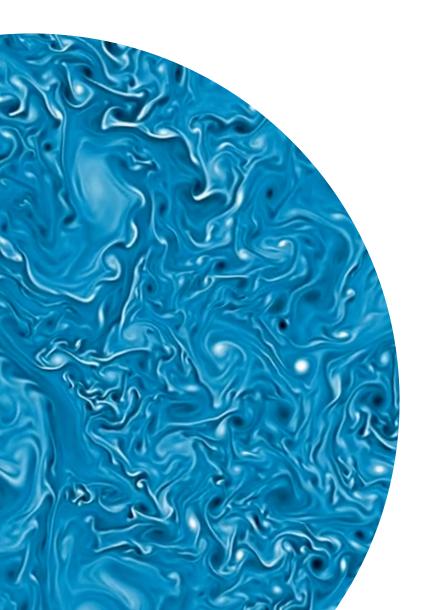


Towards Al-native hybrid (ocean) models : The need and the challenges ahead

Julien Le Sommer (IGE, Grenoble) with input from many in Brest, Paris, Toulouse and Grenoble





Défis théoriques pour les sciences du climat Grenoble | 29 May 2024





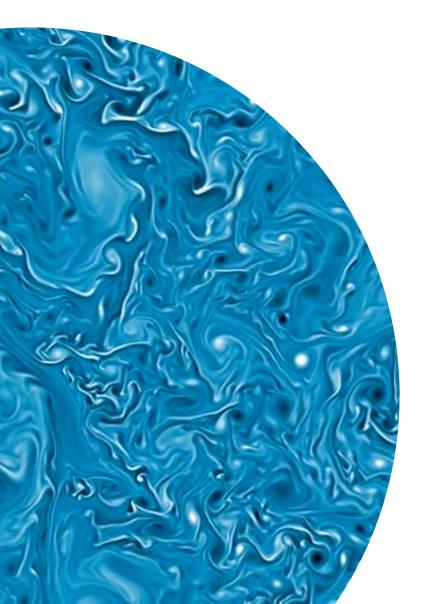




Towards Al-native hybrid (geoscientific) models : The need and the challenges ahead

Julien Le Sommer (IGE, Grenoble) with input from many in Brest, Paris, Toulouse and Grenoble





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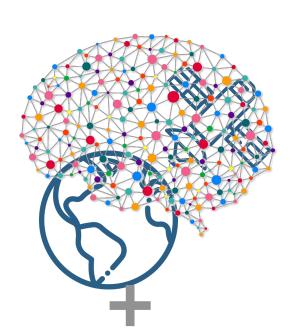
Objectives of this talk



- Illustrate why we explore augmenting models with ML
- Illustrate how this is done in practice today
- Advocate that a deep recast of our models is needed
- Integrating model-based products and observations some steps towards Al-native hybrid models

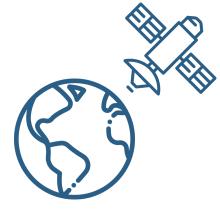


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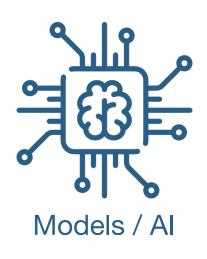




Assessing impact on downstream systems



Observations







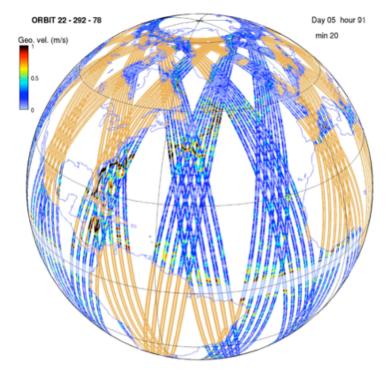
New toys in the oceanographer's toolbox

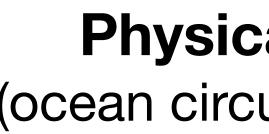


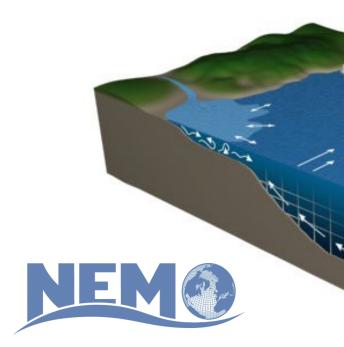
Computational oceanographer's toolbox

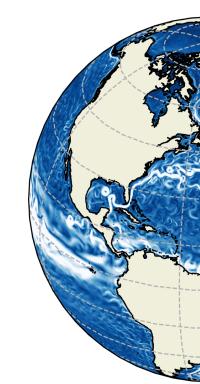
Observations (in situ/satellite)











Tools for understanding but also monitoring and forecasting ocean circulation

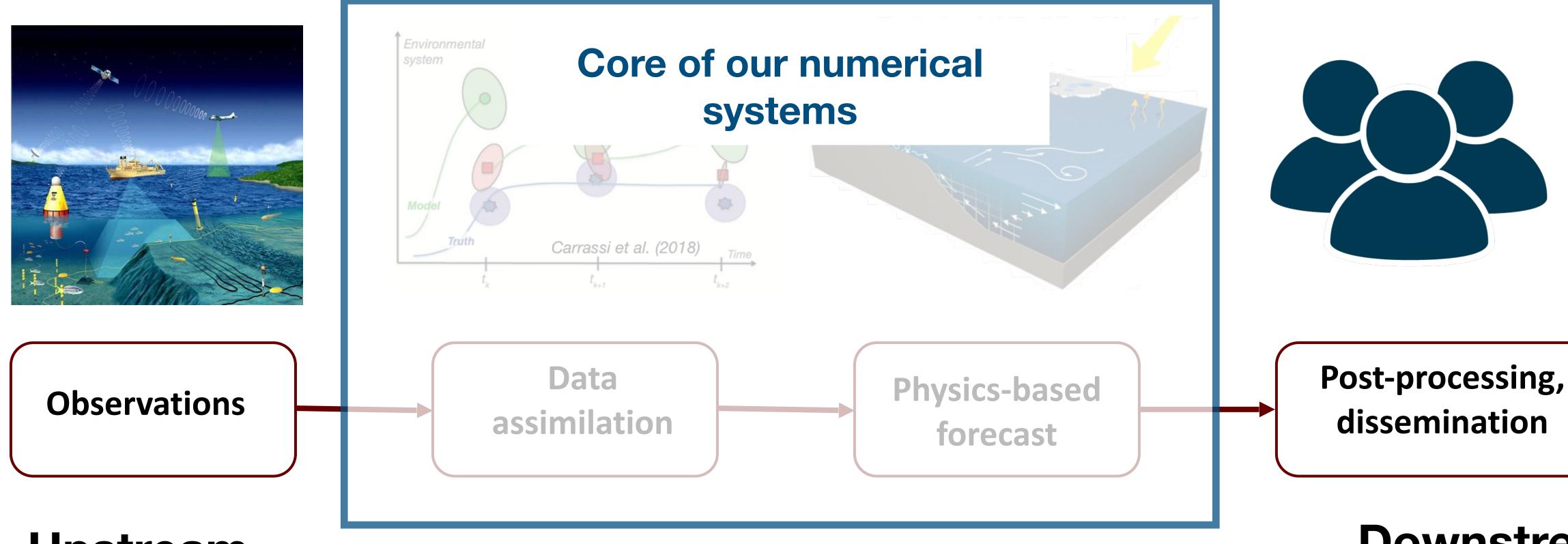
Physical models (ocean circulation models)

Inverse methods (data assimilation)

Observations Assimilation Observation errors Model Forcing $p(\omega | \mathbf{X}, \mathbf{Y}) = \frac{p(\mathbf{Y} | \omega, \mathbf{X}) p(\omega)}{p(\mathbf{Y} | \mathbf{X})}$ Improved Model Results

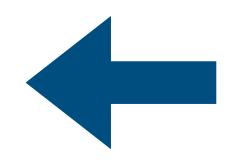


How AI is affecting our numerical systems

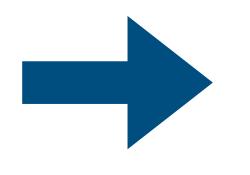


Upstream

denoising, inpainting parameter retrieval quality control



AI, machine learning & data-driven approaches **Downstream**



data fusion, tailored services data mining







Al-based ocean forecasting

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XiHe: A Data-Driven Model for Global Ocean Eddy-Resolving Forecasting

Xiang Wang, Renzhi Wang, Ningzi Hu, Pinqiang Wang, Peng Huo, Guihua Wang, Huizan Wang, Senzhang Wang, Junxing Zhu, Jianbo Xu, Jun Yin, Senliang Bao, Ciqiang Luo, Ziqing Zu, Yi Han, Weimin Zhang, Kaijun Ren, Kefeng Deng, Junqiang Song

Abstract—Global ocean forecasting is fundamentally important to support marine activities. The leading operational Global Ocean Forecasting Systems (GOFSs) use physics-driven numerical forecasting models that solve the partial differential equations with expensive computation. Recently, specifically in atmosphere weather forecasting, data-driven models have demonstrated significant potential for speeding up environmental forecasting by orders of magnitude, but there is still no data-driven GOFS that matches the forecasting accuracy of the numerical GOFSs. In this paper, we propose the first data-driven $1/12^\circ$ resolution global ocean eddy-resolving forecasting model named XiHe, which is established from the 25-year France Mercator Ocean International's daily GLORYS12 reanalysis data. XiHe is a hierarchical transformer-based framework coupled with two special designs. One is the land-ocean mask mechanism for focusing exclusively on the global ocean circulation. The other is the ocean-specific block for effectively capturing both local ocean information and global teleconnection. Extensive experiments are conducted under satellite observations, in situ observations, and the IV-TT Class 4 evaluation framework of the world's leading operational GOFSs from January 2019 to December 2020. The results demonstrate that XiHe achieves stronger forecast performance in all testing variables than existing leading operational numerical GOFSs including Mercator Ocean Physical SYstem (PSY4), Global Ice Ocean Prediction System (GIOPS), BLUElinK OceanMAPS (BLK), and Forecast Ocean Assimilation Model (FOAM). Particularly, the accuracy of ocean current forecasting of XiHe out to 60 days is even better than that of PSY4 in just 10 days. Additionally, XiHe is able to forecast the large-scale circulation and the mesoscale eddies. Furthermore, it can make a 10-day forecast in only 0.36 seconds, which accelerates the forecast speed by thousands of times compared to the traditional numerical GOFSs.

Index Terms-Global Ocean Forecasting, Deep Learning, Eddy Resolving, Data-Driven, AI for Science

[phy INTRODUCTION

rine activities. At present, the leading GOFSs (e.g. Mercator a single forecasting simulation in the numerical GOFSs may Ocean Physical SYstem (PSY4) and Real-Time Ocean Fore- take hours on a supercomputer with hundreds of computacast System (RTOFS)) use physics-driven models in fluid tional nodes [2]. Besides, improving the forecasting accuracy mechanics and thermodynamics to predict future ocean of these methods is exceedingly challenging because they motion states and phenomena based on current ocean con- heavily rely on the human cognitive abilities in understandditions [1]. The GOFSs adopt numerical methods that rely on supercomputers to solve the partial differential equa-ing the physical laws of the ocean environment [3]. With the recent advances of Artificial Intelligence (AI) tions of the physical models. Due to their desirable per- techniques, deep learning methods have been widely apformance, they are operationally run in different countries plied in various prediction/forecasting tasks of different worldwide. However, numerical forecasting methods are fields and achieved great success. Particularly, some data-

- arX Xiang Wang, Pinqiang Wang, Huizan Wang, Junxing Zhu, Jianbo Xu, Senliang Bao, Ciqiang Luo, Yi Han, Weimin Zhang, Kaijun Ren, Kefeng 410073. Chin
 - Renzhi Wang, Senzhang Wang and Jun Yin are with the School of Computer Science and Engineering, Central South University, Changsha
 - Ningzi Hu is with the College of Oceanography and Space Informatics, China University of Petroleum (East China), Qingdao 266580, China.
 - Peng Huo is with the College of Artificial Intelligence, Tianjin University of Science and Technology, Tianjin 300457, China.
 - Ziqing Zu, Key Laboratory of Marine Hazards Forecasting, National Ma-
 - ine Environmental Forecasting Center, Ministry of Natural Resources,
 - the corresponding authors

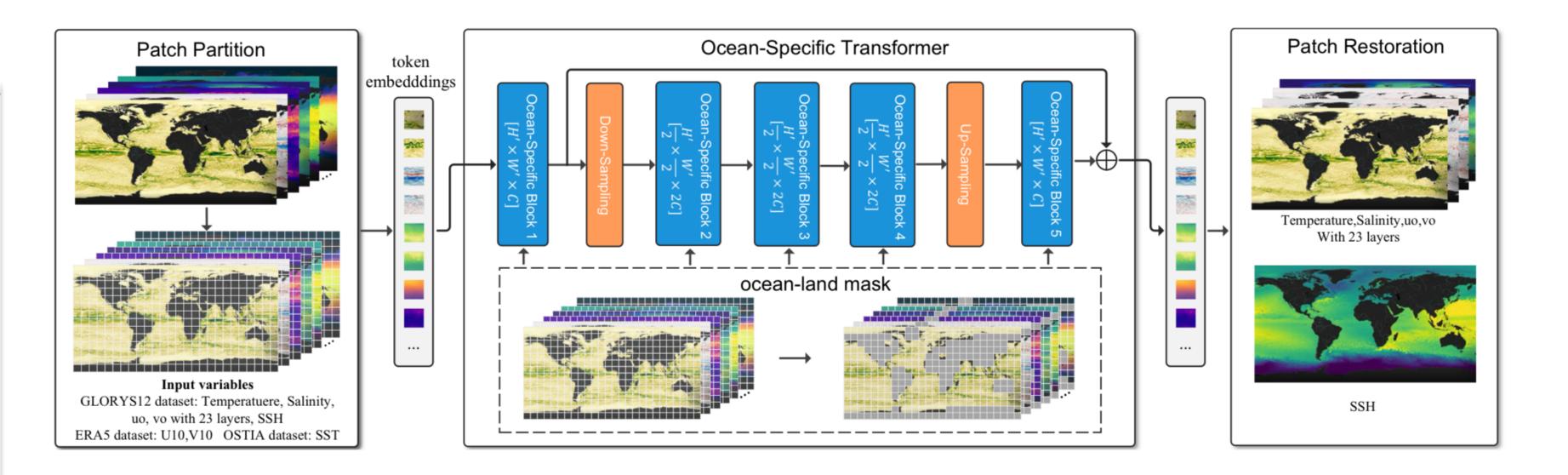
Ocean forecasting is critically important for many ma- usually computationally expensive and slow. For example,

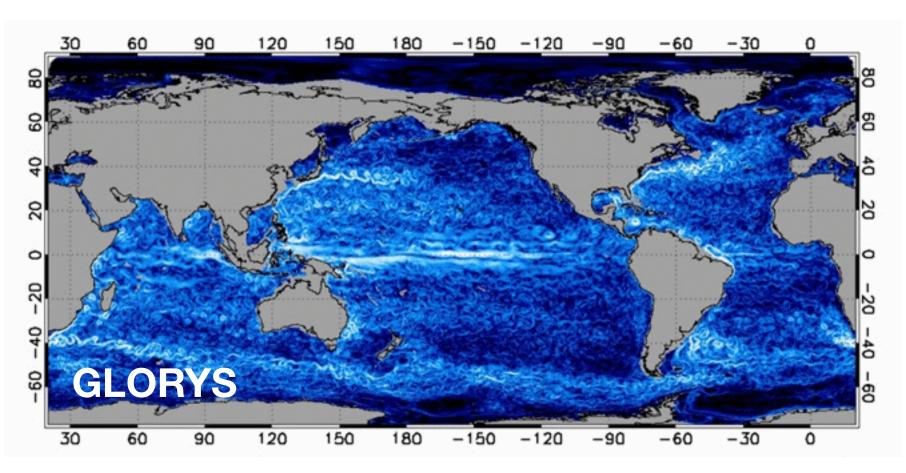
.

driven AI models have shown the potential in atmosphere weather forecasting like Pangu-Weather [4] and Graph-Cast [5]. They have achieved comparable or even better Deng, and Junqiang Song are with the College of Meteorology and Oceanography, National University of Defense Technology, Changsha prediction results in global medium-range weather fore-(NWP) methods [4], [5], [6], [7], [8], [9]. One significant advantage of data-driven models is that they can make the forecasting thousands or even tens of thousands of times faster than NWP methods [4]. Furthermore, they can automatically learn the spatial-temporal relationships from massive meteorological data, and effectively capture the Guihua Wang is with the Department of Atmospheric and Oceanic Sciences, Fudan University, Shanghai 200438, China.
 rules of weather changing, without introducing the prior knowledge of physics mechanisms. knowledge of physics mechanisms.

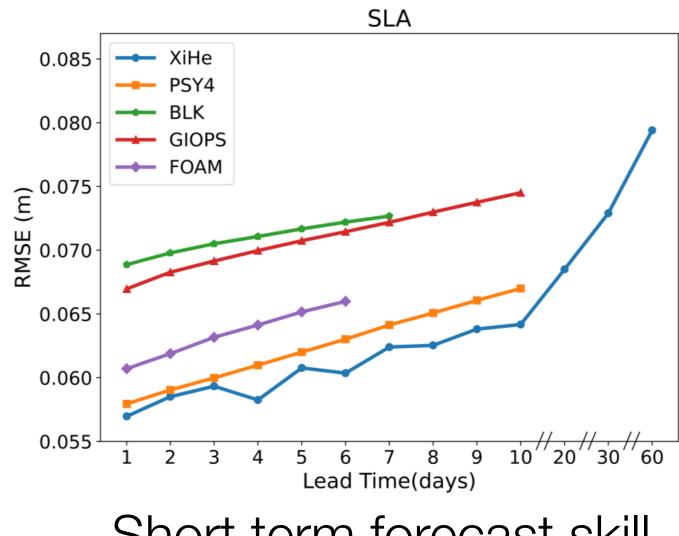
Although data-driven models have achieved promising results in atmosphere weather forecasting, how to build a Beijing 100081, China. Guihua Wang, Huizan Wang, Senzhang Wang, and Weimin Zhang are more accurate and efficient data-driven ocean forecasting model remains an open research issue due to the following

https://arxiv.org/abs/2402.02995 Wang et al. (2024)





Trained from ocean reanalyses



Short term forecast skill



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Al-native hybrid geoscientific models

(a)

Inputs

Neural General Circulation Models for Weather and Climate

Dmitrii Kochkov^{1*†}, Janni Yuval^{1*†}, Ian Langmore^{1†}, Peter Norgaard^{1†}, Jamie Smith^{1†}, Griffin Mooers¹, Milan Klöwer⁴, James Lottes¹, Stephan Rasp¹, Peter Düben³, Sam Hatfield³, Peter Battaglia², Alvaro Sanchez-Gonzalez², Matthew Willson², Michael P. Brenner^{1,5}, Stephan Hoyer^{1*†}

¹Google Research, Mountain View, CA. ²Google DeepMind, London, UK. ³European Centre for Medium-Range Weather Forecasts, Reading, UK. ⁴Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology.

⁵School of Engineering and Applied Sciences, Harvard University.

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Abstract

General circulation models (GCMs) are the foundation of weather and climate prediction. GCMs are physics-based simulators which combine a numerical solver for large-scale dynamics with tuned representations for small-scale processes such as cloud formation. Recently, machine learning (ML) models trained on reanalysis data achieved comparable or better skill than GCMs for deterministic weather forecasting. However, these models have not demonstrated improved ensemble forecasts, or shown sufficient stability for long-term weather and climate simulations. Here we present the first GCM that combines a differentiable solver for atmospheric dynamics with ML components, and show that it can generate forecasts of deterministic weather, ensemble weather and climate on par with the best ML and physics-based methods. NeuralGCM is competitive with ML models for 1-10 day forecasts, and with the European Centre for Medium-Range Weather Forecasts ensemble prediction for 1-15 day forecasts. With prescribed sea surface temperature, NeuralGCM can accurately track climate metrics such as global mean temperature for multiple decades, and climate forecasts with 140

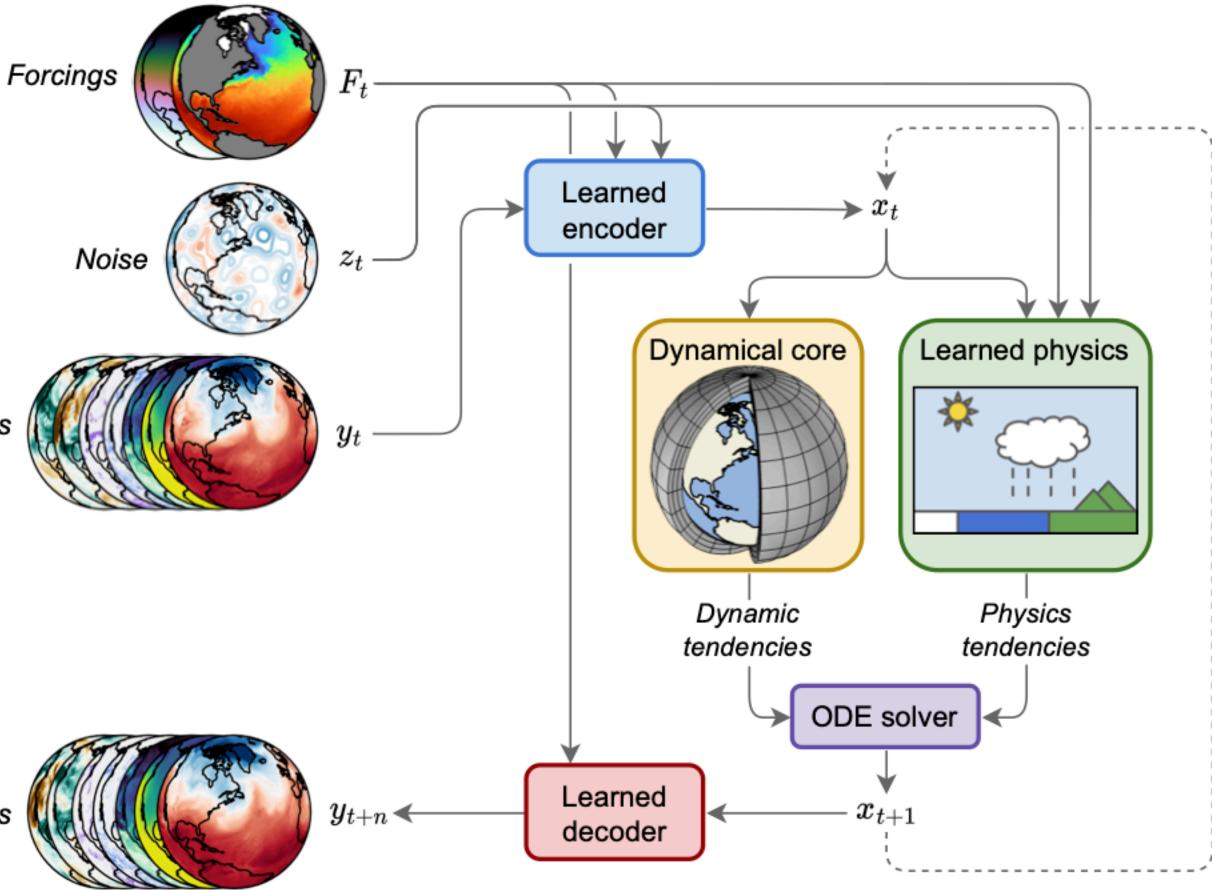
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Outputs

https://arxiv.org/abs/2311.07222

Kochkov et al. (2024)





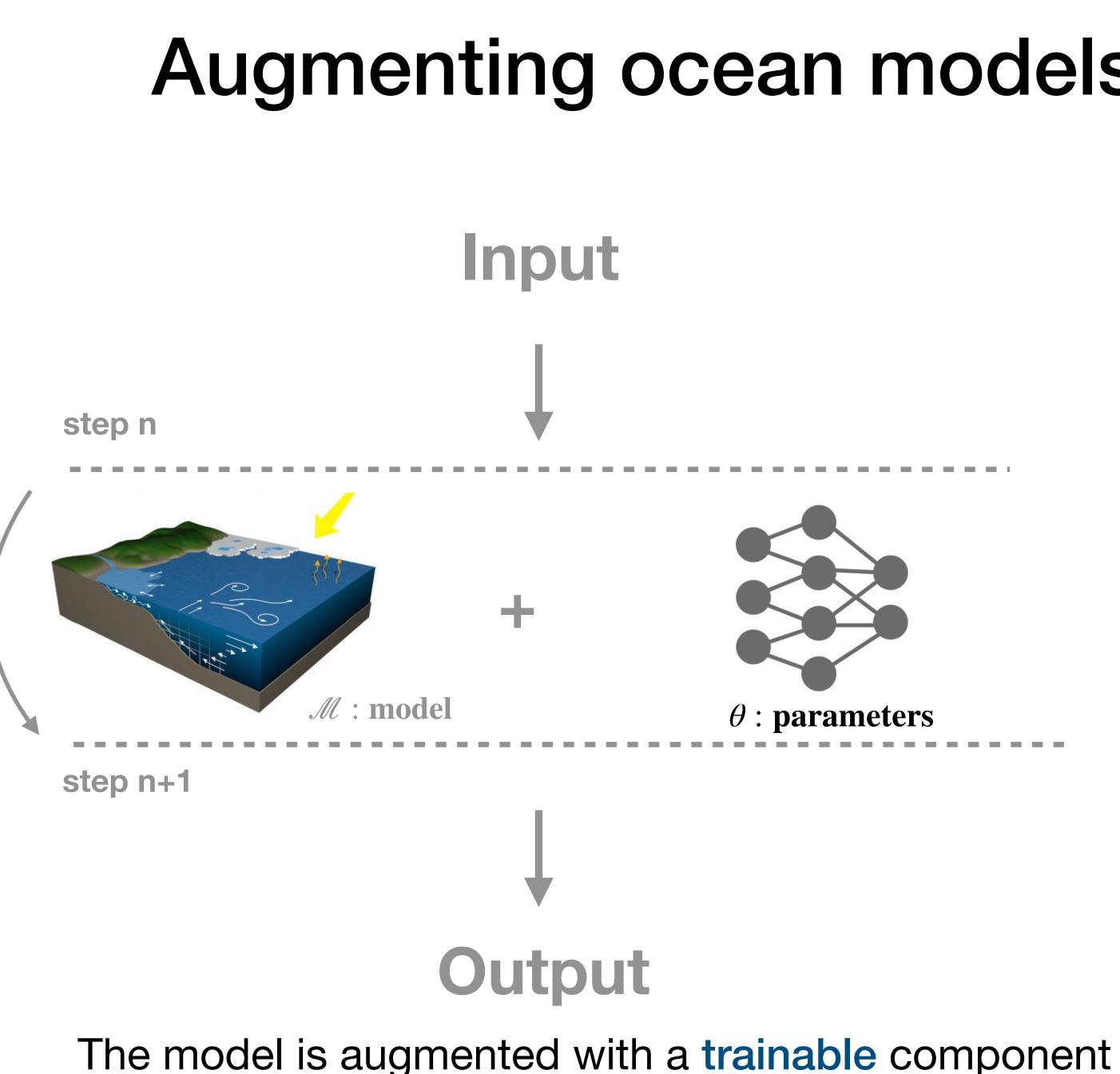
https://github.com/google-research/dinosaur https://github.com/google-research/neuralgcm

Φ tim μ Repeat

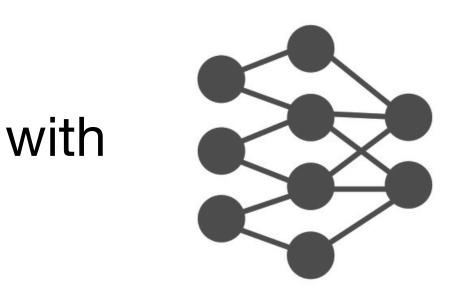


Hybrid models combining physics and ML





Augmenting ocean models with ML components



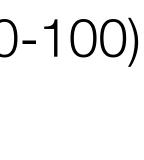
 θ : parameters

trained to minimise :

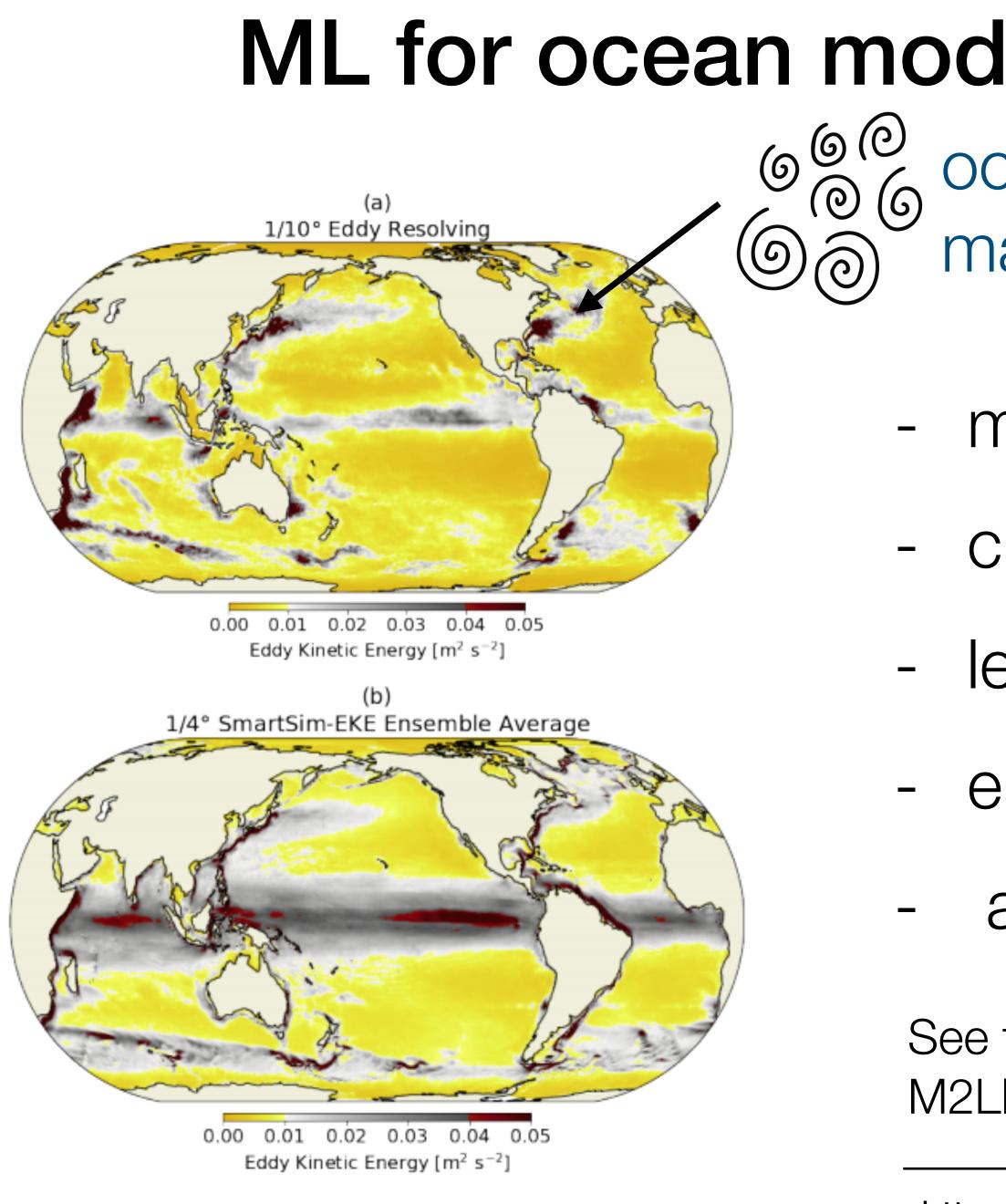
$\mathscr{L}(\theta) = \text{training objective}$

- correcting model errors (vs obs.)
- replacing some components (x10-100)
- improving physical consistency
- NB : does not have to be deterministic









Partee et al. (2022)

ML for ocean models subgrid physics (1/2)ocean macro-turbulence

- missing terms from resolved quantities
- closures for turbulent processes
 - leveraging hi-res/process model data
 - encoded as closed forms or ML models
 - a very active field (5-10 papers / months)
- See for instance : M2LInES consortium

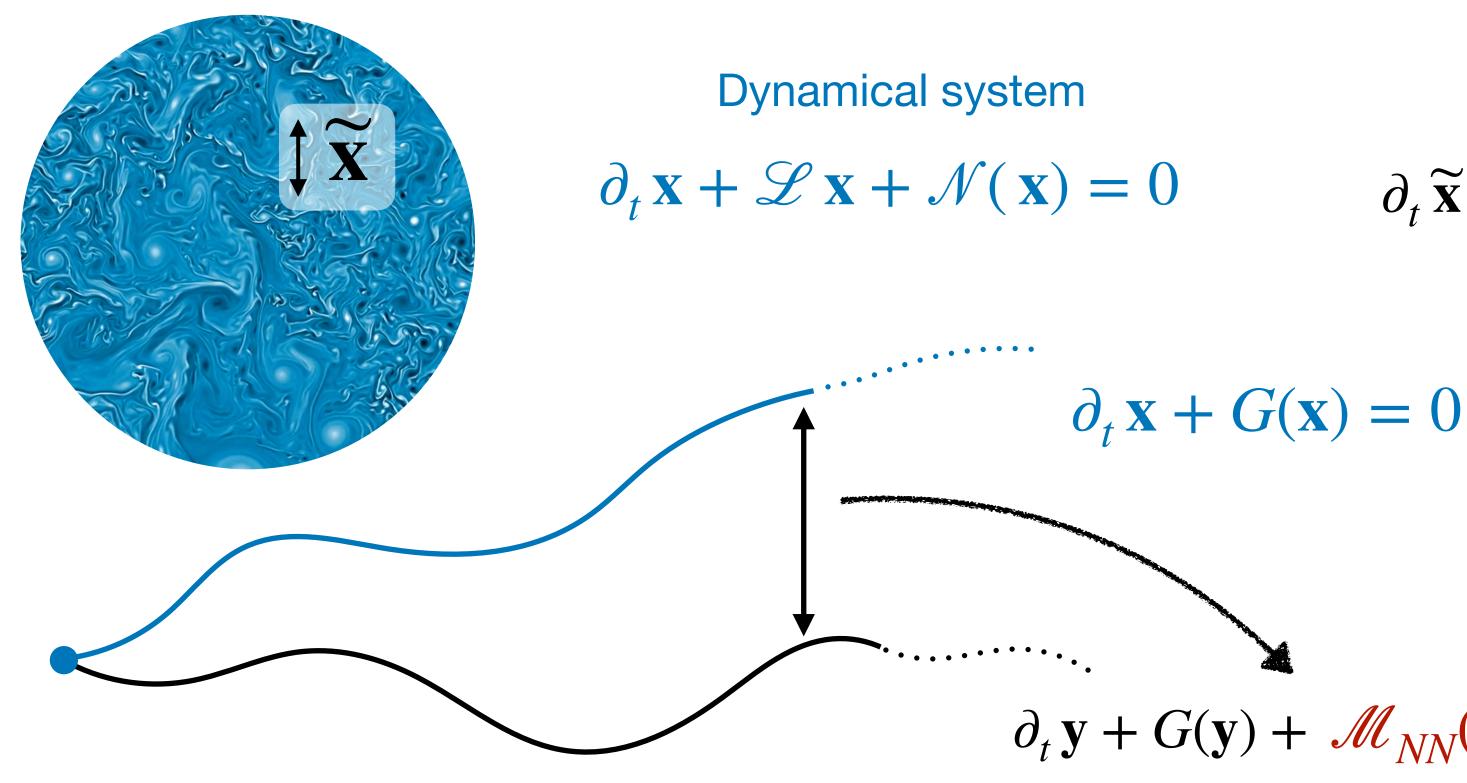
https://m2lines.github.io

M²LInES - Multiscale Machine Learning In **Coupled Earth System** Modeling





ML for ocean models subgrid physics (2/2)



Frezat et al. (2021) **Physical consistency**

Symmetries, invariances loss function / architecture

Frezat et al. (2022) **End-to-end training**

Differentiable programming, different loss function w/ same architecture

Resolved equations

$\partial_t \widetilde{\mathbf{x}} + \mathscr{L} \widetilde{\mathbf{x}} + \mathscr{N}(\widetilde{\mathbf{x}}) = \mathscr{N}(\widetilde{\mathbf{x}}) - \mathscr{N}(\mathbf{x})$

Subgrid closure

 $\mathcal{M}(\widetilde{\mathbf{X}}) \simeq \mathcal{N}(\widetilde{\mathbf{X}}) - \widetilde{\mathcal{N}(\mathbf{X})}$

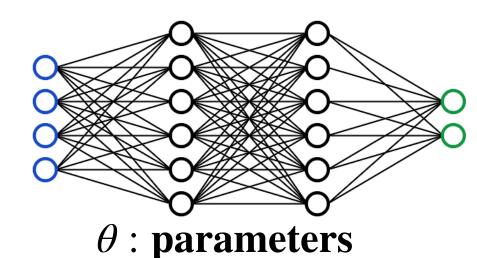
 $\partial_t \mathbf{y} + G(\mathbf{y}) + \mathcal{M}_{NN}(\mathbf{y}) = 0$

Frezat et al. (2023) **Gradient-free training**

training model emulator for approx. gradient wrt NN. parameters

Learning the mapping

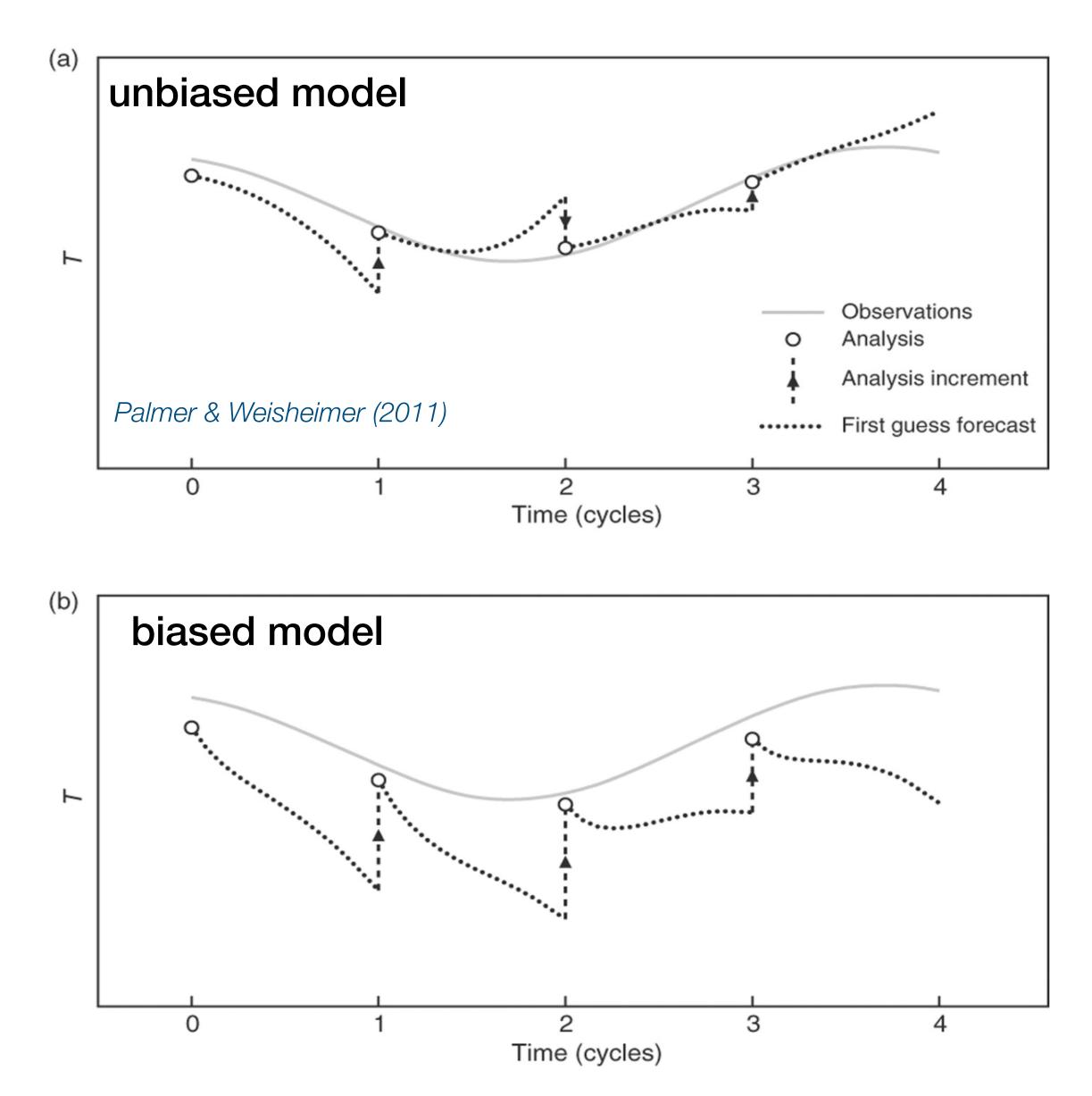
 $\widetilde{\mathbf{x}}(t) \to \mathscr{M}(\widetilde{\mathbf{x}}(t))$

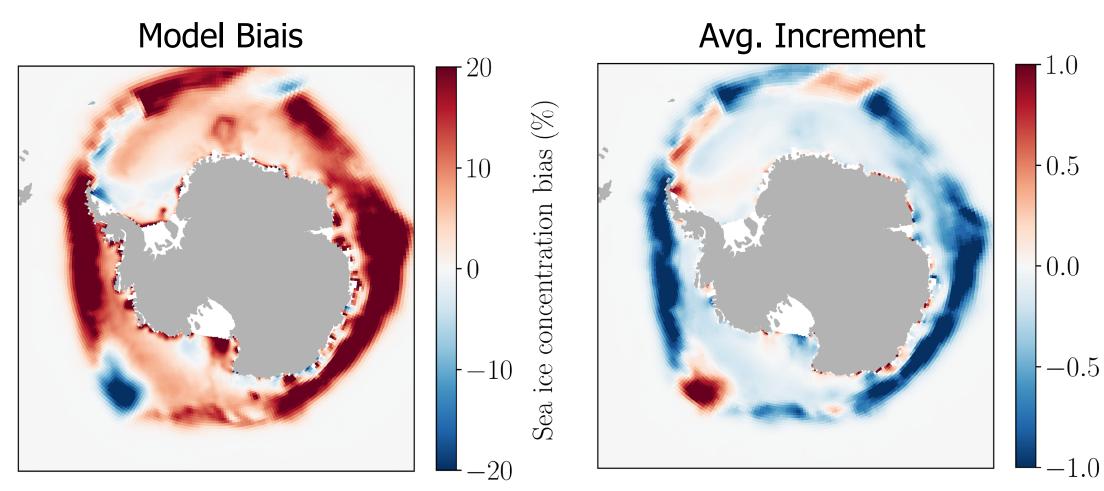


Performance, stability **Generalisation**, interpretability



Learning model error from DA increments (1/3)



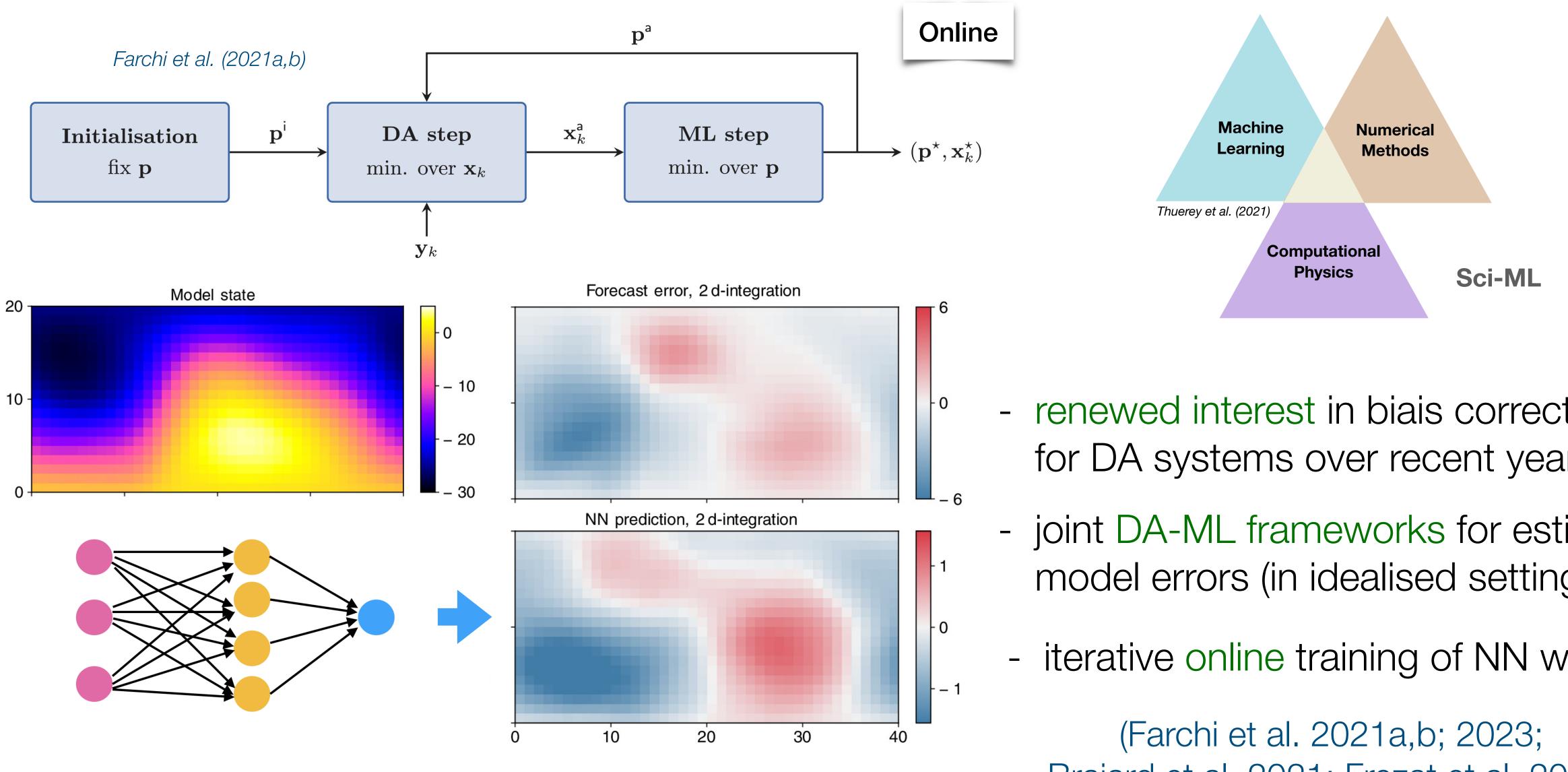


Gregory et al. (2023)

- w/ unbiased observations, analysis increments compensate for model biais
- estimating state-dependent bias corrections (Leith, 1978; Saha, 1992; DelSole and Hou, 1999)
- state-dependent biais corrections provide a representation of model errors



Learning model error from DA increments (2/3)



Online estimation of model errors w/ a joint DA-ML 4DVAR (weak)

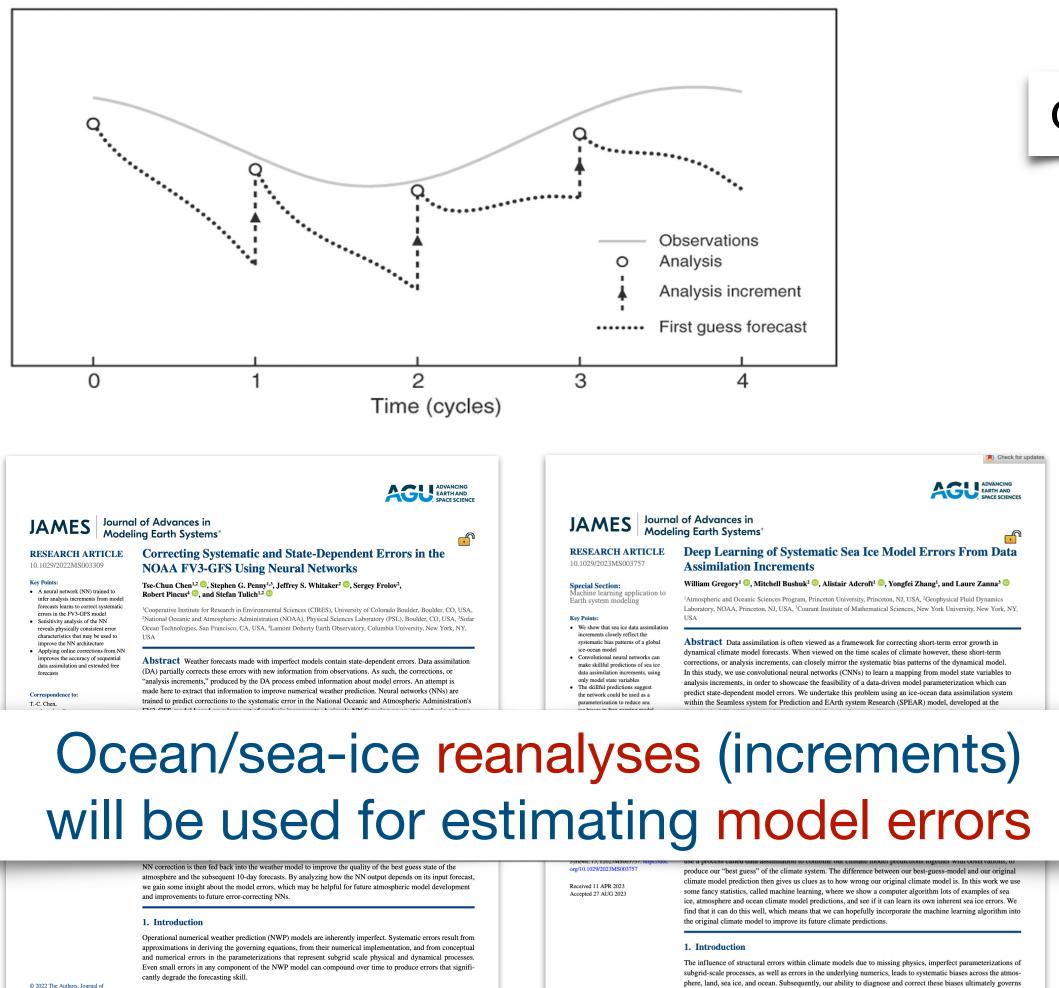
- renewed interest in biais corrections for DA systems over recent years
- joint DA-ML frameworks for estimating model errors (in idealised settings)
 - iterative online training of NN with DA

Brajard et al. 2021; Frezat et al. 2022)





Learning model error from DA increments (3/3)



Systematic errors can be addressed with a wide range of approaches. One approach is to improve the model components—the dynamical core and subgrid scale physics parameterizations. The forecast system as a whole can be improved, say by adopting stochastic parameterizations that account for uncertainty, or by increasing spatial resolution. Model forecasts can also be further improved by an "offline" post-processing using statistical methods (e.g., Model Output Statistics) or machine learning (ML) methods applied to the model output after the completion of model forecast. However, the model errors may be convoluted over time and become more nonlinear as forecast progresses, leading to errors that are more difficult to represent.

https://doi.org/10.1029/2022MS003309

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GREGORY ET AL

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https://doi.org/10.1029/2023MS003757

the accuracy of numerical weather and climate predictions on different time scales (Stevens & Bony, 2013). In the

context of sea ice for example, much effort has been afforded to the improvement of model physics and subgrid

parameterizations through the development of for example, ice thickness distribution (Bitz et al., 2001; Thorndike

melt-pond (Flocco et al., 2012), ice drift (Tsamados et al., 2013) and lateral melt parameterizations (M. Smith

et al., 2022), as well as sea ice rheology (Dansereau et al., 2016; Hibler, 1979; Ólason et al., 2022). Such studies

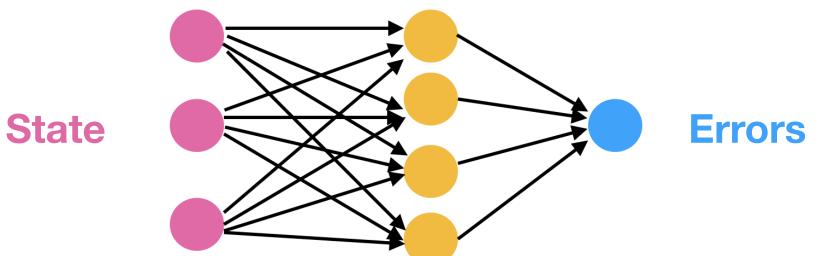
have shown how the improved representation of sea ice physics produces model simulations which more closely

reflect observations in terms of either their mean sea ice volume, drift, or ice thickness distribution. Despite this,

1 of 23

et al., 1975) and floe-size distribution theory (Horvat & Tziperman, 2015; Rothrock & Thorndike, 1984

Offline



- NN for learning state-dependant biais corrections from analysis increments
- w/ applications in GCMs (atmosphere and ocean/sea-ice)
- showing success in improving the modeled climate state & forecast skill

(Bonavita and Laloyaux, 2020; Watt-Meyer et al., 2021; Chen et al., 2022; Gregory et al. 2023; Chapman and Berner 2023)





Hybrid modelling with existing codes



Interfacing ocean models with DL frameworks (1/3)



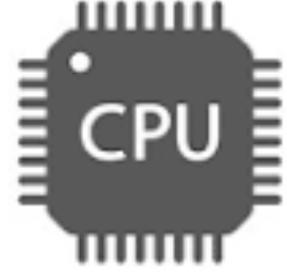
stable, robust, low abstraction languages



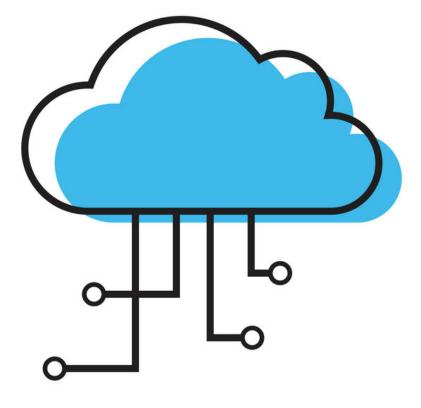
high abstraction, fast evolving languages

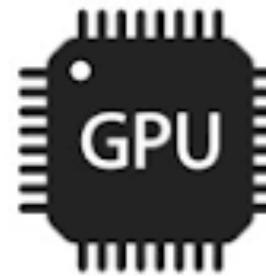






runs only on CPUs



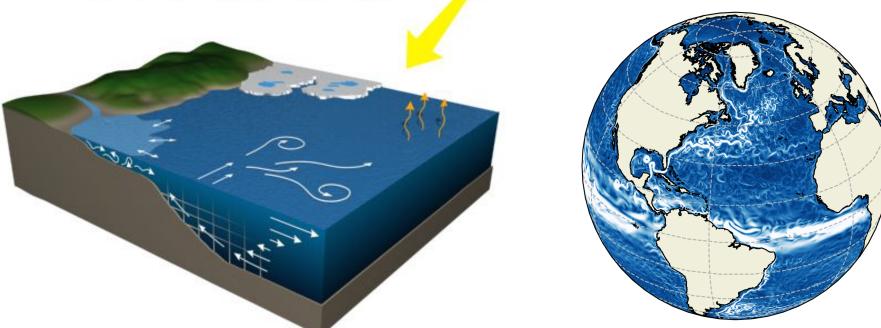


cloud ready

natively runs on GPUs



Interfacing ocean models with DL frameworks (2/3) Input **Ocean circulation models Trainable components** (closures, error corrections) step n PyTorch step n+1





Output



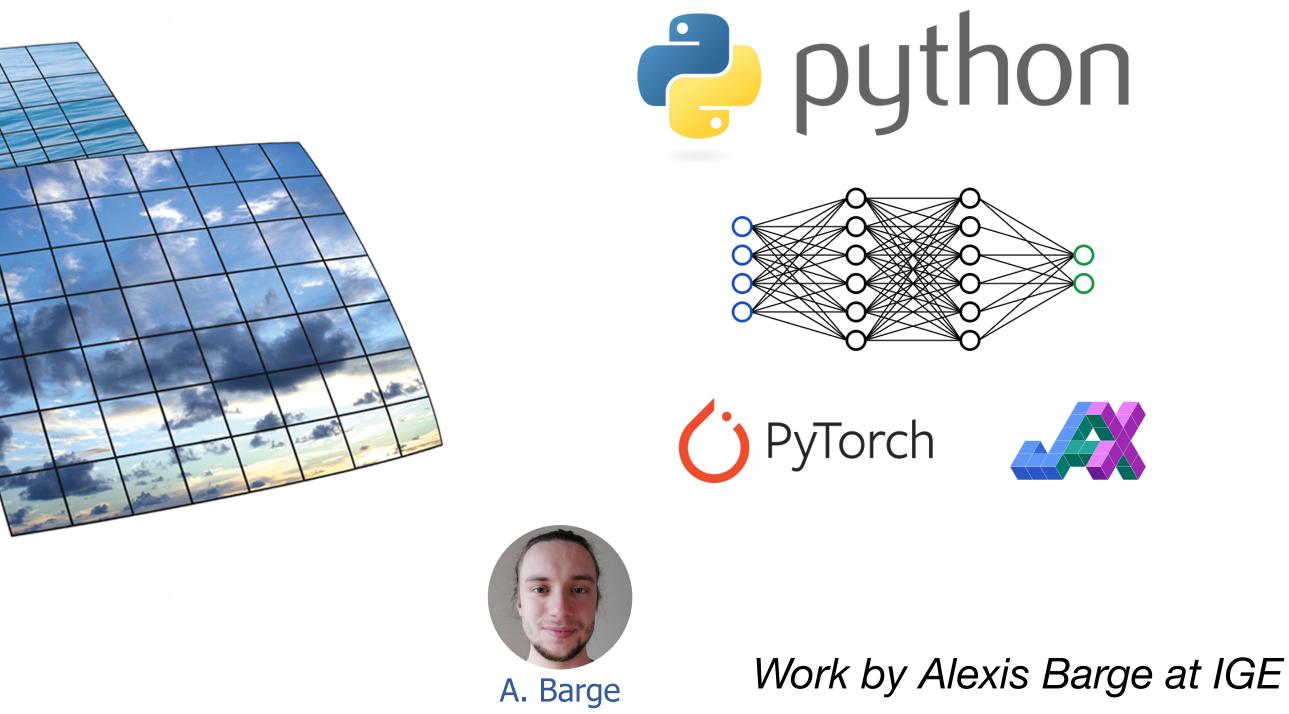




Interfacing ocean models with DL frameworks (3/3)

 ⇒ Code ⊙ Issues 2 I Pull requests ⊙ Act 	ions 田 Projects 😲 Security		ype [] to search			
eophis Public			③ Unwatch 4			
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alexis-barge fix wrong Logbuffer varia	ble name	5b86bb1 · last mo	onth 🕚 49 Commits	Deploy Inferences Models with Earth- System simulation codes		
boos	add docs		3 months ago	🛱 Readme		
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tests	update info for merging		last month	☆ 3 stars	_	()A
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	add license		2 months ago	Report repository		
C README.md	update info for merging		last month	Releases		
pyproject.toml	add license		2 months ago	No releases published	-	EO
다 README 책 MIT license			Ø i=	Create a new release		I
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♂ Eophis				No packages published <mark>Publish your first package</mark>		Do
E O P H I S					-	
Eophis is a collection of tools to deploy			s (Inference	Languages		
Models) within Fortran/C/Python writte		SIS.		• Python 98.9% • Makefile 1.1%		
Also it is the currently oldest known	snake ancestra <u>(2023)</u>			Suggested workflows		Key

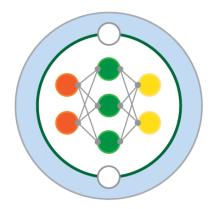
https://github.com/meom-group/eophis



- SIS : exchange of 3D data between different codes
- phis : simplified deployment of ML models w/ OASIS
- quires some change to the NEMO code
- Key : portability, domain decomposition

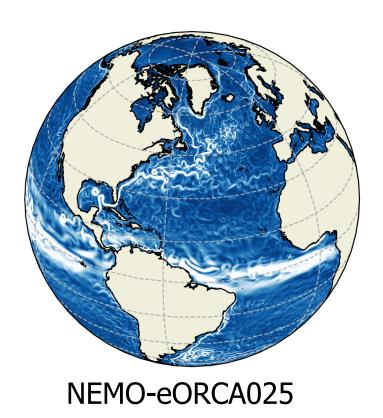


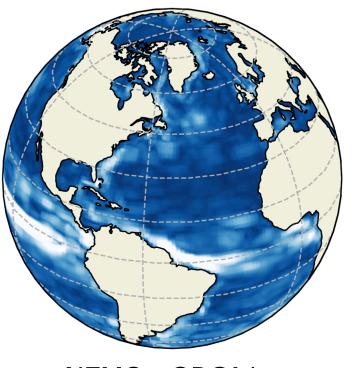




ML for ocean macro-turbulence

Target NEMO configurations

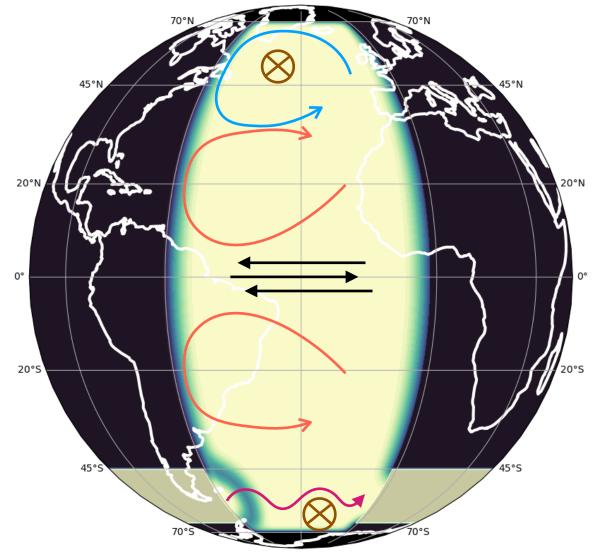




NEMO-eORCA1

On-going work : Subgrid momentum forcing due to mesoscale eddies





Light-weight test-bed

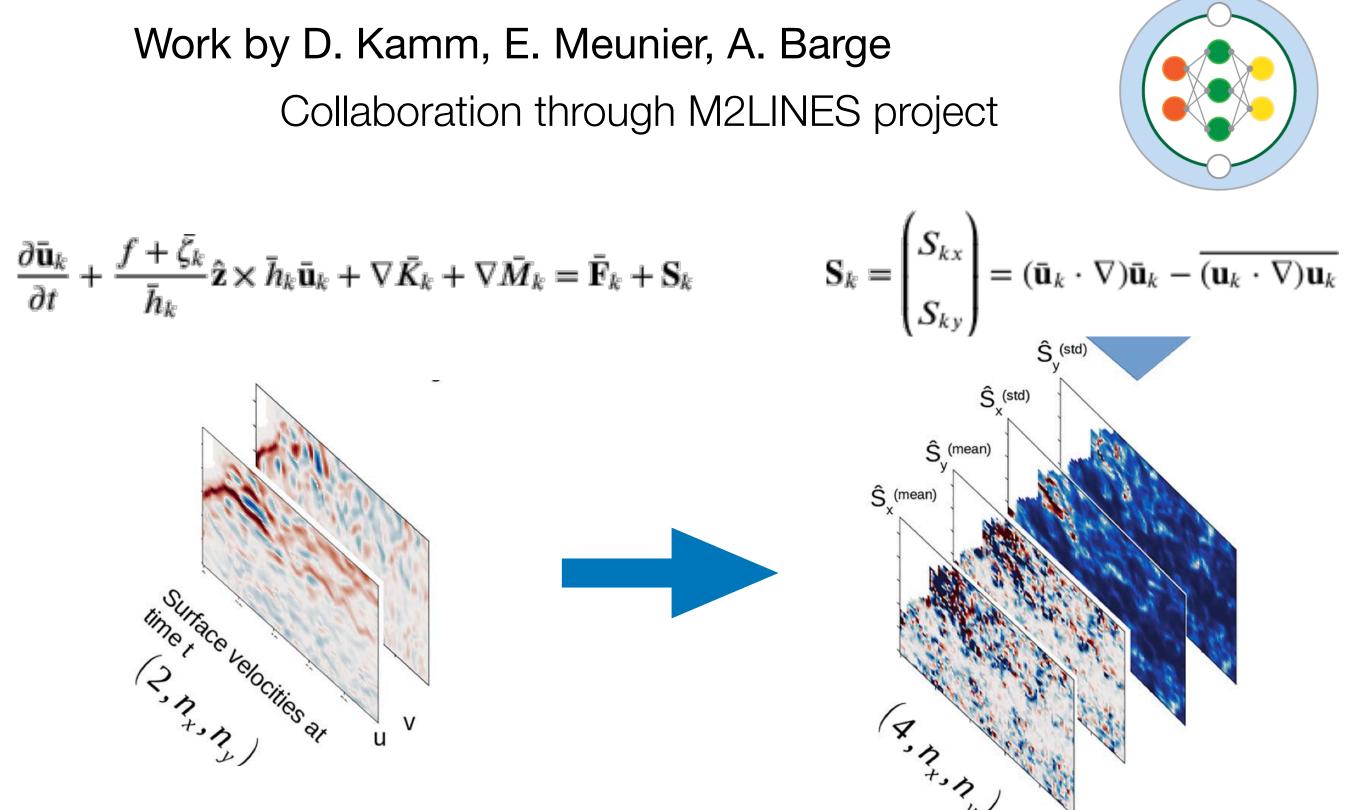
resolutions ~ 1° , $1/4^{\circ}$, 1km

- D. Kamm
- E. Meunier
- J. Deshayes

CEAN



DINO : Diabatic Neverworld



Guillaumin and Zanna 2021

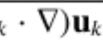
Zhang et al. 2023

https://doi.org/10.1029/2021MS002534

https://doi.org/10.1029/2023MS003697



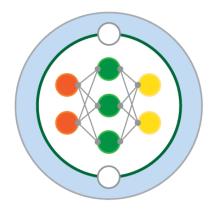




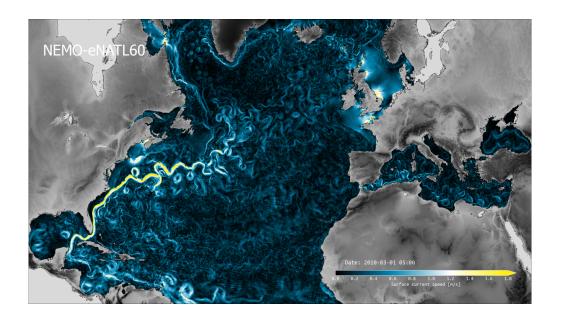




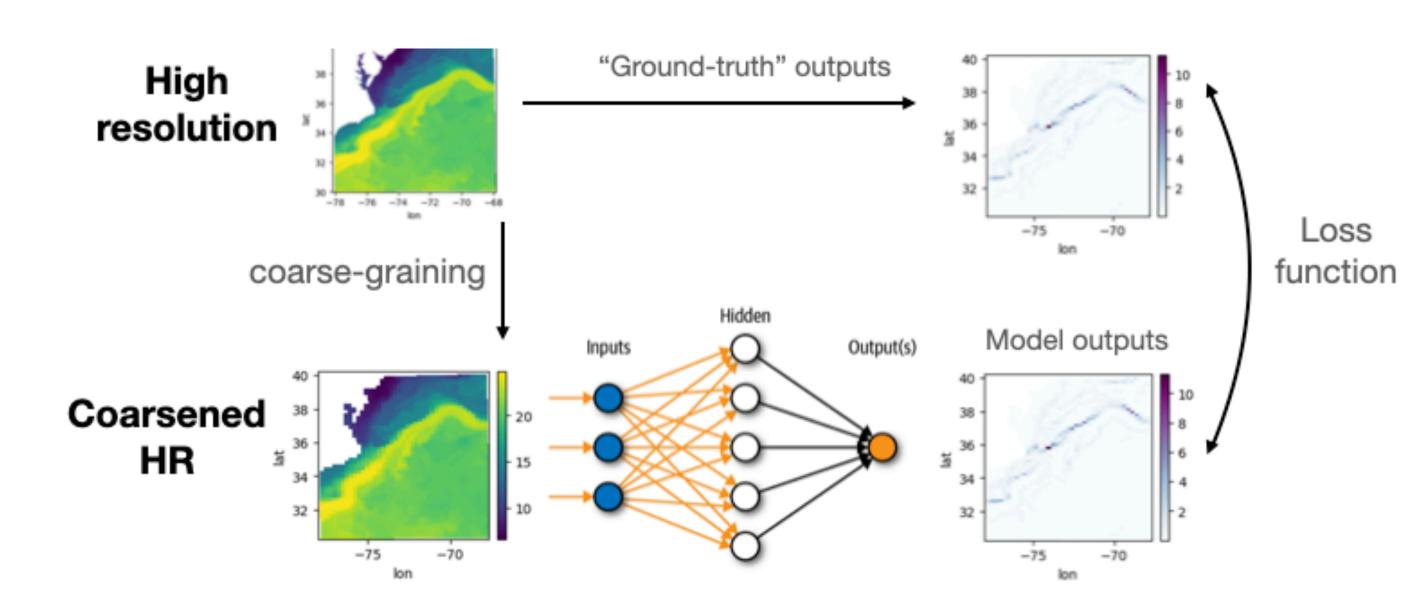




Training from realistic ocean models



- geometry, grid, coastlines
- heterogeneous regimes
- optimal coarse graining
- data structure / orchestration

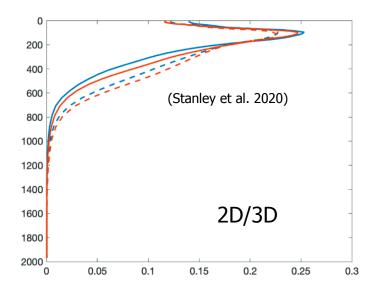


Problem formulation

sub-mesoscale temperature variance

 $\sigma_T^2 = \langle T^2 \rangle - \langle T \rangle^2$

w/ simple baseline (eq. state)

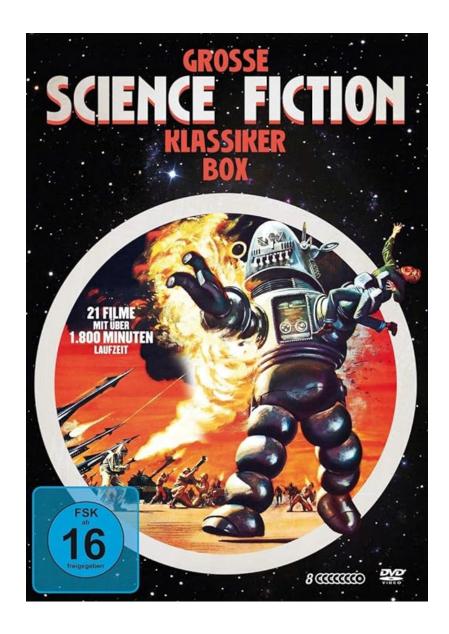


anastasiaGor / geoTrainFlow		Q Type [/] to search	>_ + - O II
Code O Issues 11 Pull requests			
geoTrainFlow Public		⊙ Watch 1	▼ ⁹ Fork 0 ▼ ☆ Star 0
🤔 main 👻 🥲 1 branch 🔊 0 tags		Go to file Add file - Code -	About
anastasiaGor debugged workflow f	or 2d case	e1f1784 on May 5 🗿 commits	Workflow for supervised training w geospatial data
source	debugged workflow for 2d case	4 months ago	🛱 Readme
workflow_demo_2d_surface_data	debugged workflow for 2d case	4 months ago	-∿ Activity ☆ 0 stars
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geoTrainFlow · Ge	eospatial ML predic	tion workflow	Releases
4 main step: data preparation, trai	w for supervised training on sets of g ning, prediction and diagnostics. The emperature variance in the ocean for		Packages No packages published
4 main step: data preparation, trai example of prediction of subgrid t Application	ning, prediction and diagnostics. The	workflow is demonstrated on the 2D surface and 3D interior datasets.	-
4 main step: data preparation, trai example of prediction of subgrid t Application This type of workflow can be appl	ning, prediction and diagnostics. The emperature variance in the ocean for in the ocean for	workflow is demonstrated on the 2D surface and 3D interior datasets.	No packages published
4 main step: data preparation, trai example of prediction of subgrid t Application This type of workflow can be appl	ning, prediction and diagnostics. The emperature variance in the ocean for in the ocean for	workflow is demonstrated on the 2D surface and 3D interior datasets. ated in the following way. There is a	No packages published Languages Jupyter Notebook 99.0%
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GeoTrainFlow training pipeline



A. Gorbunova



The need for Al-native hybrid models



Avoid having to bridge the technological gap



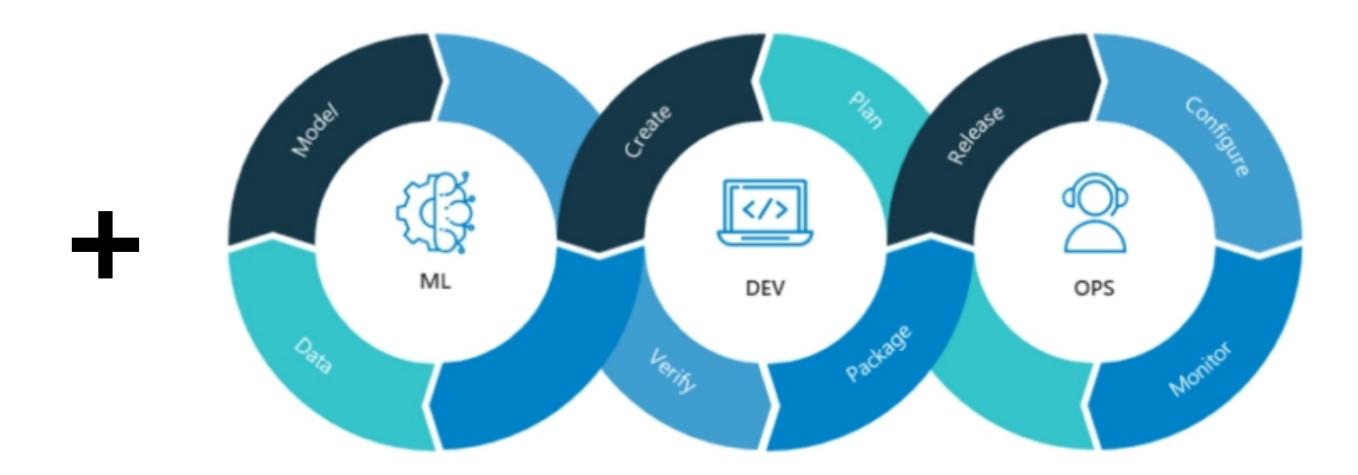
stable, robust, low abstraction languages



high abstraction, fast evolving languages



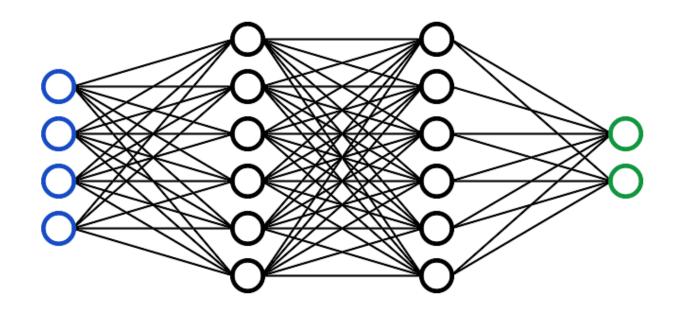
Less robust software design (APIs)



Clean APIs and MLOPs

Training ML components for physical models

offline learning



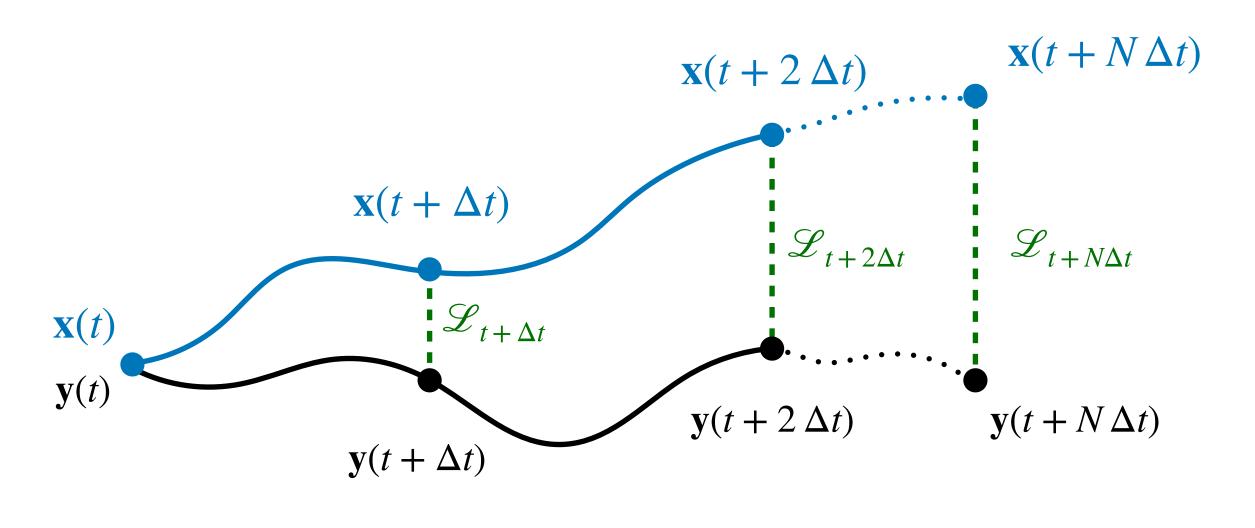


at fixed time t

Frezat et al. 2022, JAMES

How does online training affects : performance, stability, generalisation

online learning

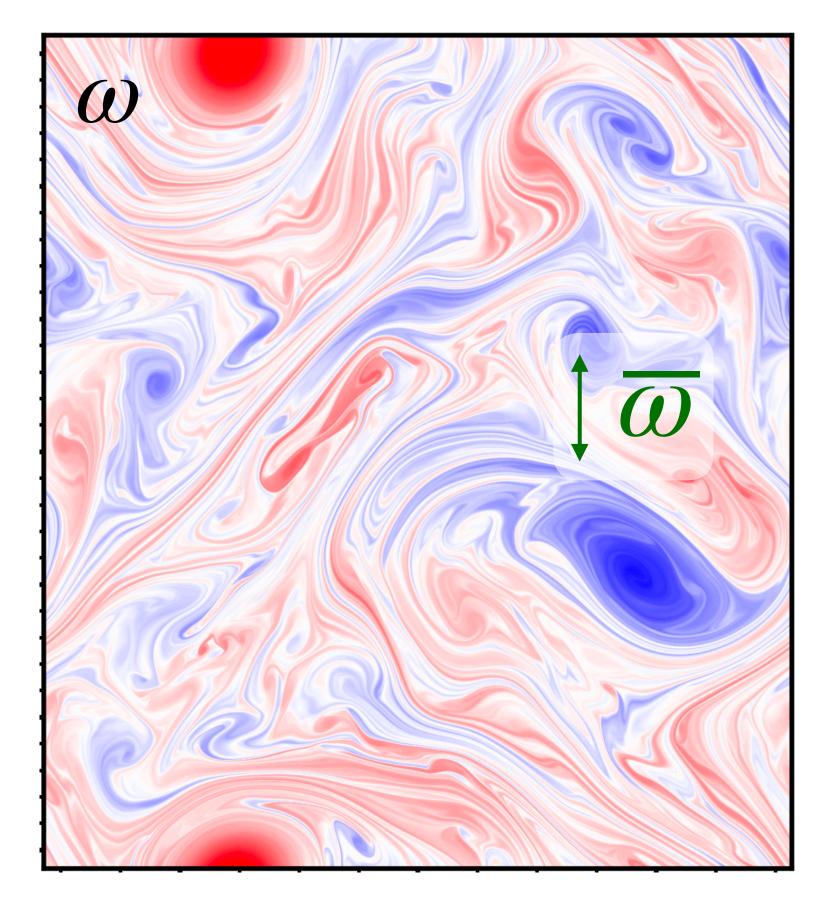


 $\partial_t \mathbf{y} + G(\mathbf{y}) + \mathcal{M}_{NN}(\mathbf{y}) = f$

along a trajectory

(a.k.a : a posteriori, solver-in-the-loop, end-to-end)

ML closure for ocean macro-turbulence (1/3) $\partial_t \omega + J(\psi, \omega) = J(\psi, \omega)$



See e.g. Graham and Ringler (2013)

$$\nu \nabla^2 \omega - \mu \omega - \beta \partial_x \psi + F$$

$$\boldsymbol{\omega} = \nabla^2 \boldsymbol{\psi}$$
 $\mathbf{u} = (-\partial_y \boldsymbol{\psi}, \partial_x \boldsymbol{\psi})$
vorticity velocity

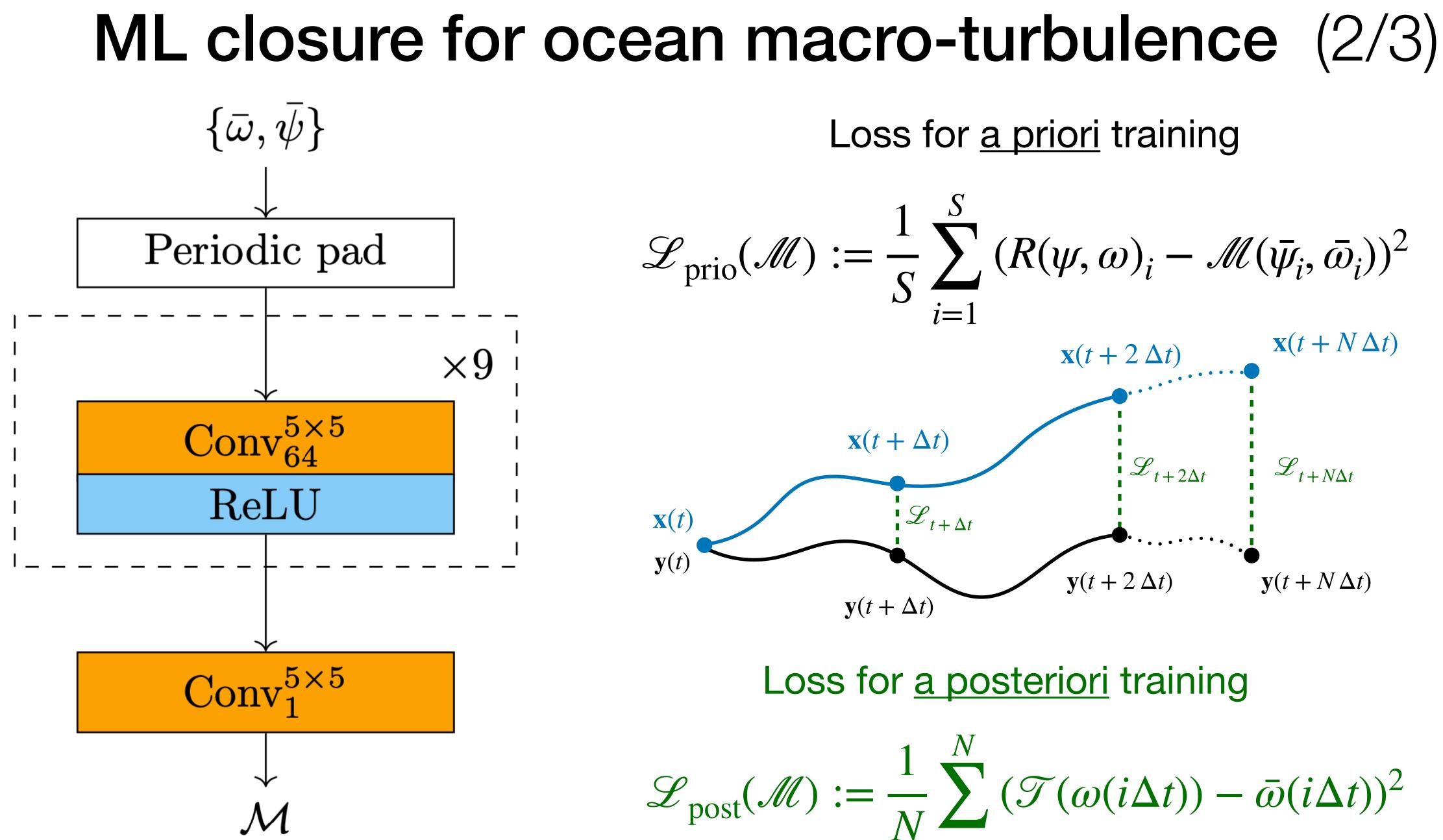
Filtering
$$\overline{\omega} := \int \omega(\mathbf{x}') G(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$

Filtered eq. $\partial_t \bar{\omega} + J(\bar{\psi}, \bar{\omega}) = rhs + R(\psi, \omega)$

SGS term
$$R(\psi, \omega) = \nabla \cdot (\bar{\mathbf{u}} \, \bar{\omega} - \bar{\mathbf{u}} \, \omega)$$

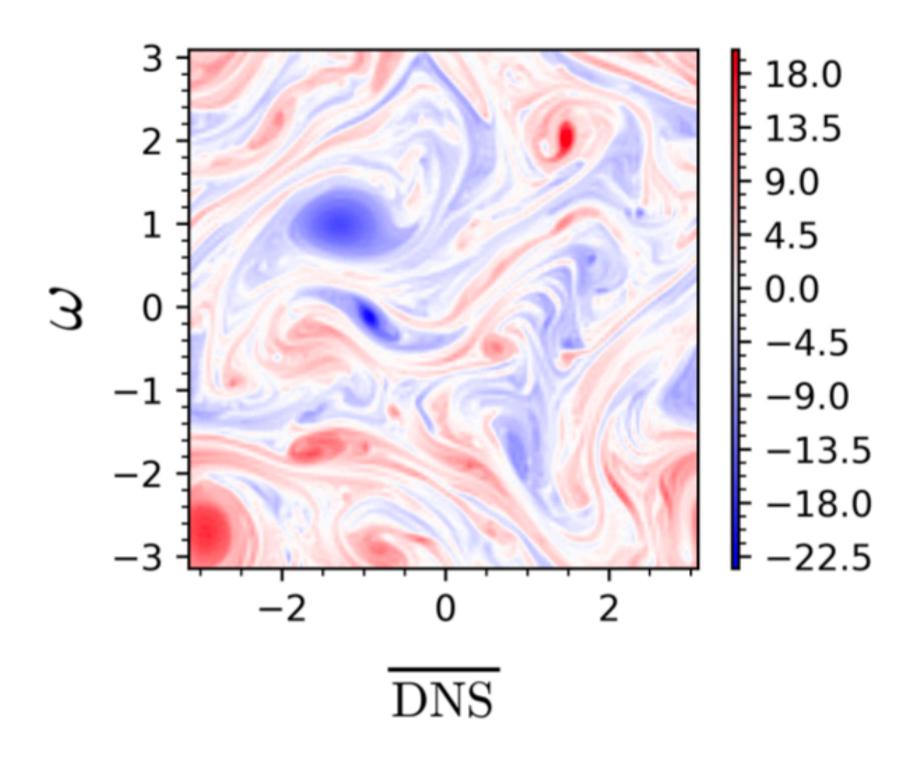
Closure pbm $R(\psi, \omega) \simeq \mathscr{M}_{\theta}^{NN}(\bar{\psi}, \bar{\omega})$





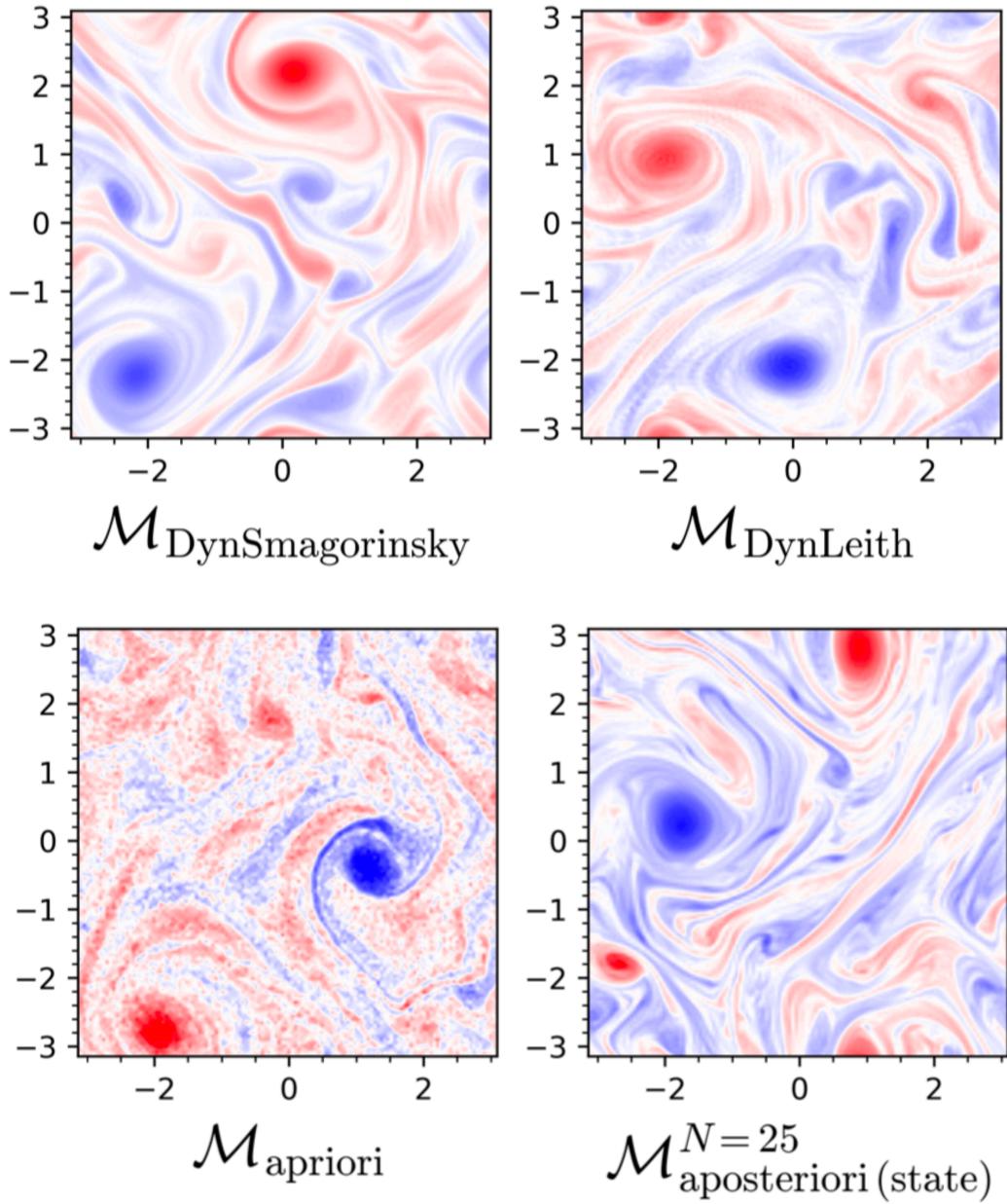
$$p_{\text{ost}}(\mathcal{M}) := \frac{1}{N} \sum_{i=1}^{N} \left(\mathcal{T}(\omega(i\Delta t)) - \bar{\omega}(i\Delta t) \right)^2$$

ML closure for ocean macro-turbulence (3/3) Frezat et al. 2022 JAMES

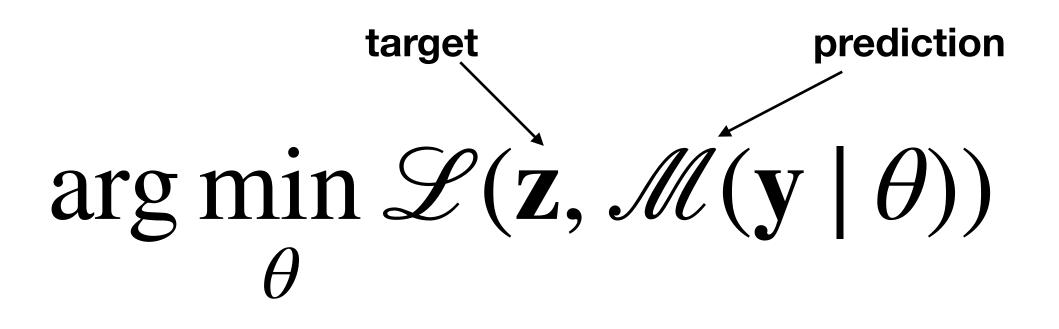


- baselines : over-diffusive
- offline learning : unstable
- online : stable and accurate

See also List et al. (2022, 2024)



The need for differentiable numerical solvers



For time evolving problems, with

$$\mathbf{y}(t + \Delta t) = E_m \circ \cdots \circ E_1(\mathbf{y}(t))$$

The gradient of the loss involves tricky without Automatic Differenciation (AD)

$$\frac{\partial \mathscr{M}}{\partial \theta} \equiv \frac{\partial E}{\partial \theta} = \frac{\partial (E_m \circ \cdots \circ E_1)}{\partial \theta}$$

$$\frac{\partial \mathscr{L}}{\partial \theta} (\mathbf{z}, \mathscr{M}(\mathbf{y} \mid \theta)) = \frac{\partial \mathscr{M}}{\partial \theta} (\mathbf{y} \mid \theta) \frac{\partial \mathscr{L}}{\partial \mathscr{M}}$$

gradient of the loss

 $\mathcal{M} \equiv E$ temporal evolution operator



 ∂E_m $\partial E_2 \ \partial E_1$ ∂E_{m-1} $\partial E_1 \quad \partial \theta$

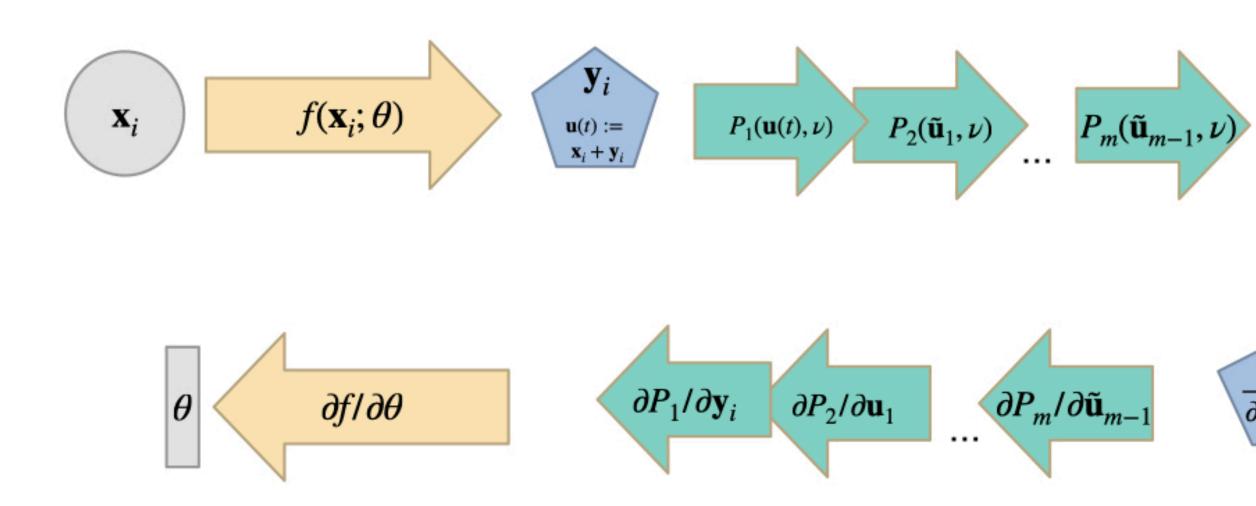
But AD not available in ocean models...

Leveraging differentiable programming

 $\left| \mathbf{u}_{i}(t + \Delta t) \right|$

 ∂L

 $\partial \mathbf{u}_i(t + \Delta t)$



- programs composed of differentiable building blocks
- building blocks : trainable and procedural code components
- trainable end-to-end with gradient based optimisation

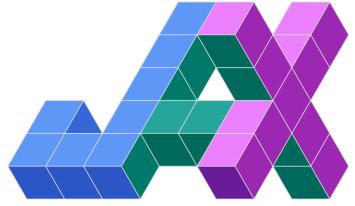
a generalisation of deep learning

See eg Thuerey et al. 2021

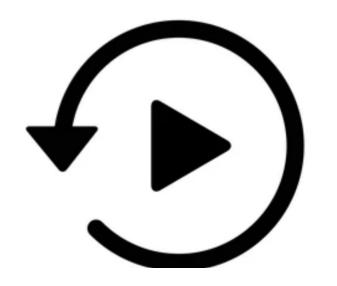
https://arxiv.org/abs/2109.05237

Supervised or residual loss L

specific languages



Differentiable numerical simulations of physical systems



2024

8 Mar

[physics.ao-ph]

2v3

2311.07

Al-native hybrid geoscientific models

(a)

Inputs

Neural General Circulation Models for Weather and Climate

Dmitrii Kochkov^{1*†}, Janni Yuval^{1*†}, Ian Langmore^{1†}, Peter Norgaard^{1†}, Jamie Smith^{1†}, Griffin Mooers¹, Milan Klöwer⁴, James Lottes¹, Stephan Rasp¹, Peter Düben³, Sam Hatfield³, Peter Battaglia², Alvaro Sanchez-Gonzalez², Matthew Willson², Michael P. Brenner^{1,5}, Stephan Hoyer^{1*†}

¹Google Research, Mountain View, CA. ²Google DeepMind, London, UK. ³European Centre for Medium-Range Weather Forecasts, Reading, UK. ⁴Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology.

⁵School of Engineering and Applied Sciences, Harvard University.

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Abstract

General circulation models (GCMs) are the foundation of weather and climate prediction. GCMs are physics-based simulators which combine a numerical solver for large-scale dynamics with tuned representations for small-scale processes such as cloud formation. Recently, machine learning (ML) models trained on reanalysis data achieved comparable or better skill than GCMs for deterministic weather forecasting. However, these models have not demonstrated improved ensemble forecasts, or shown sufficient stability for long-term weather and climate simulations. Here we present the first GCM that combines a differentiable solver for atmospheric dynamics with ML components, and show that it can generate forecasts of deterministic weather, ensemble weather and climate on par with the best ML and physics-based methods. NeuralGCM is competitive with ML models for 1-10 day forecasts, and with the European Centre for Medium-Range Weather Forecasts ensemble prediction for 1-15 day forecasts. With prescribed sea surface temperature, NeuralGCM can accurately track climate metrics such as global mean temperature for multiple decades, and climate forecasts with 140

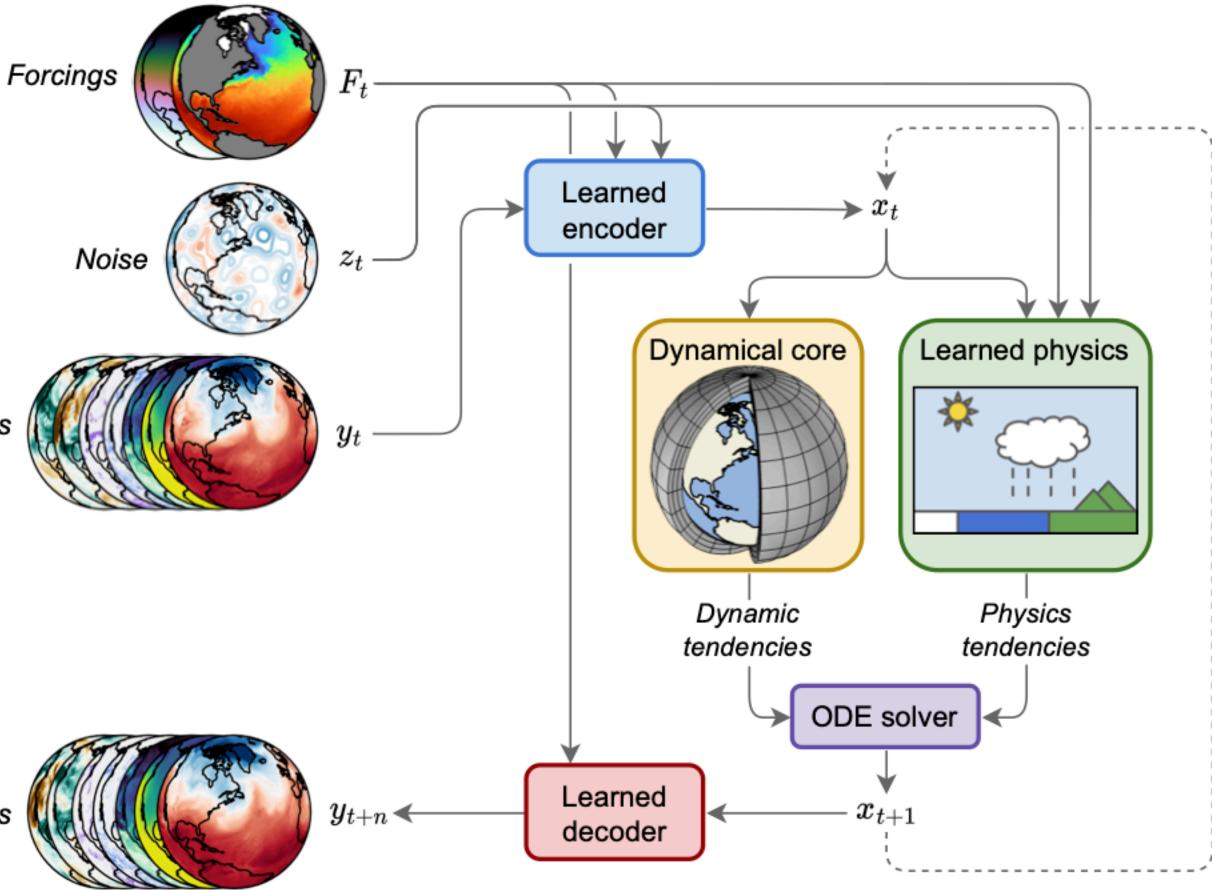
1

Outputs

https://arxiv.org/abs/2311.07222

Kochkov et al. (2024)





https://github.com/google-research/dinosaur https://github.com/google-research/neuralgcm

C tim μ Repeat

Al-native hybrid geoscientific models

Earth System Observation Data

Ground truth for the validation of process-based models

Physical Equation-driven Earth and Climate Modelling

Main tool for quantifying the Earth's state under ongoing anthropogenic forcing

Contains persistent error sources

Process-based models and neural networks will be coupled as actively learning hybrid models

> Successive research on explainable AI will make hybrid models more physically interpretable

Combining the advantages of process-based with machine learning models

Neural Earth System Modelling

Irrgang et al. (2021)

Available data pool for neural network training environments

Earth Data-driven Machine Learning

Highly specialized agents that uncover hidden patterns and geophysical quantities

Lack of process knowledge

Hybrid models start to outperform the predictive power of traditional models Allowing to optimise

- model parameters
- numerical schemes
- subgrid closures

...and better exploit observations and hi-res simulations

Differentiable programming in earth system models







Path towards Al-native hybrid ocean models



The choice of the programming language

$\bullet \bullet \bullet \bullet \blacksquare \lor \prec \to \bullet$ ⊕ ⊕ + ⊕ veros.readthedocs.io/en/latest/ \equiv Veros 1.5.1+51.g4039f76.dirty documentation jo ⊒ 0 Versatile Ocean Simulation in Pure Python Veros, the versatile ocean simulator, aims to be the swiss army knife of ocean modeling. It is a fullfledged primitive equation ocean model that supports anything between idealized toy models and realistic, high-resolution, global ocean simulations. And because Veros is written in pure Python, the days of struggling with complicated model setup workflows, ancient programming environments, and obscure legacy code are finally over. In a nutshell, we want to enable high-performance ocean modelling with a clear focus on flexibility and usability. Veros supports a NumPy backend for small-scale problems, and a high-performance JAX backend with CPU and GPU support. It is fully parallelized via MPI and supports distributed execution on any number of nodes, including multi-GPU architectures (see also our benchmarks). The dynamical core of Veros is based on pyOM2, an ocean model with a Fortran backend and Fortran and Python frontends. If you want to learn more about the background and capabilities of Veros, you should check out A short introduction to Veros. If you are already convinced, you can jump right into action, and learn how to get started instead! ... because the Baroque is over See also We outline some of our design philosophy and current direction in this blog post. START HERE A short introduction to Veros The vision Features Getting started Installation Setting up a model Running Veros Enhancing Veros Advanced installation Using JAX

Examples of (almost) Al-native ocean models

but not fully Al-ready yet

●●● □ - < 🔒 clima.github.io/OceananigansDocumentation/ 👌 Home 0 2 4 ^

Oceananigans.jl

Search and friendly fluid dynamics on CPUs and GPUs.

Oceananigans is a fast, friendly, flexible software package for finite volume simulations of the nonhydrostatic and hydrostatic Boussinesq equations on CPUs and GPUs. It runs on GPUs (wow, fast!), though we believe Oceananigans makes the biggest waves with its ultra-flexible user interface that makes simple simulations easy, and complex, creative simulations possible.

Oceananigans is written in Julia by the Climate Modeling Alliance and heroic external collaborators.

Quick install

Oceananigans is a registered Julia package. So to install it,

- 1. Download Julia.
- 2. Launch Julia and type

julia> using Pkg

julia> Pkg.add("Oceananigans")

Julia 1.9 is required

Oceananigans requires Julia 1.9 or later.

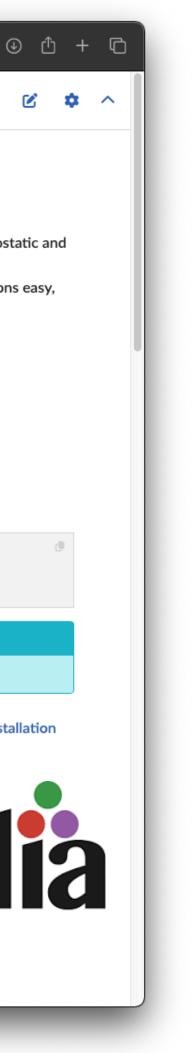
If you're new to Julia and its wonderful Pkg manager, the Oceananigans wiki provides more detailed installation instructions.

The Oceananigans "knowledge base"

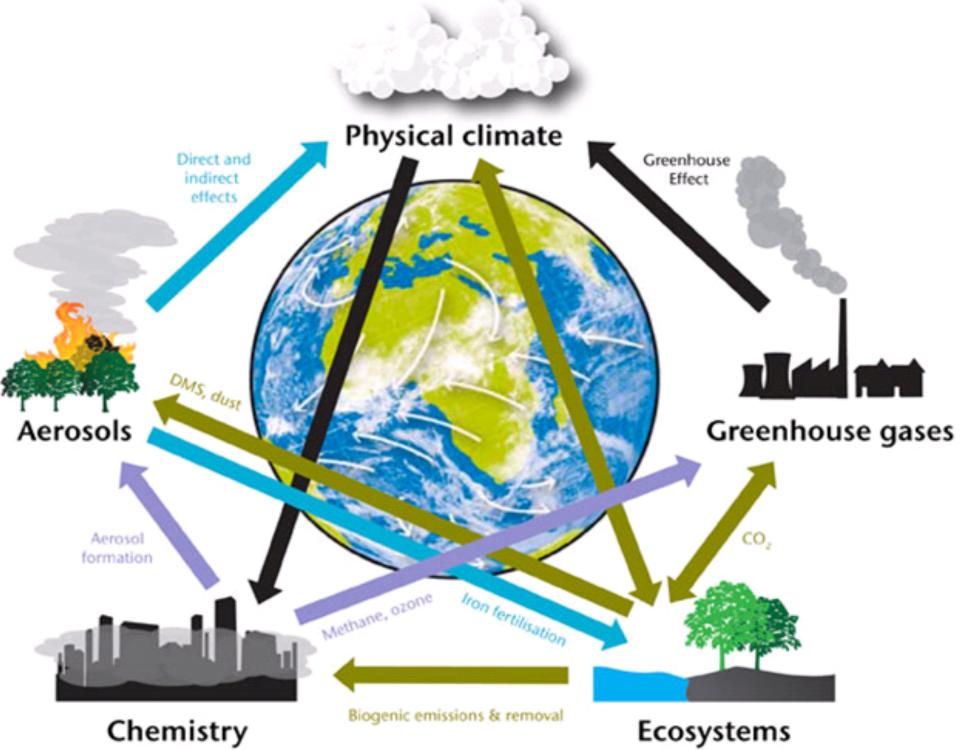
It's deep and includes:

- This documentation, which provides
 - example Oceananigans scripts,
 - tutorials that describe key Oceananigans objects and functions,
 - explanations of Oceananigans finite-volume-based numerical methods,
 - details of the dynamical equations solved by Oceananigans models, and

Our Graal : Al-ready, differentiable, fast, high-level abstraction, long-lasting.

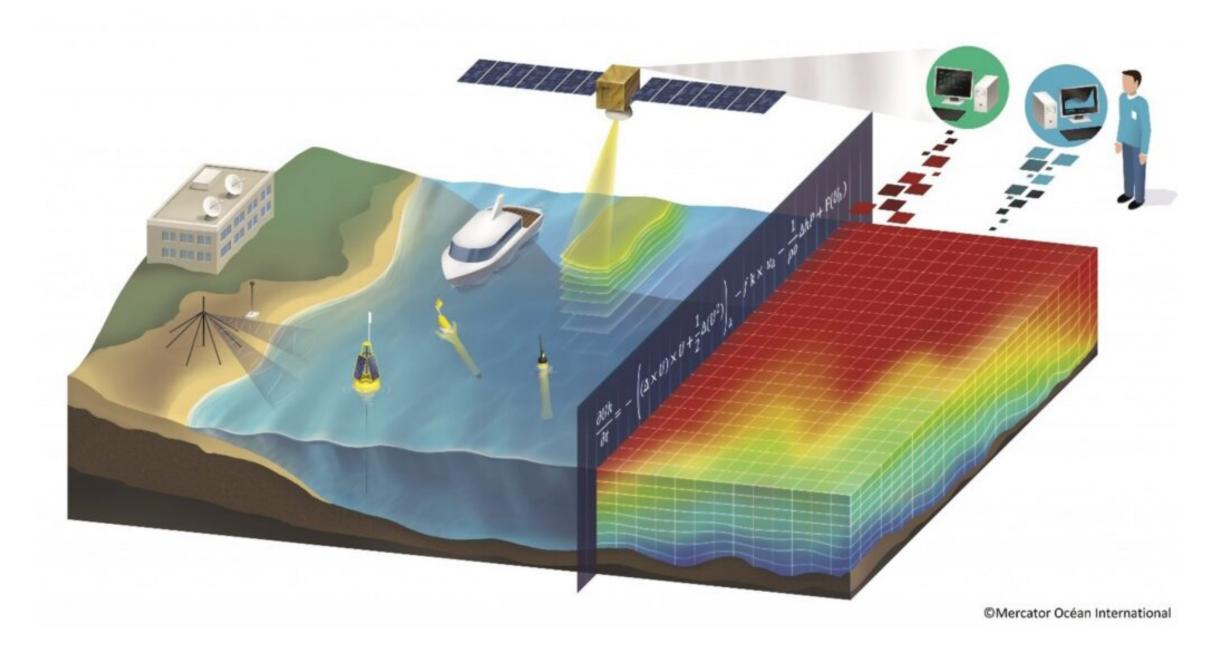


Revisiting our systems' APIs Copernicus **Marine Service**



Earth System models (IPCC)

Systems build over decades, based on low level abstraction No clearly defined APIs for ocean models.



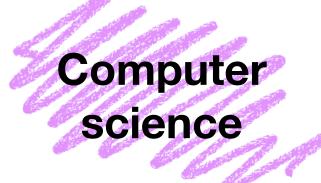
Operational prediction systems (Copernicus)

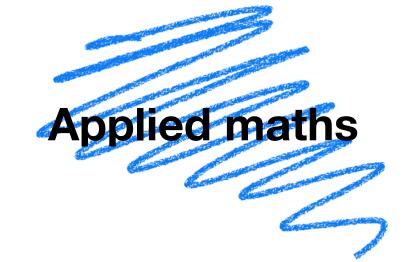


The need for cross-disciplinary efforts

Use cases

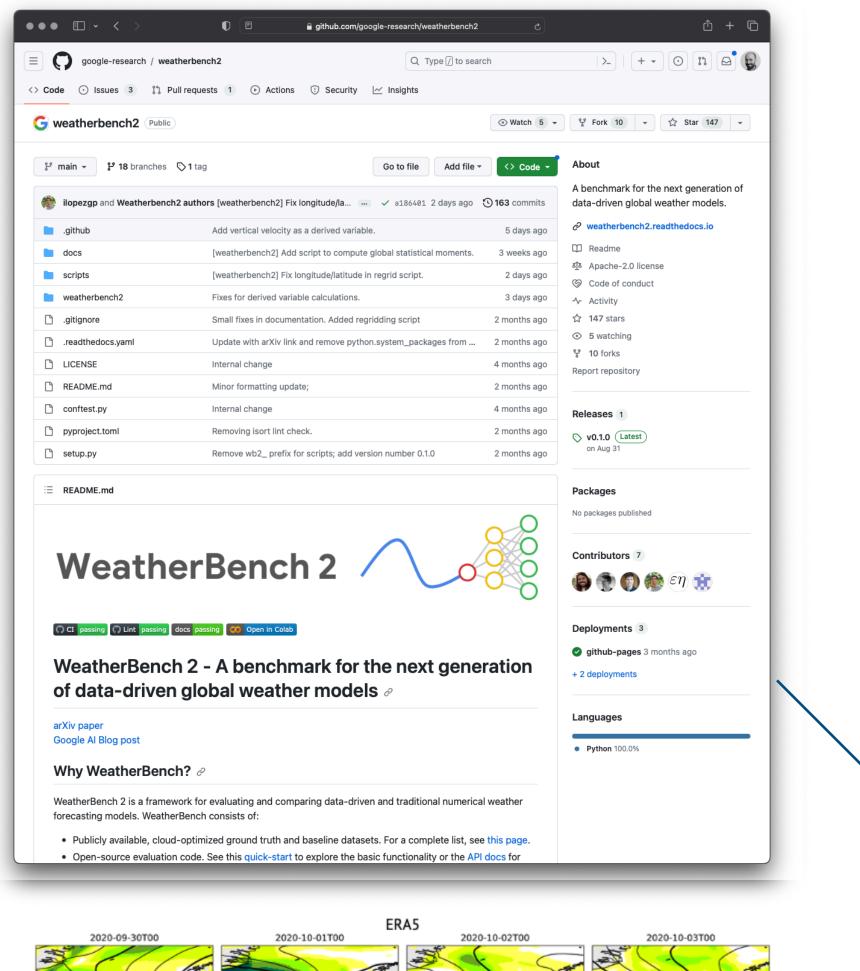






Accelerating progress with open benchmarks (1/2)

https://github.com/google-research/weatherbench2

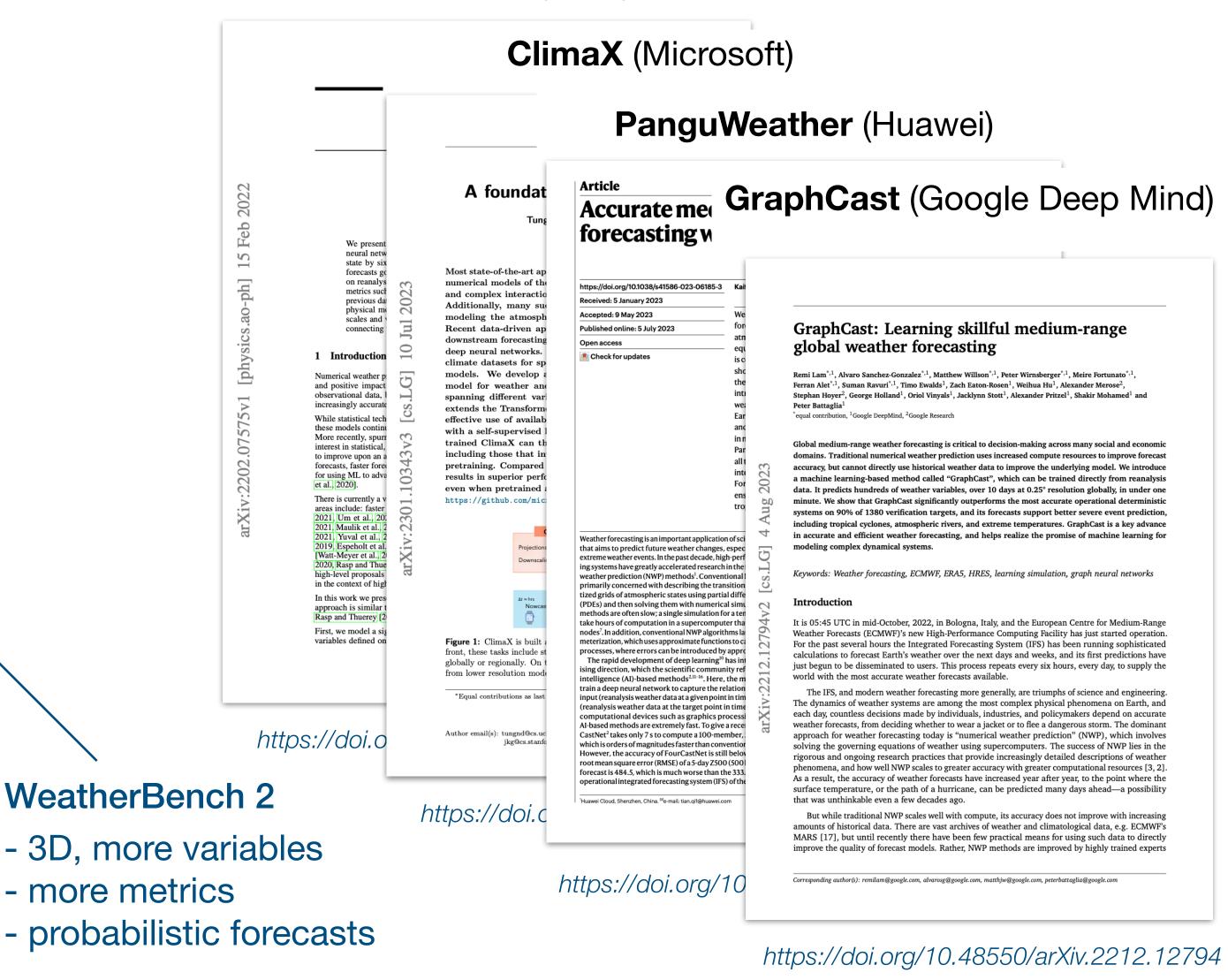


data source : ERA5 reanalysis

WeatherBench 2

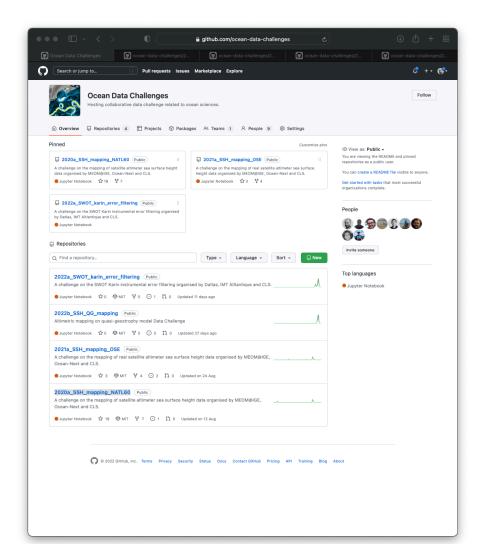
- 3D, more variables
- more metrics

Keisler et al. (2022)





Accelerating progress with open benchmarks (2/2)



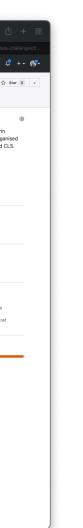
Collaborative data-challenges

- problem description + baseline
- data, metrics (with codes)
- tools for collaboration and papers

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mballaro Update README.md	38851	bf on 12 Aug 3105 commits	A challenge on the mapping of satellite altimeter sea surface height data	notebooks	Improving notebooks	27 days ago	4 watching	ENSE	Initial commit	2 months ago	O Create a new release
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Mativation								itext & Motiva			
Motivation			Languages	his repository contains	codes and sample notebooks for downloading a	and processing the SSH QG mapping			level SWOT products are very much expecte ns which will make them an unprecedented L		
The goal is to investigate how to best reconstru satellite altimetry observations. This data challe			Jupyter Notebook 100.0%	ita challenge.				data will however	be contaminated by instrumental and geophy	sical errors (Gauthier et al., 2016; Peral	
framework: "Real" full SSH are from a numerical	I simulation with a realistic, high-res	olution ocean circulation		Context an	d motivation				2018). In order to be able to observe front, m e specific processing. Also, these errors are		
model: the reference simulation. Satellite obser- based on realistic orbits of past, existing or futu				. Oomext un				econd derivatives o	f the SSH data which are used for the compu le to remove the SWOT errors will be of sign	utation of geostrophic currents and	
provided (see below) and the practical goal of the described below and in Jupyter notebooks.					napping challenges have been proposed to the o oal of this simplified altimetric mapping data ch				e currents and vertical mixing.	ricant importance to recover	
					mmunities to play and bring their outside knowle			WOT errors are exp	ected to generate noises that are both correl	lated on the swath and spatially	
Reference simulation				eneral goal							
The reference simulation is the NATL60 simulati doi:10.1029/2019JC015827). The simulation is r		i et al. 2020									
	and the recently.				e how to best reconstruct sequences of sea surf vations. The end goal is to have efficient method						
Observations				formation from the par	tial (in time and space) satellite data in order to . In this OSSE experimental context i.e. where	generate fully resolved maps of the				I I I	1
The SSH observations include simulations of To altimeter data. This nadir altimeters constellatio					 In this OSSE experimental context i.e. where - the methods' performances are assessed by of 				mod	el data	a /
considered as a historical optimal constellation simulates the addition of SWOT to this reference	in terms of spatio-temporal coverage	e. The data challenge								σι υαι	u / '
simulates the addition of SWOT to this reference challenge.	e constellation. No observation error	r is considered in this									

see : https://github.com/ocean-data-challenges/



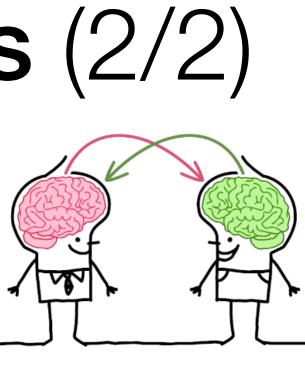


Leaderboard

Method	μ(RMSE)	σ(RMSE)	λx (degree)	λt (days)	Notes	Reference
baseline OI 1 nadir	0.69	0.03	3.31	33.32	Covariances not optimized	quickstart.ipynb
baseline OI 4 nadirs	0.83	0.04	2.25	15.67	Covariances not optimized	quickstart.ipynb
baseline Ol 1 swot	0.85	0.05	1.22	12.38	Covariances not optimized	quickstart.ipynb
duacs 4 nadirs	0.92	0.01	1.42	12.0	Covariances DUACS	eval_duacs.ipynt
bfn 4 nadirs	0.92	0.02	1.23	10.6	QG Nudging	eval_bfn.ipynb
dymost 4 nadirs	0.91	0.01	1.36	11.79	Dynamic mapping	eval_dymost.ipyr
miost 4 nadirs	0.93	0.01	1.35	10.19	Multiscale mapping	eval_miost.ipynb
4DVarNet 4 nadirs 🏆	0.94	0.01	1.18	10.34	4DVarNet mapping	eval_4dvarnet.ip
duacs 1 swot + 4 nadirs	0.92	0.02	1.22	11.15	Covariances DUACS	eval_duacs.ipynt
bfn 1 swot + 4 nadirs	0.93	0.02	0.8	10.09	QG Nudging	eval_bfn.ipynb
dymost 1 swot + 4 nadirs	0.93	0.02	1.2	10.07	Dynamic mapping	eval_dymost.ipyr
miost 1 swot + 4 nadirs	0.94	0.01	1.18	10	N. 4. (A) -	SS
4DVarNet 1 swot + 4 nadirs	0.95	0.01	0.82	6.	and the second se	33

µ(RMSE): average RMSE score. σ(RMSE): standard deviation of the RMSE score. λx: minimum spatial scale resolved. λt: minimum time scale resolved.

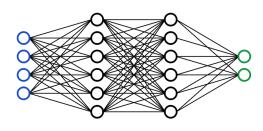
Le Guillou et al. 2021 Febvre et al. 2021 Beauchamp et al. 2022

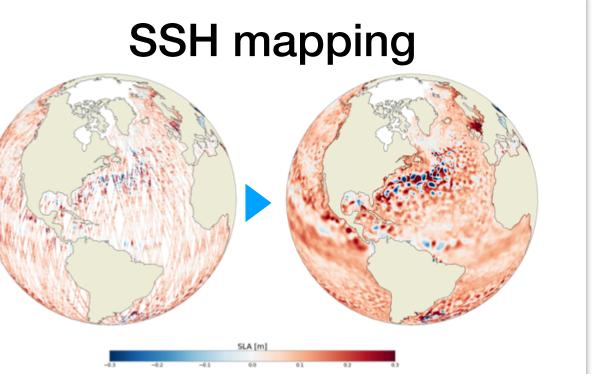


interdisciplinary

collab. IGE, IMT-Atl, Datlas, CLS

supported by CNES, CMEMS





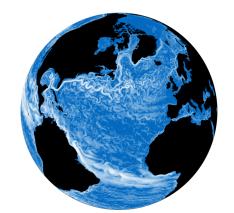








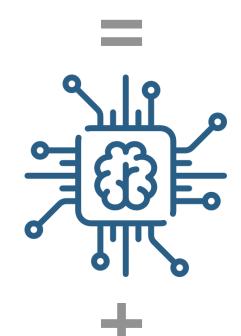




- Illustrated why we are augmenting models with ML
- Described how this is done in practice today —
- Advocated that a deep recast of our models is needed

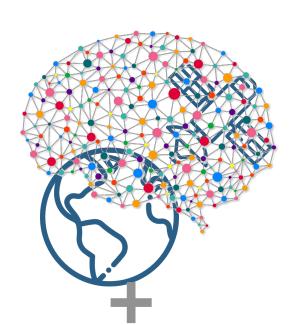
Integrating model-based





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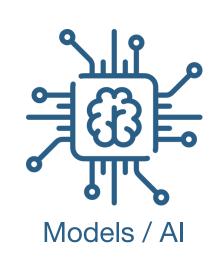
Assessing impact on downstream systems

Summary

- Discussed some steps towards Al-native hybrid models
- products and observations including the need for large cross-disciplinary efforts



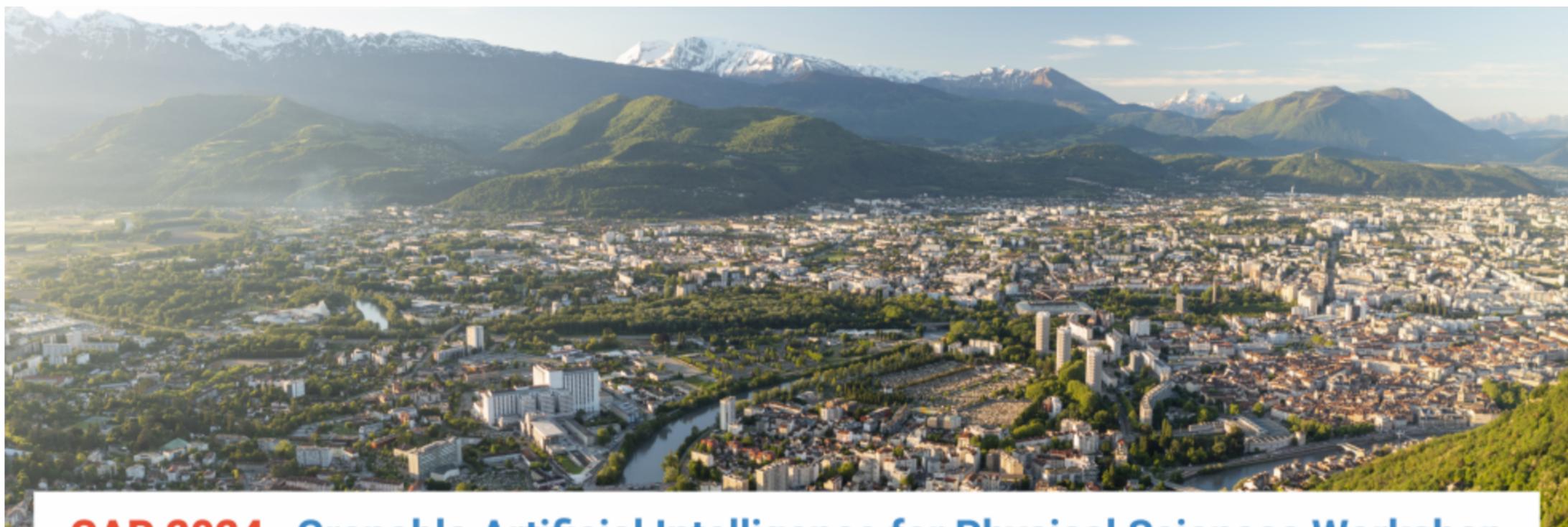








A cross-disciplinary event later today



GAP 2024 Grenoble Artificial Intelligence for Physical Sciences Workshop

Scientific seminars from 29 to 30 May 2024 at MaCi, Grenoble, France Julia tutorial on 31 May 2024 at IMAG building, Grenoble, France

https://gap2024.sciencesconf.org

Starting today at 1:30PM