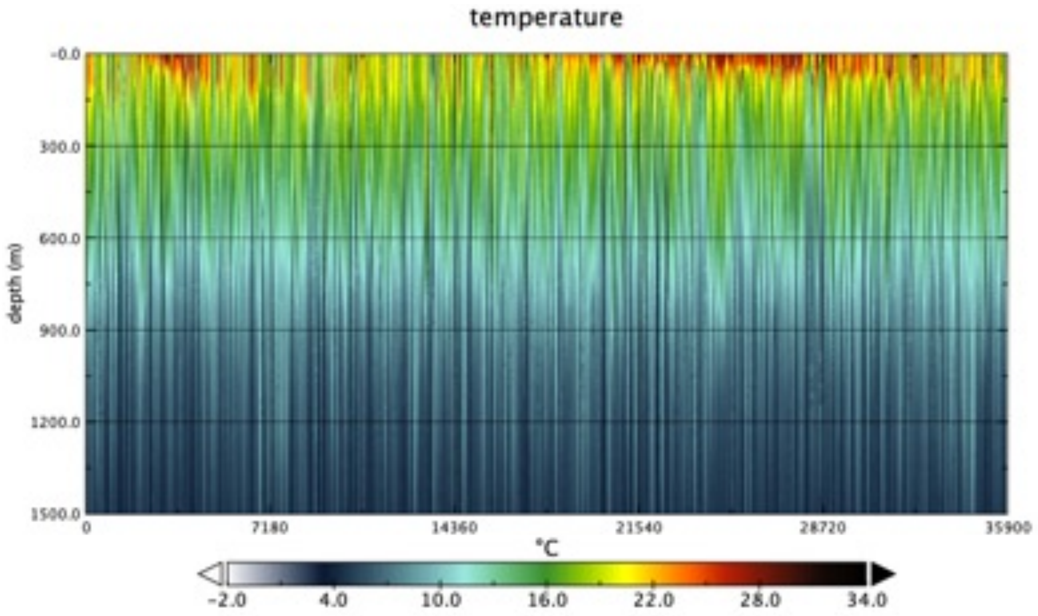
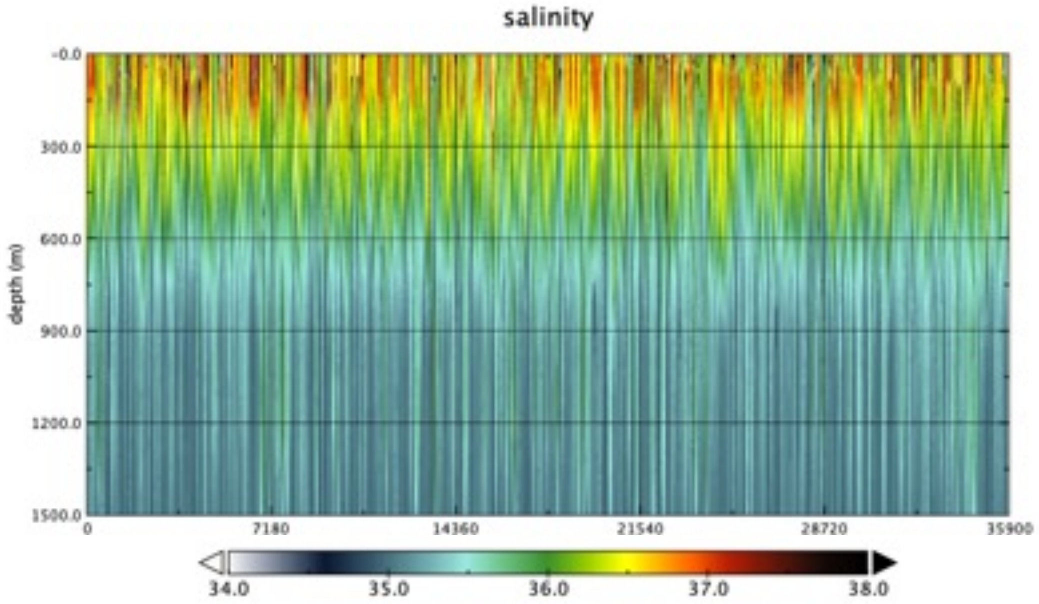
In situ vertical profiles

→ CMEMS CORA 5.2 quality controlled temperature and salinity from CTD and Argo profiles (Szekely et al., 2019)

→ WORLD OCEAN ATLAS 13 monthly objectively analyzed (1°x1° grid) climatological fields of in situ temperature, salinity







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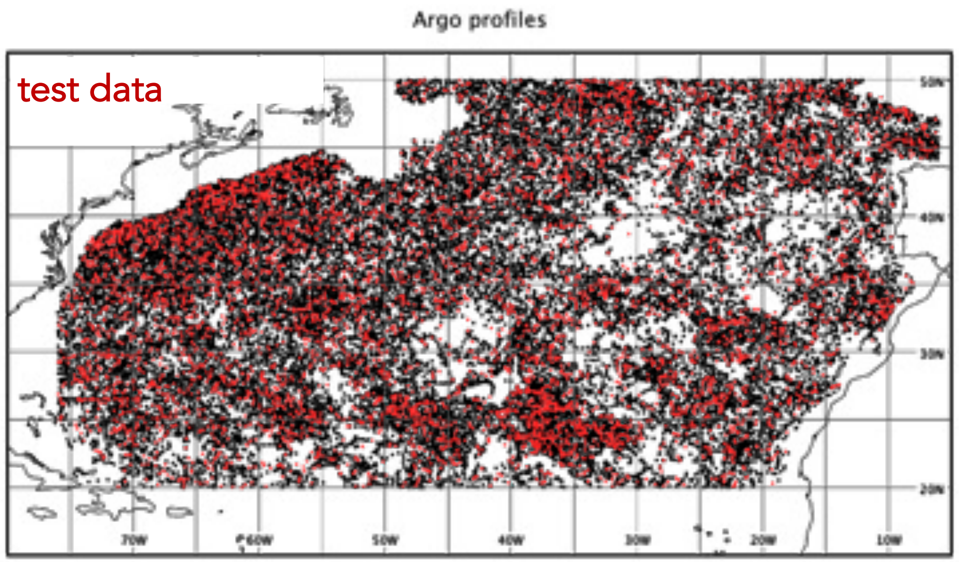
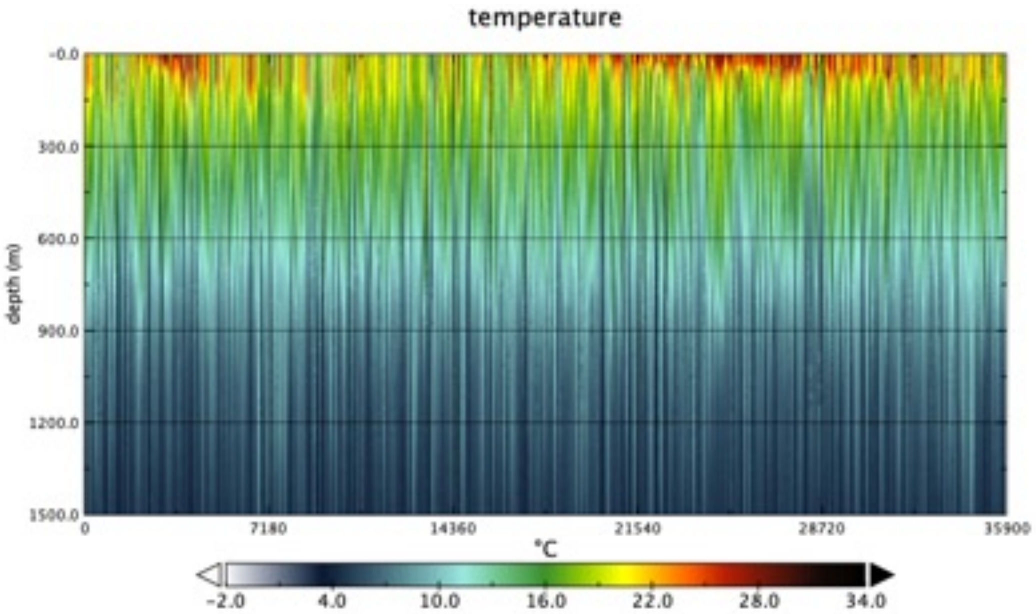
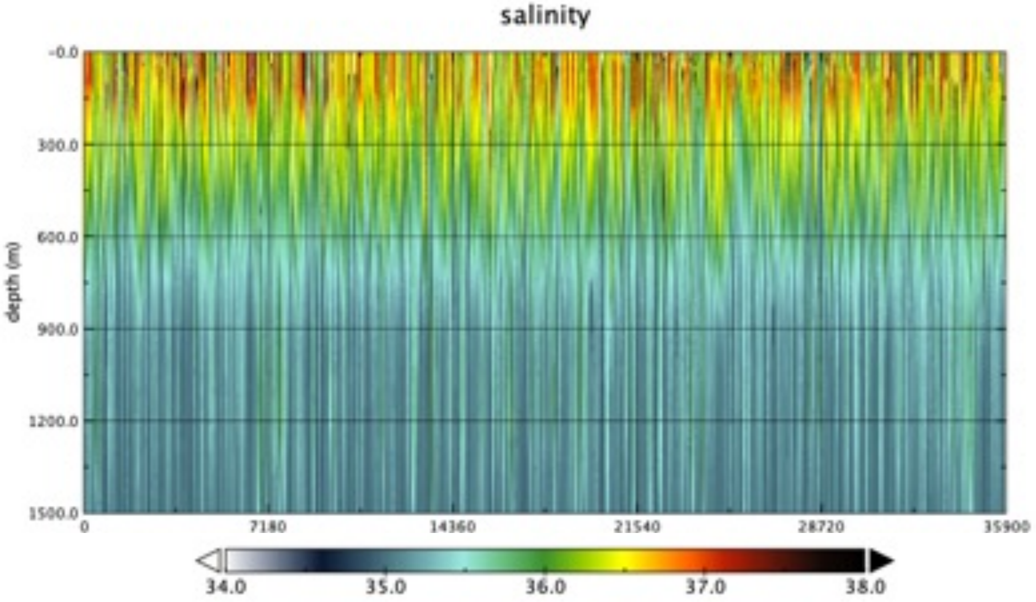
>35000 in situ vertical profiles

Assessment of reconstruction techniques requires
- training dataset
- test dataset (independent from training)

→ **15% of profiles kept for test (>5000)**







multivariate EOF reconstruction

The **multivariate Empirical Orthogonal Function reconstruction (mEOF-r)** is based on the EOF decomposition of a state vector that includes T,S,SH climatological anomalies from ARGO profiles

Hypotheses: few modes explain the most of the variability, surface values are known (SSS, SST, adjusted ADT)

→including Steric Heights favours extraction of dynamical information (but altimeter data require specific adjustment)
→anomalies computed vs WOA13 climatology

state vector=$[T(1),T(2),\ldots,T(m),S(1),S(2),\ldots,S(m),SH(1),SH(2),\ldots,SH(m)]$

known from surface input

$$T(z,t)=\sum_{k=1}^{n}a_k(t)L_k(z)$$

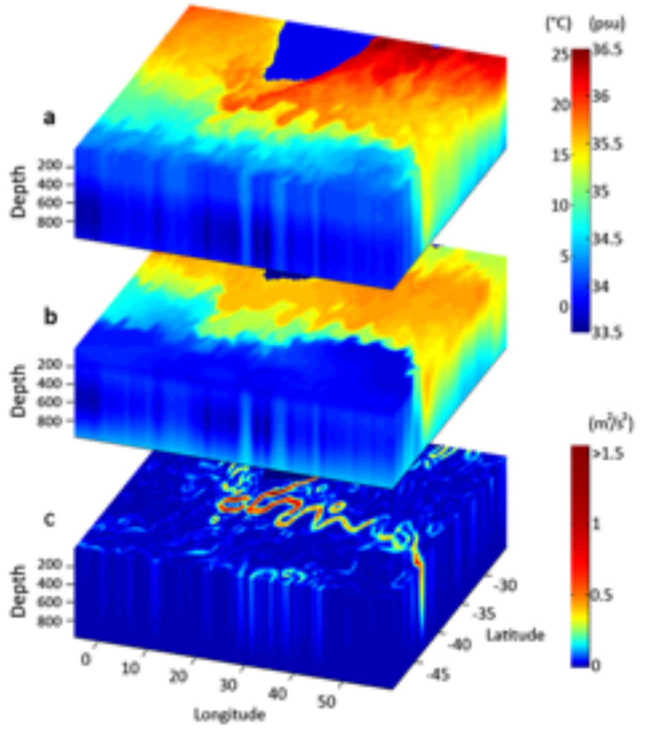
$$S(z,t)=\sum_{k=1}^{n}a_k(t)M_k(z)$$

$$SH(z,t)=\sum_{k=1}^{n}a_k(t)N_k(z)$$

mEOF decomposition

Core of mEOF-R method

$$\boxed{\begin{cases} a_1(t)L_1(0)+a_2(t)L_2(0)+a_3(t)L_3(0)=T(0,t) \\ a_1(t)M_1(0)+a_2(t)M_2(0)+a_3(t)M_3(0)=S(0,t) \\ a_1(t)N_1(0)+a_2(t)N_2(0)+a_3(t)N_3(0)=SH(0,t) \end{cases}}$$



k-th EOF amplitude = $a_k(t)$

k-th EOF pattern = $[L_k(1), L_k(2),\ldots, L_k(m), M_k(1), M_k(2),\ldots, M_k(m), N_k(1), N_k(2),\ldots, N_k(m)]$

Buongiorno Nardelli B., Santoleri R., *J. Atmos. Ocean. Tech*. 2005
Buongiorno Nardelli B. et al., *J. Geophys. Res*.2006
Buongiorno Nardelli B. et al., *Ocean Sci*.2012
Buongiorno Nardelli, JGR, 2013
Buongiorno Nardelli et al., JGR, 2018a,b

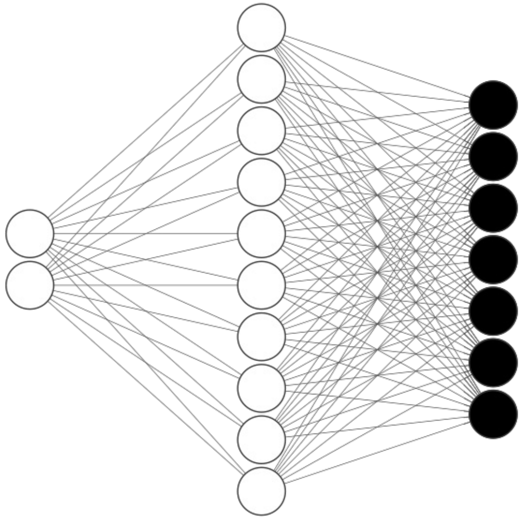
solution proposed initially within ESA-WOC contract
→version 0 of WOC_NATL3D (not released to the public)

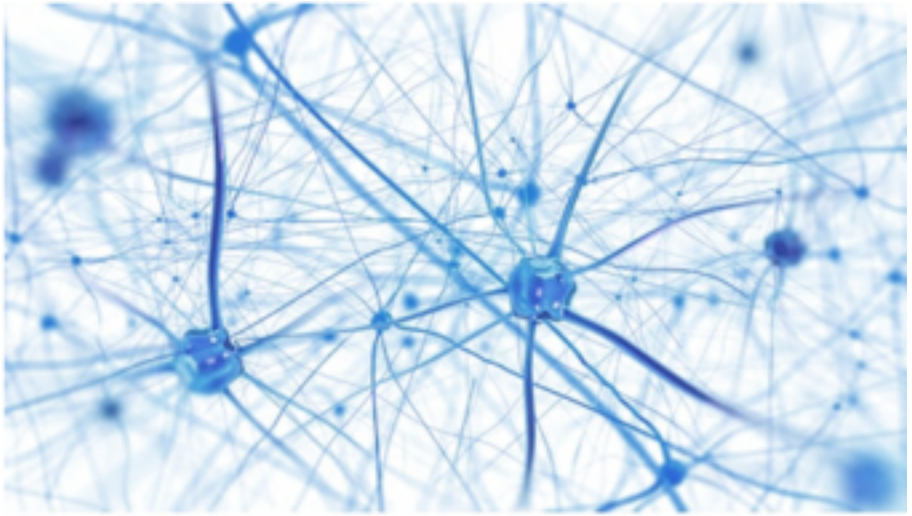
Artificial Neural Networks (ANN) are perfect candidates for regression/prediction problems

→ loosely inspired by the functioning of animal brains
→ built as non-linear models
→ parameters estimated by "learning" from available data

input vector variable **x (predictor)** related to an output vector (or scalar) variable **y (target)** by nesting several non linear functions:

$$\boldsymbol{y} = \mathcal{M}(\boldsymbol{x}) = f(h(\dots(\boldsymbol{x}))$$





"Learning" is the process of "fitting" ANN model parameters to observed data (a.k.a. optimization). This is done by minimizing differences between model output and observed data (*loss function*).

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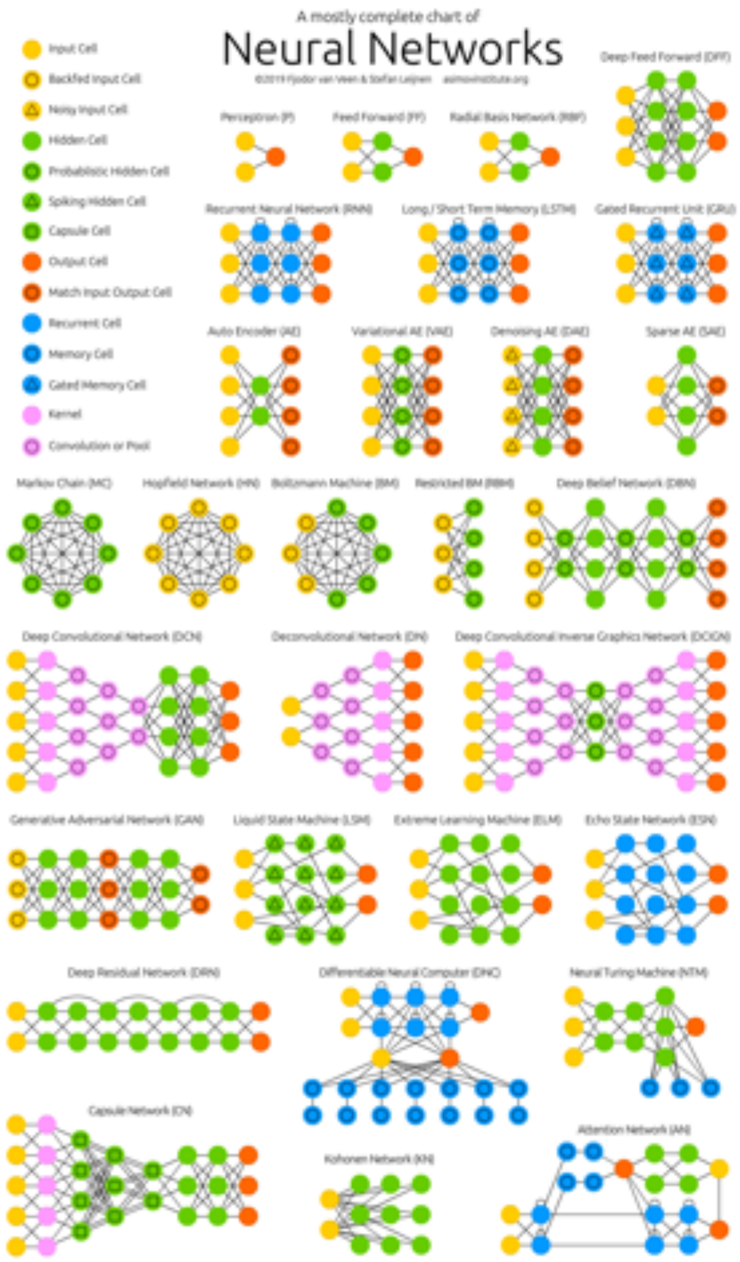
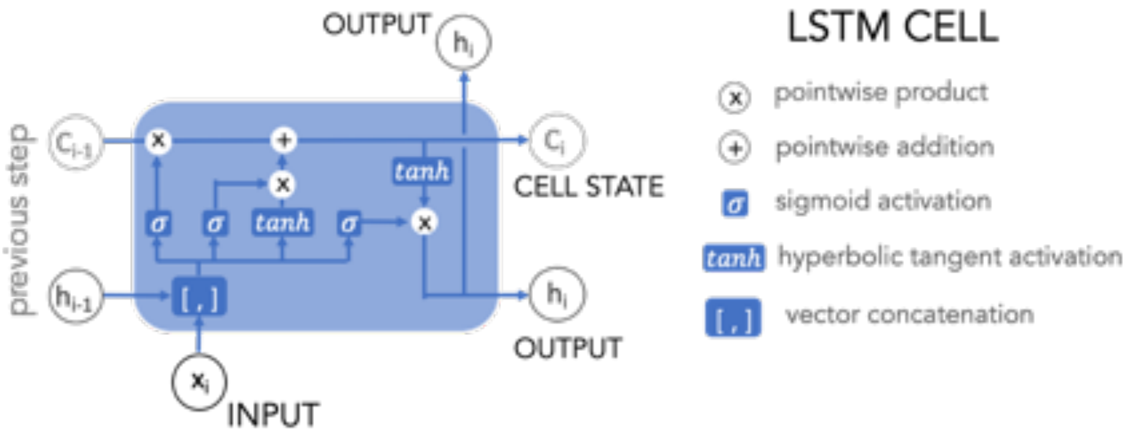


The choice of network architecture defines the "family" of solutions that can be learned from data

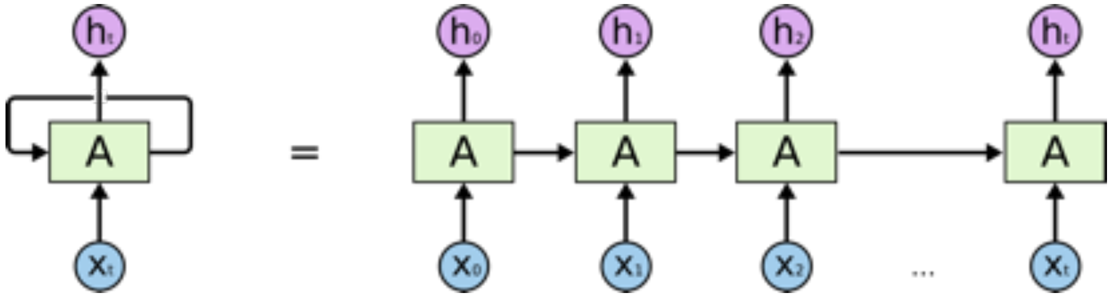
LSTM reconstruction: architecture

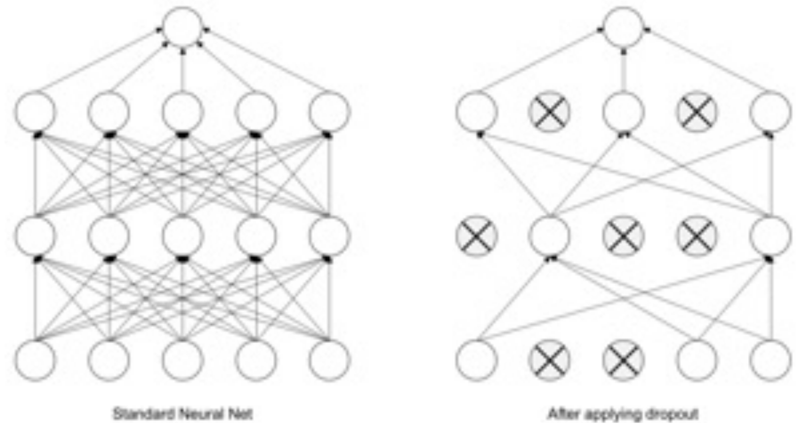
Long Short Term Memory network coupled to a **Monte Carlo dropout** method to estimate vertical profiles and associated errors

Long Short Time Memory (LSTM) Networks are efficient in exploiting the information present in sequences of data. They do this by iteratively processing input sequences through cells that combine input data and information from the previous step… the core information is included in the cell state that is directly transmitted to the next cell (acting as a network "memory")



GENERIC RECURRENT NETWORK ARCHITECTURE

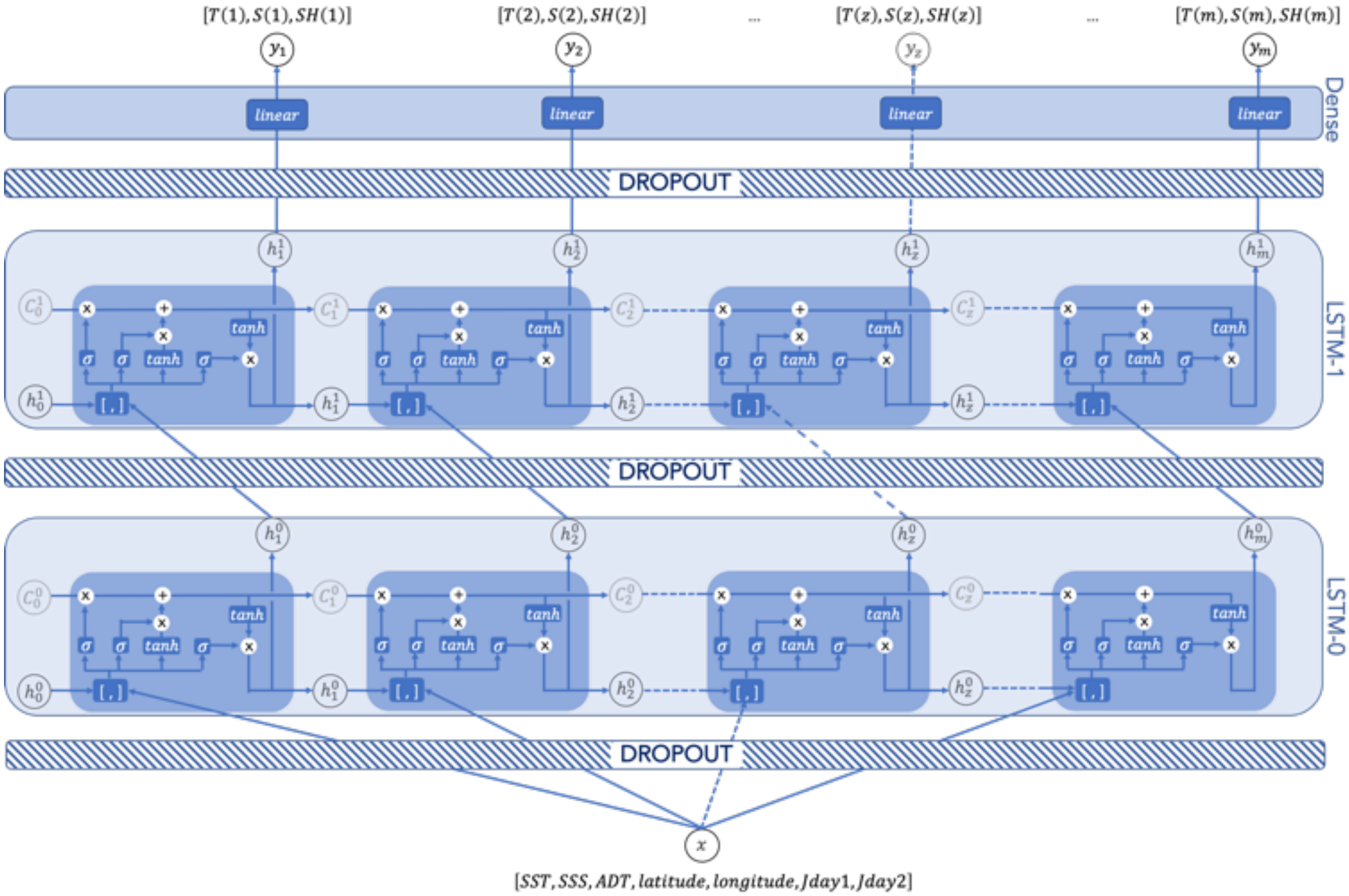




Dropout: Running a neural network regression several times with dropout during testing generates different output for the same input. These output are equivalent to Monte-Carlo sampling (Srivastava, et al. 2014). Thus, ensemble mean and variance provide the network’s output values and related uncertainty, respectively.

LSTM reconstruction: architecture

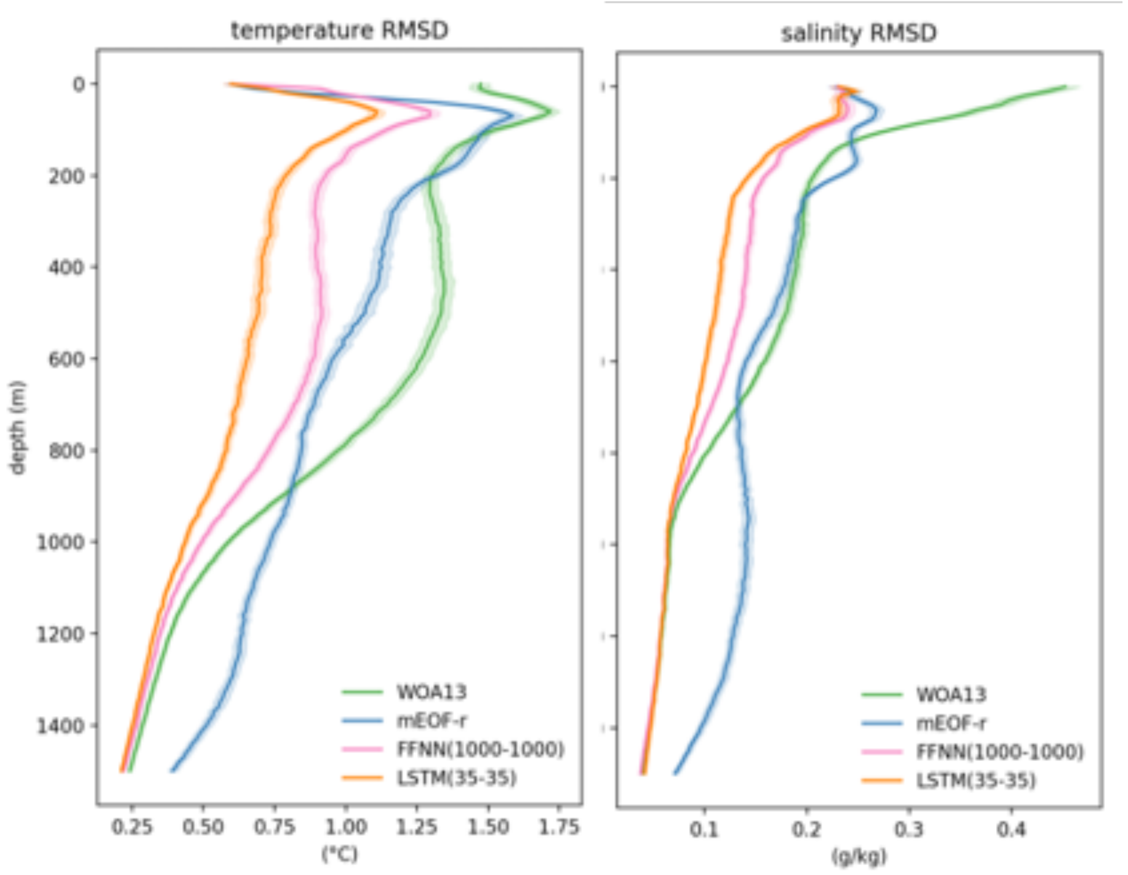
WOC-NATL3D stacked Long Short Term Memory network



Accuracy

→ RMSD between observed and reconstructed vertical profiles (independent test dataset) compared to RMSD between observed profiles and:

- standard feed-forward neural network (FFNN)
- multivariate EOF reconstruction (mEOF)
- climatology (WOA13)



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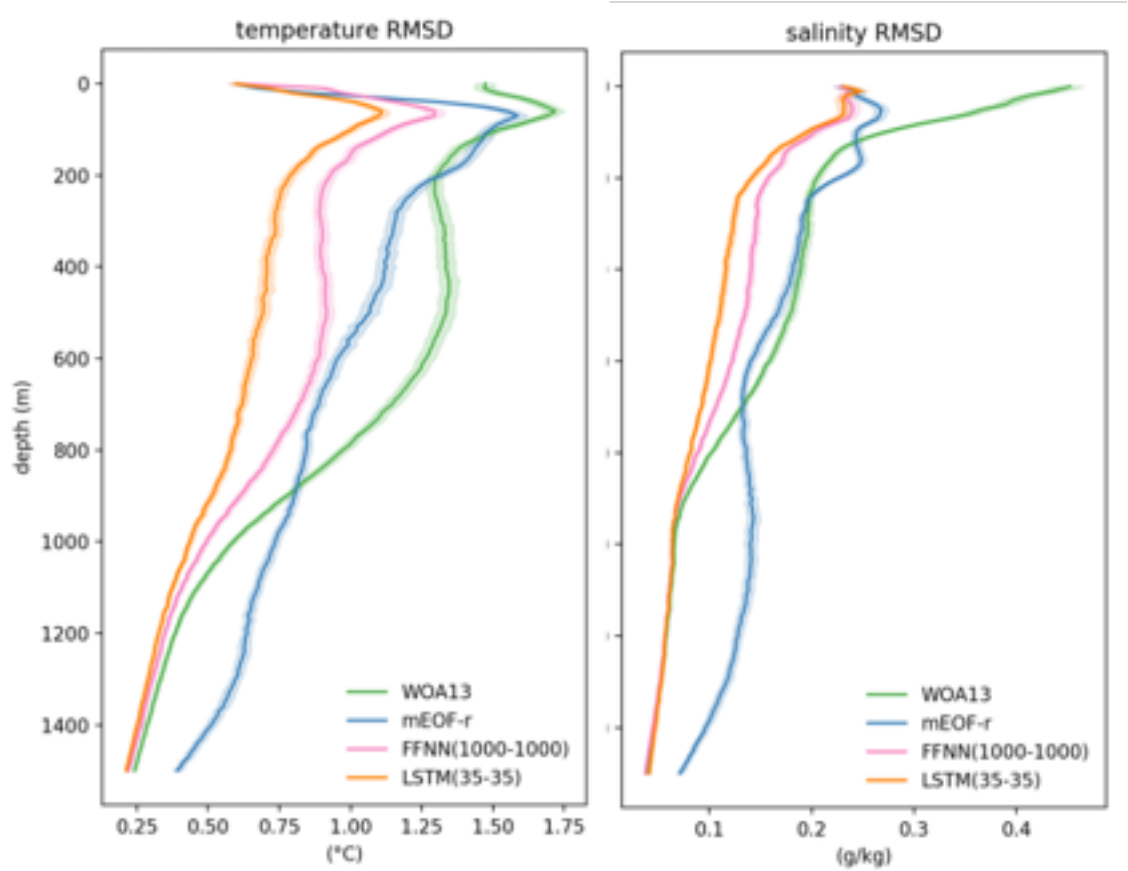

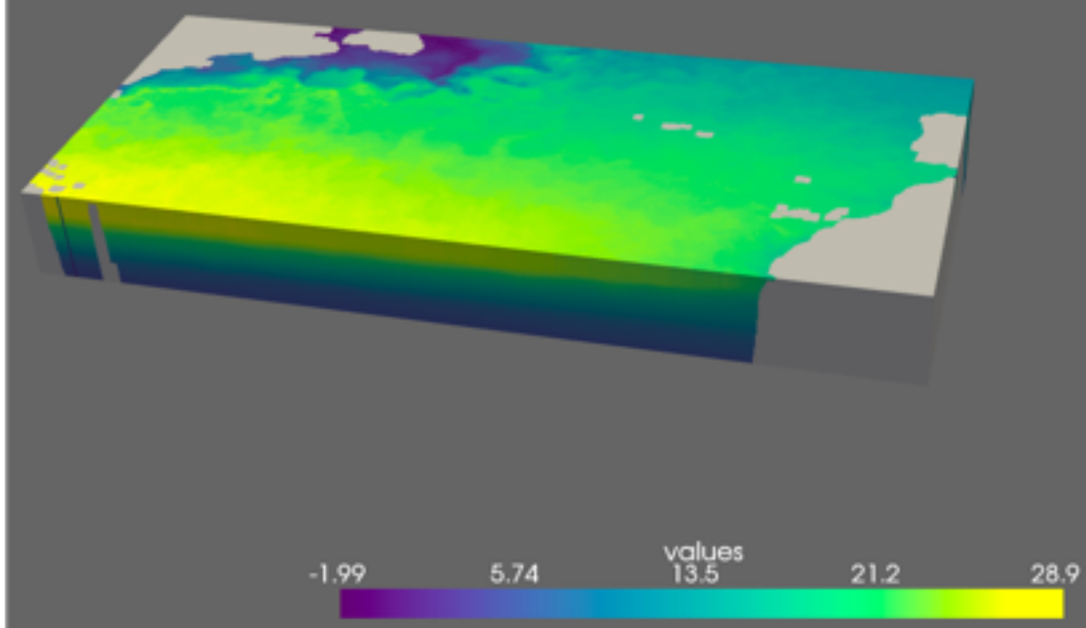

Surface data + LSTM model provide **4D reconstruction** of:

- temperature
- salinity
- geostrophic currents

Q-vector formulation of the quasi-geostrophic Omega equation solved to get the vertical velocity fields

$$\nabla^2{}_h(N^2 w) + f^2\frac{\partial^2 w}{\partial z^2} = \nabla_h \cdot \boldsymbol{Q} \qquad \boldsymbol{Q} = 2\boldsymbol{Q_{twg}} + \boldsymbol{Q_{th}} + \boldsymbol{Q_{dm}}$$

kinematic deformation

$$\mathbf{Q}_{\boldsymbol{twg}} = \frac{g}{\rho_0}\left(\frac{\partial u_g}{\partial x}\frac{\partial \rho}{\partial x} + \frac{\partial v_g}{\partial x}\frac{\partial \rho}{\partial y}, \frac{\partial u_g}{\partial y}\frac{\partial \rho}{\partial x} + \frac{\partial v_g}{\partial y}\frac{\partial \rho}{\partial y}\right)$$

turbulent momentum

$$\mathbf{Q}_{\boldsymbol{dm\_COP}} = \frac{f}{\rho_0}\left(\frac{\partial^2}{\partial z^2}\left[\rho \boldsymbol{K}_m\left(\frac{\partial v_g}{\partial z} - \boldsymbol{\gamma_v}\right)\right], -\frac{\partial^2}{\partial z^2}\left[\rho \boldsymbol{K_m}\left(\frac{\partial u_g}{\partial z} - \boldsymbol{\gamma_v}\right)\right]\right)$$

turbulent buoyancy

$$\mathbf{Q}_{\boldsymbol{th}} = -\frac{g}{\rho_0}\nabla_h\left(\frac{\partial}{\partial z}\left[K_\rho\left(\frac{\partial \rho}{\partial z} - \gamma_\rho\right)\right]\right) = \nabla_h\left(\frac{\partial}{\partial z}\left[K_\rho\left(N^2 + \frac{g}{\rho_0}\gamma_\rho\right)\right]\right)$$

→ KPP parameterization of viscosity/diffusivity (K_{x},) and non-local effective gradients γ_{x},. (Smyth et al., 2001)

Q-vector formulation of the quasi-geostrophic Omega equation solved to get the vertical velocity fields

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turbulent momentum

$$\mathbf{Q}_{dm\_woc} = \frac{f}{\rho_0}\left(\frac{\partial^2}{\partial z^2}\left[\rho \boldsymbol{K}_m\left(\frac{\partial v_g}{\partial z} + \frac{\boldsymbol{\partial v_{Ekman}}}{\boldsymbol{\partial z}} \cancel{-\gamma_v}\right)\right], -\frac{\partial^2}{\partial z^2}\left[\rho \boldsymbol{K}_m\left(\frac{\partial u_g}{\partial z} + \frac{\boldsymbol{\partial u_{Ekman}}}{\boldsymbol{\partial z}} \cancel{-\gamma_v}\right)\right]\right)$$

→combination of empirical estimates and KPP for tracers ~~and momentum (Smyth et al., 2001)~~ non-local effective gradient, γ_ρ, and viscosity/diffusivity, K_x.

turbulent buoyancy

$$\mathbf{Q}_{th} = -\frac{g}{\rho_0}\nabla_h\left(\frac{\partial}{\partial z}\left[K_\rho\left(\frac{\partial \rho}{\partial z} - \gamma_\rho\right)\right]\right) = \nabla_h\left(\frac{\partial}{\partial z}\left[K_\rho\left(N^2 + \frac{g}{\rho_0}\gamma_\rho\right)\right]\right)$$

background Ekman velocity approximated through an analytical fit to CMEMS Ekman empirical reconstruction (MULTIOBS_GLO_PHY_REP_015_004)

$$u_{Ekman}(z) = e^{\frac{z}{D_{amp}}}[\,u_0\cos(z/D_{rot}) - v_0\sin(z/D_{rot})]$$

$$v_{Ekman}(z) = e^{\frac{z}{D_{amp}}}[\,u_0\sin(z/D_{rot}) + v_0\cos(z/D_{rot})]$$

viscosity in the Ekman layer constrained by analytical profile (defined as in *Nagai et al*., 2006) estimated empirically (i.e.limited by local Ekman amplitude decay scale)

$$K_m(z) = K_{max}\left[1 + \tanh\left(\frac{z - D_{amp}}{\delta}\right)\right] \qquad K_{max} = \frac{f D_{amp}^2}{2}$$

→horizontal ageostrophic components

Once the Omega equation is solved for *w*, horizontal ageostrophic components can be estimated by integrating two expressions that are obtained during the analytical derivation of the omega equation:

$$u_a(z) = \int_{REF}^{z} \frac{\partial u_a}{\partial z} dz = \frac{1}{f^2} \int_{REF}^{z} \left(\frac{\partial}{\partial x}(N^2 w) - \frac{f}{\rho_0} \frac{\partial}{\partial z}\left(\frac{\partial \tau_{yz}}{\partial z}\right) - 2\frac{g}{\rho_0}\left(\frac{\partial u_g}{\partial x}\frac{\partial \rho}{\partial x} + \frac{\partial v_g}{\partial x}\frac{\partial \rho}{\partial y}\right) - \frac{g}{\rho_0}\frac{\partial}{\partial x}\left(\frac{\partial \mathrm{F}_{\rho z}}{\partial z}\right)\right) dz$$

$$v_a(z) = \int_{REF}^{z} \frac{\partial v_a}{\partial z} dz = \frac{1}{f^2} \int_{REF}^{z} \left(\frac{\partial}{\partial y}(N^2 w) + \frac{f}{\rho_0} \frac{\partial}{\partial z}\left(\frac{\partial \tau_{xz}}{\partial z}\right) - 2\frac{g}{\rho_0}\left(\frac{\partial u_g}{\partial y}\frac{\partial \rho}{\partial x} + \frac{\partial v_g}{\partial y}\frac{\partial \rho}{\partial y}\right) - \frac{g}{\rho_0}\frac{\partial}{\partial y}\left(\frac{\partial \mathrm{F}_{\rho z}}{\partial z}\right)\right) dz$$

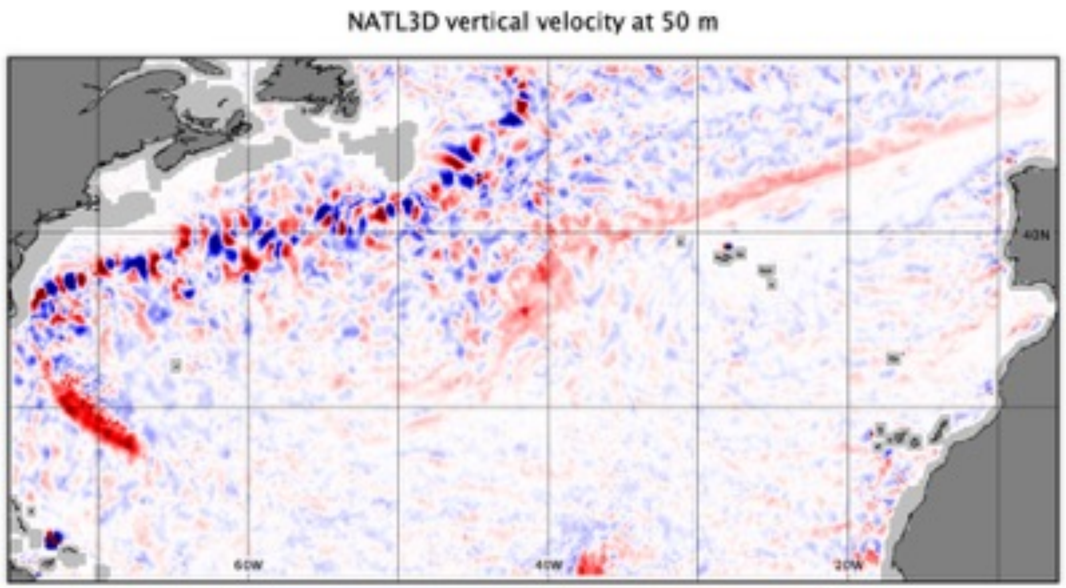
where we have defined:

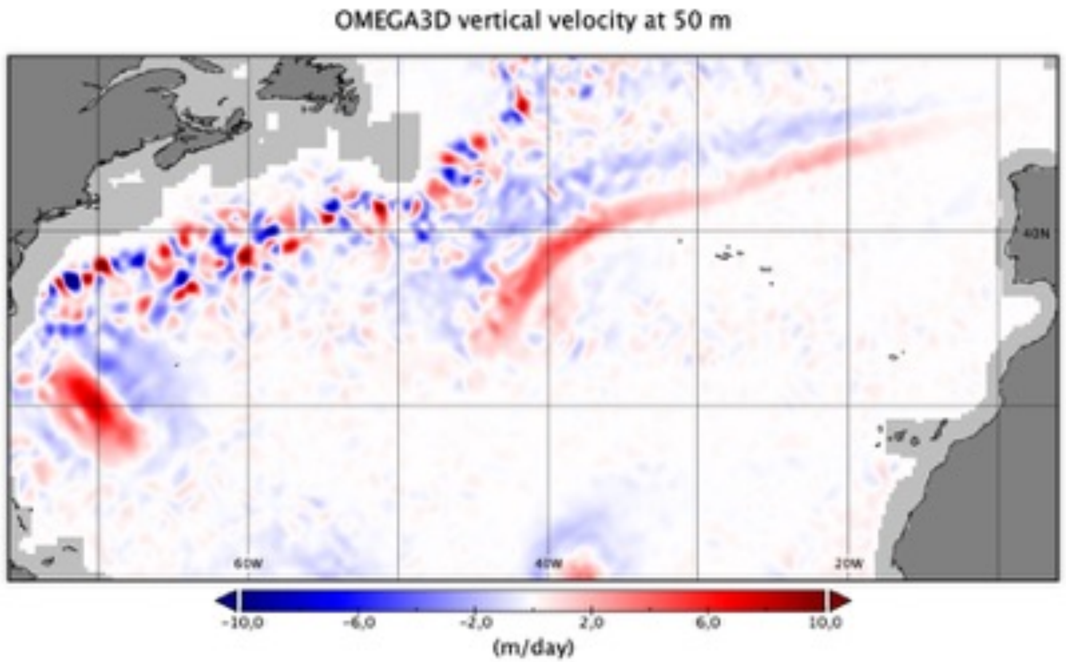
$$\tau_{xz} = \rho K_m \left(\frac{\partial u}{\partial z}\right)$$

$$\tau_{yz} = \rho K_m \left(\frac{\partial v}{\partial z}\right)$$

$$\mathrm{F}_{\rho z} = K_\rho \left(\frac{\partial \rho}{\partial z} - \gamma_\rho\right)$$

and assumed that the ageostrophic velocities can be neglected at the reference layer considered in the integral (here taken as the deepest level).

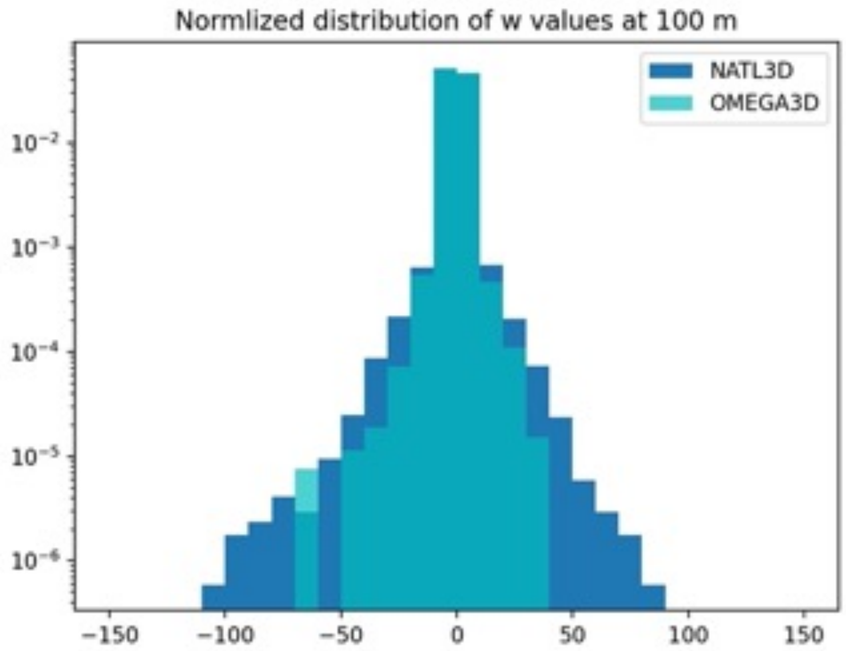




Qualitative comparison

NATL3D vertical velocity and OMEGA3D vertical velocity at 50 m on 2018-09-12

Histogram of the differences between NATL3D and OMEGA3D vertical velocities at 100 m depth on 2018-09-12

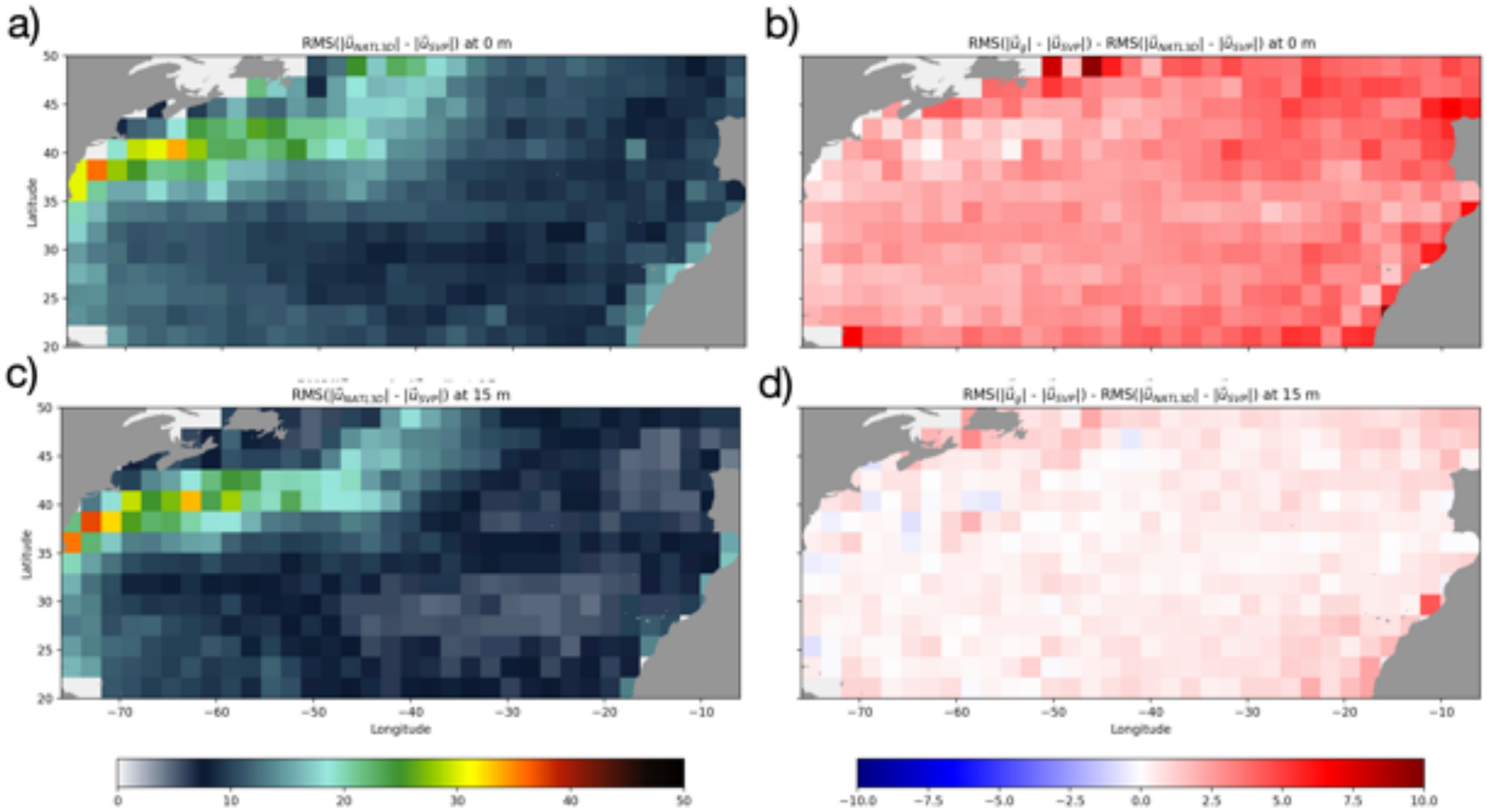


Validation

Total horizontal and geostrophic components have been compared with independent estimates of the ocean currents retrieved from SVP drifting buoys over the **entire timeseries** (2010-2019).

Total horizontal velocities RMSD: **0.119±0.001** m/s at 0 m and **0.113±0.001** m/s at 15 m
Geostrophic velocities RMSD: **0.145±0.001** m/s at 0 m and **0.117±0.001** m/s at 15 m

matchups used to compute the statistics: 311735 for undrogued SVP velocities (at 0) m and 243742 for drogued SVP data (at 15 m). Confidence intervals are estimated with bootstrapping (1 σ).



Positive values indicate an improvement with respect to geostrophy

WOC-NATL3D algorithm includes several improvements with respect to Copernicus, involving all processing steps.

Planned future research:

→ test different parameterizations of vertical mixing
→ test impact of improved surface stress estimates
→ test new surface Ekman current estimates

Present **roadmap for** further **improvements** includes:

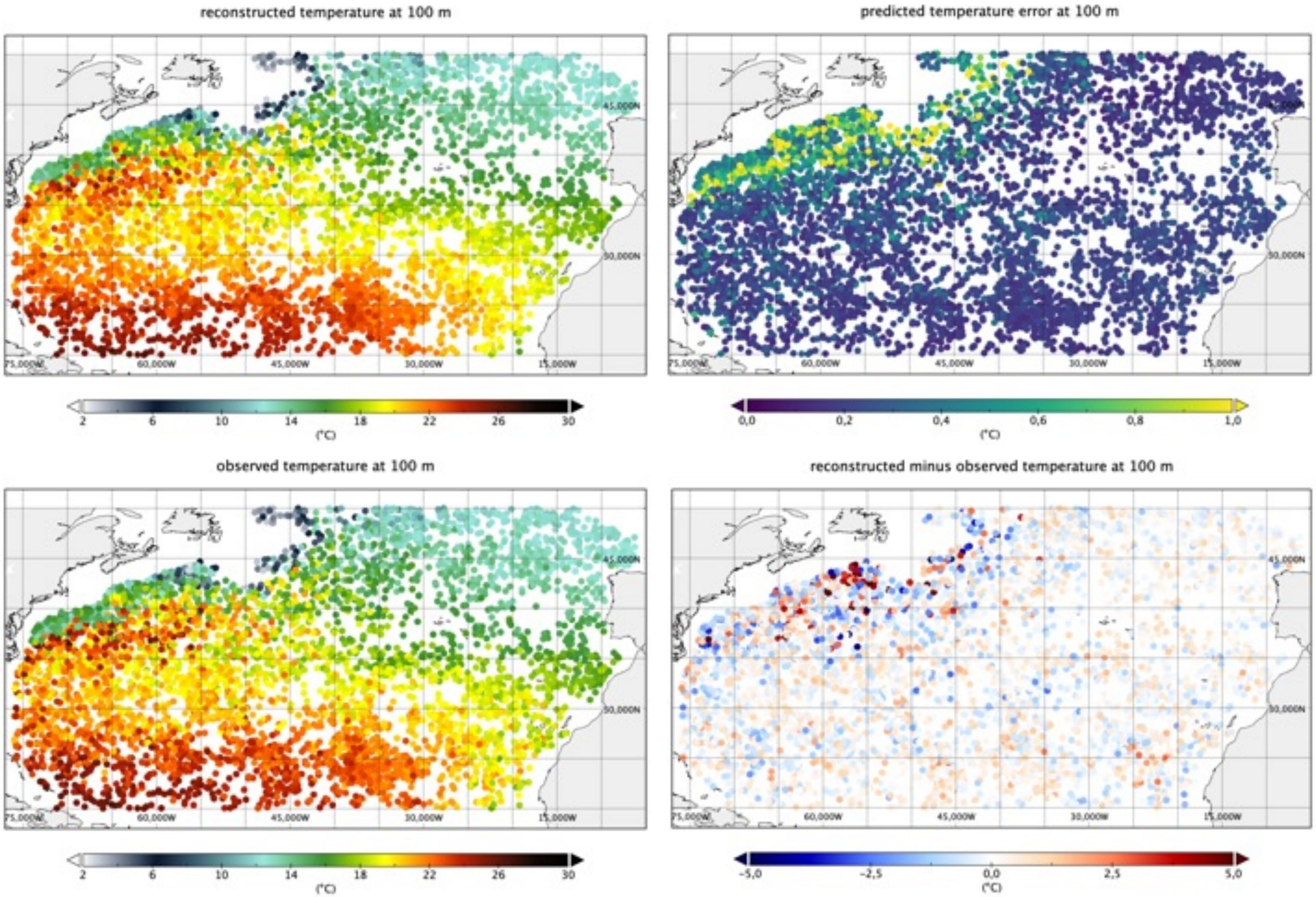
→ **New algorithms/set-up for surface input data retreival**
- SSS based on in situ+SMOS+SMAP data
- test of super-resolution deep convolutional neural network algorithms for ADT and joint SST/ADT retrieval (also though physically-informed approach)

→ test of **new/refined 3D reconstruction** deep learning algorithms
→ development of **3D Omega solvers** based on deep learning

Additional slides

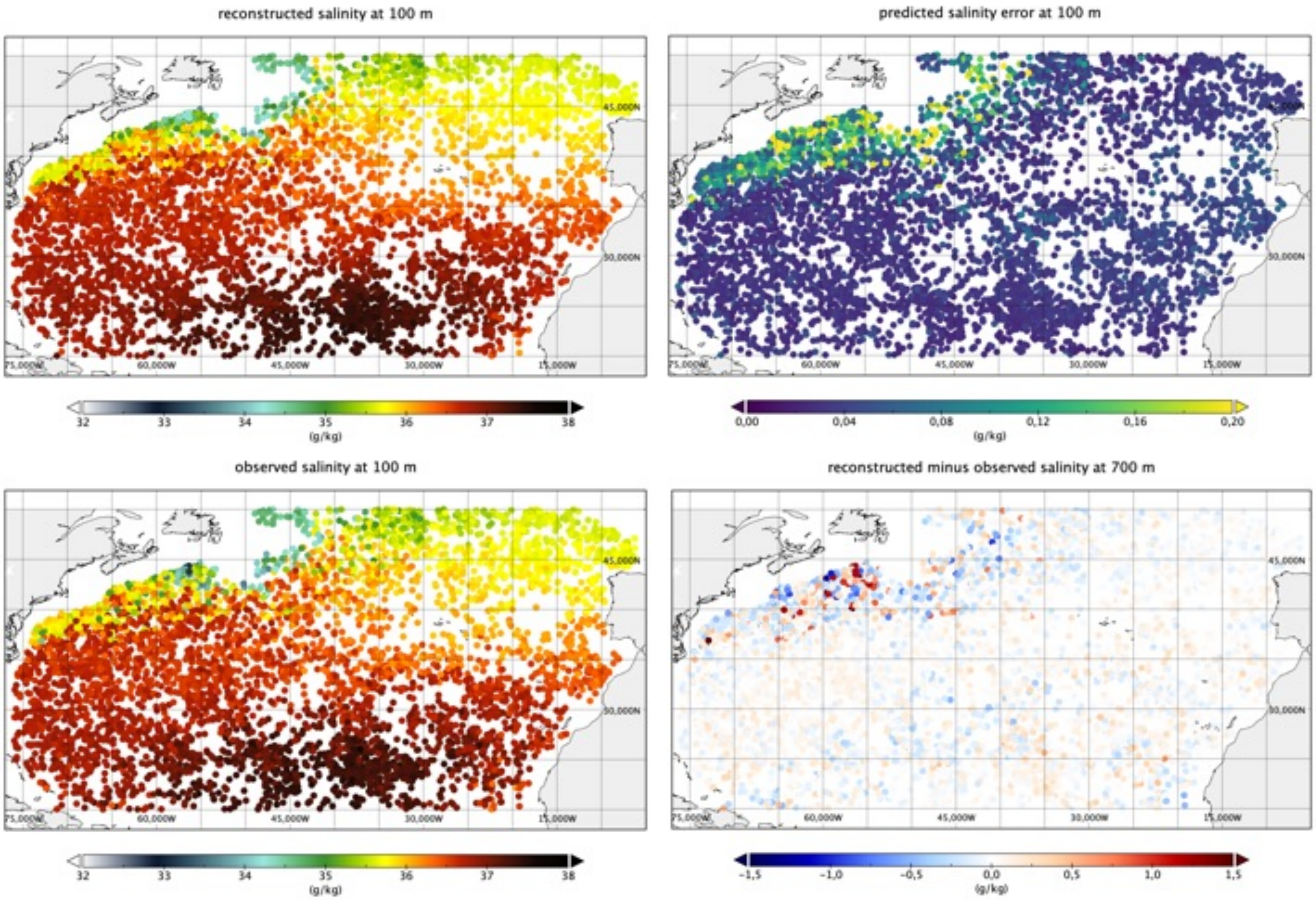
Stacked LSTM model

1-Stacked LSTM to project surface information at depth: **temperature reconstruction uncertainties**



Stacked LSTM model

1-Stacked LSTM to project surface information at depth: **salinity reconstruction uncertainties**



Stacked LSTM model

remote sensing

MDPI

Letter

A Deep Learning Network to Retrieve Ocean Hydrographic Profiles from Combined Satellite and In Situ Measurements

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bbuong / 3Drec

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bbuong Update README.md · 7941d76 on 25 Sep · 13 commits

LICENSE	Initial commit	2 months ago
README.md	Update README.md	2 months ago
WOC_FFNN3D_model_github.py	Add files via upload	2 months ago
WOC_LSTM3D_model_github.py	Add files via upload	2 months ago

README.md

3Drec

Made with Python

3Drec provides the implementation of two deep learning networks designed to reconstruct the 3D ocean structure from 2D satellite data: one based on a deep feed-forward network (**FFNN3D**) and one based on a stacked Long-Short Term Memory network (**LSTM3D**).

GitHub

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July 14, 2020 · Dataset · Open Access

ESA-WOC North Atlantic Sea Surface Salinity maps from a multivariate combination of satellite and in situ surface measurements (2010-2018)

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Developing a deep Learning network to retrieve ocean hydrographic profiles in the North Atlantic from combined satellite and in situ measurements: training datasets

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CMEMS Algorithm
→issues in the surface layer

In depth analysis of OMEGA3D data revealed **low performance wind-driven surface currents** retrieval at the surface

Data Type	Eastward error	Northward error	Norm error	Field speed	percentage
015_004	0.1109	0.1080	0.1105	0.2180	38.7053
001_024_d	0.1333	0.1254	0.1274	0.2072	44.3085
015_002	0.1301	0.1091	0.1201	0.1784	45.9299
015_007	0.2047	0.2331	0.2357	0.3752	52.0173

OceanDataLab

Primitive Equation Omega

$$\nabla^2{}_h(N^2 w) + f^2 \frac{\partial^2 w}{\partial z^2} = \nabla_h \cdot \boldsymbol{Q}$$

$$\boldsymbol{Q} = 2\boldsymbol{Q}_{twg} + \boldsymbol{Q}_{th} + \boldsymbol{Q}_{dm} + \boldsymbol{Q}_{dag} + \boldsymbol{Q}_{dr}$$

Likely due to dynamical inconsistency related to more than one factor:

- Diabatic forcing term estimated from **geostrophic shear** and KPP does not include iterative adjustment →computationally not feasible
- **Thermal Wind Inbalance forcing terms (Q_{dr},Q_{dag})** not negligible if too far from Ekman balance (not stationary)

$$\mathbf{Q}_{dm} = \frac{f}{\rho_0}\left(\frac{\partial^2}{\partial z^2}\left[\rho K_m\left(\frac{\partial v_g}{\partial z} + \frac{\partial v_a}{\partial z} - \gamma_v\right)\right], -\frac{\partial^2}{\partial z^2}\left[\rho K_m\left(\frac{\partial u_g}{\partial z} + \frac{\partial u_a}{\partial z} - \gamma_u\right)\right]\right)$$

$$\mathbf{Q}_{dr} = f\left(\frac{D}{Dt}\left(\frac{\partial v_a}{\partial z}\right), -\frac{D}{Dt}\left(\frac{\partial u_a}{\partial z}\right)\right)$$

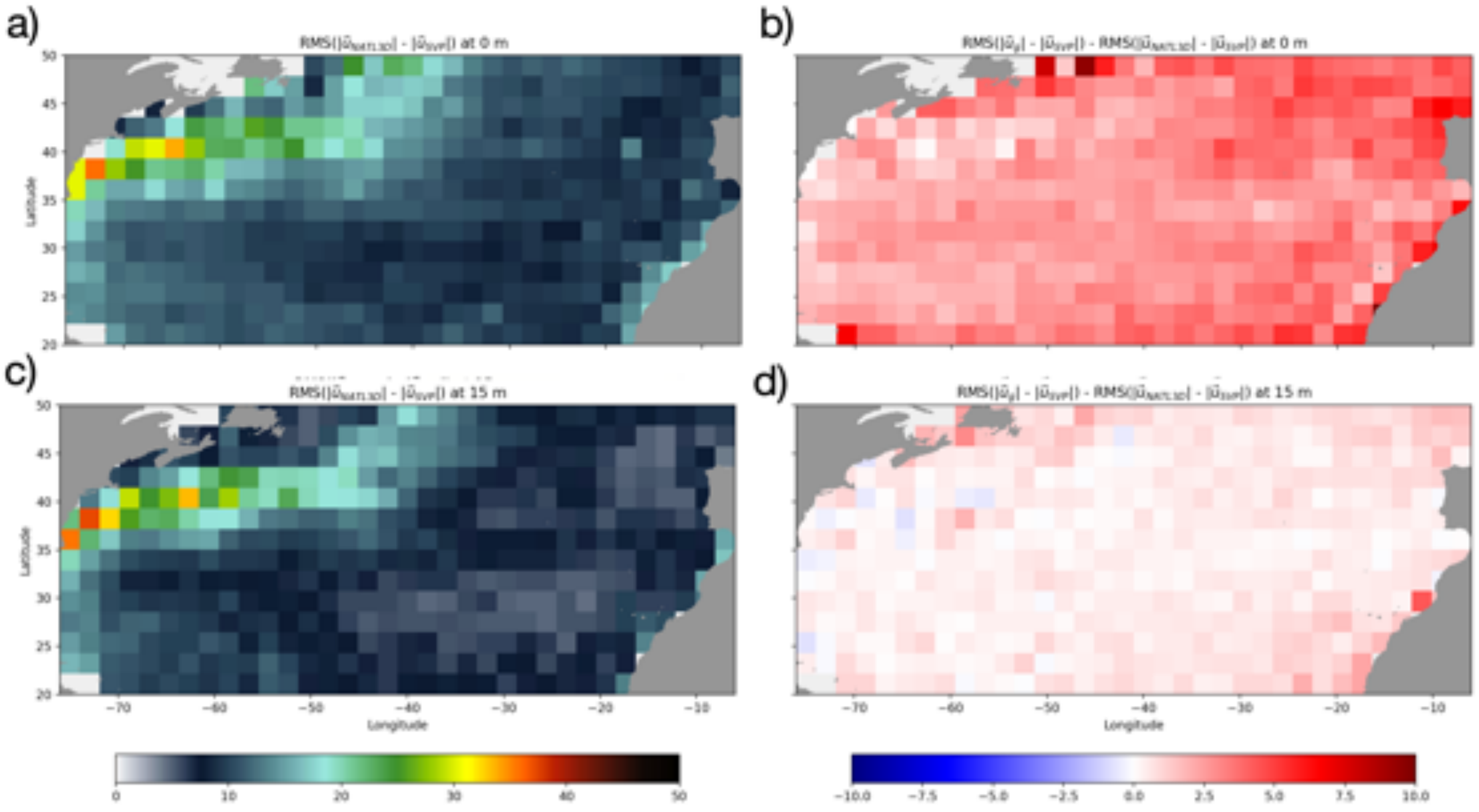
$$\mathbf{Q}_{dag} = f\left(\frac{\partial v}{\partial x}\frac{\partial u_a}{\partial z} - \frac{\partial u}{\partial x}\frac{\partial v_a}{\partial z}, \frac{\partial v}{\partial y}\frac{\partial u_a}{\partial z} - \frac{\partial u}{\partial y}\frac{\partial v_a}{\partial z}\right)$$

Validation

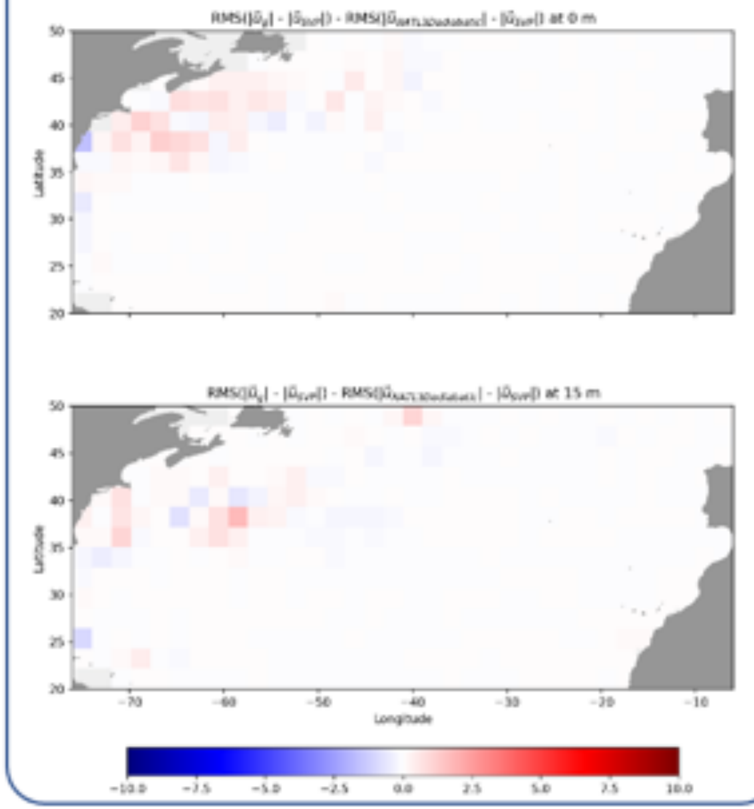
Total horizontal and geostrophic components have been compared with independent estimates of the ocean currents retrieved from SVP drifting buoys over the **entire timeseries** (2010-2019).

Total horizontal velocities RMSD: 0.119±0.001 m/s at 0 m and 0.113±0.001 m/s at 15 m
Geostrophic velocities RMSD: 0.145±0.001 m/s at 0 m and 0.117±0.001 m/s at 15 m

matchups used to compute the statistics: 311735 for undrogued SVP velocities (at 0) m and 243742 for drogued SVP data (at 15 m). Confidence intervals are estimated with bootstrapping (1 σ).

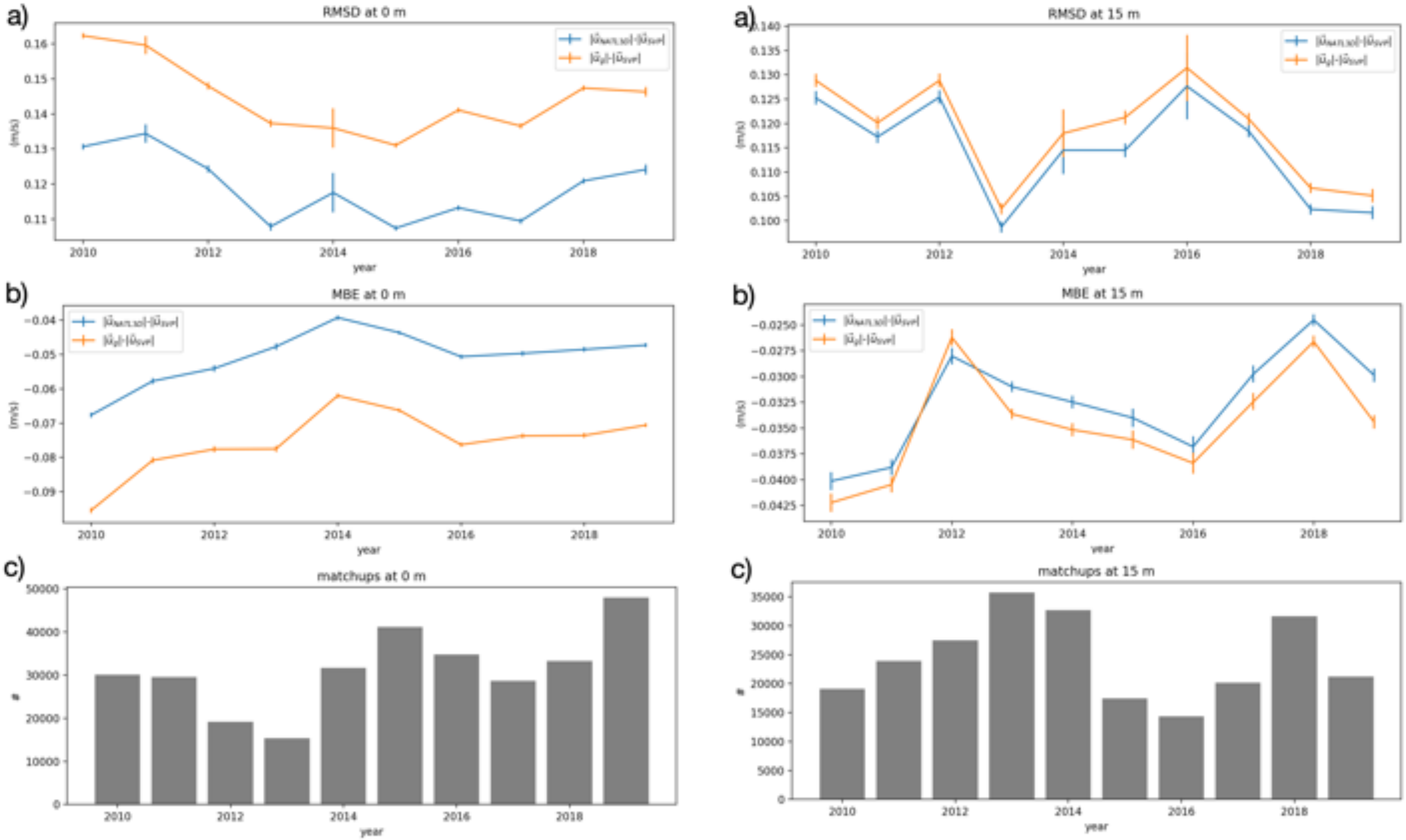


only adiabatic component

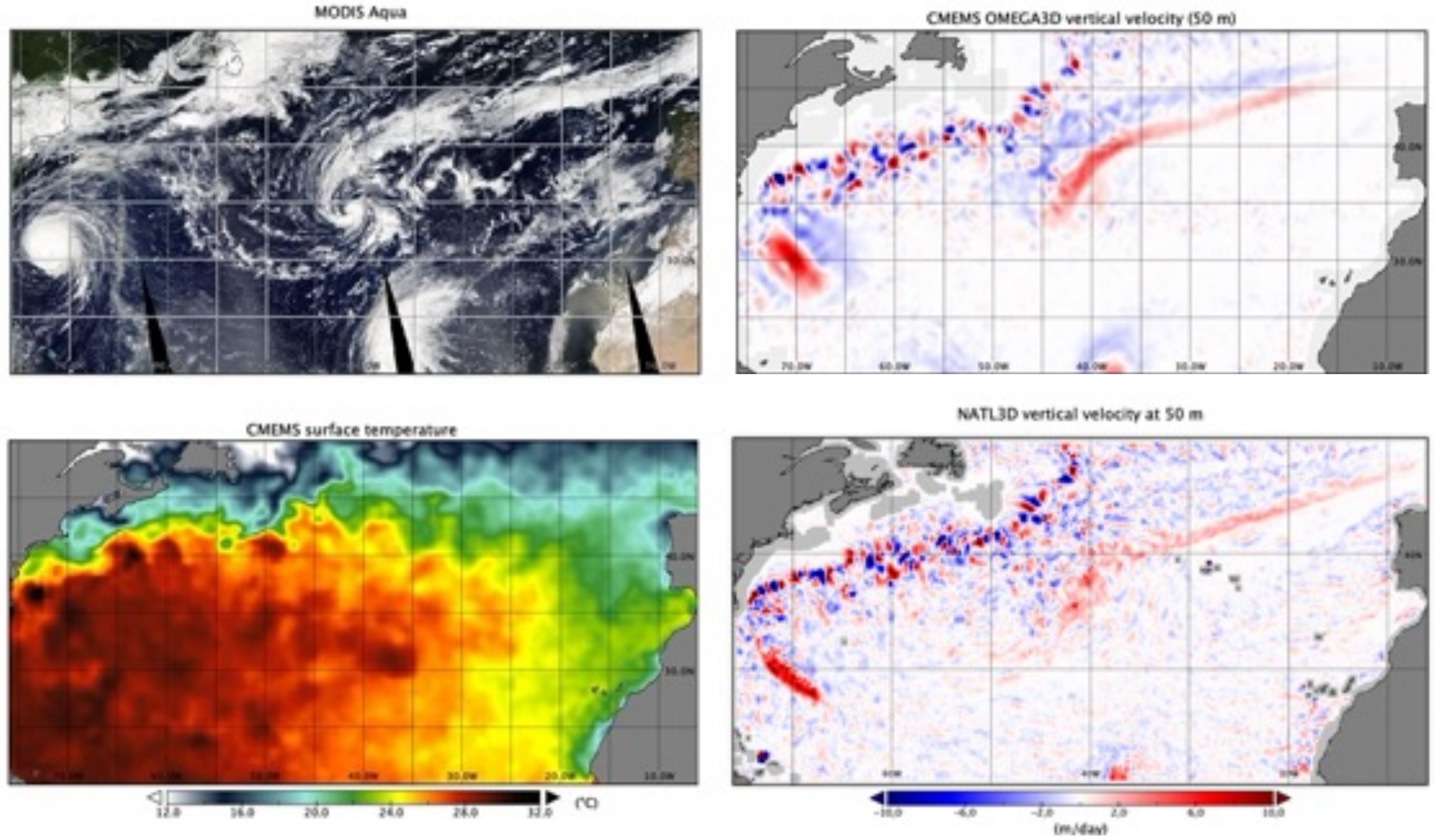


Validation

Yearly validation metrics
indicate stable performances
along the entire timeseries
(2010-2019)



The new product



CMEMS-OMEGA:
-mesoscale "permitting" resolution
-inaccurate surface Ekman currents

Weekly 1/4°x1/4° (global)
3D multilinear regression (CMEMS-ARMOR3D)
surface geostrophic currents (AVISO)
ERA-interim

WOC-NATL3D:
-mesoscale "resolving" resolution
-more accurate surface Ekman currents

Daily, 1/10°x1/10° (regional)
3D neural network model (WOC-LSTM3D)
surface geostrophic currents (WOC-NATL2D
ERA5
Empirical Ekman current shear (CMEMS)

12 September 2018
MODIS true colour image (top-left), CMEMS OMEGA3D vertical velocities at 50 m depth (top-right),
CMEMS SST (bottom-left), WOC_NATL3D vertical velocities at 50 m depth (bottom-right).
Vertical velocities are modulated at different scales by hurricane Florence, visible in the left part of the domain, and by the mesoscale meanders and eddies along the Gulf Stream