Défis théoriques pour les sciences du climat

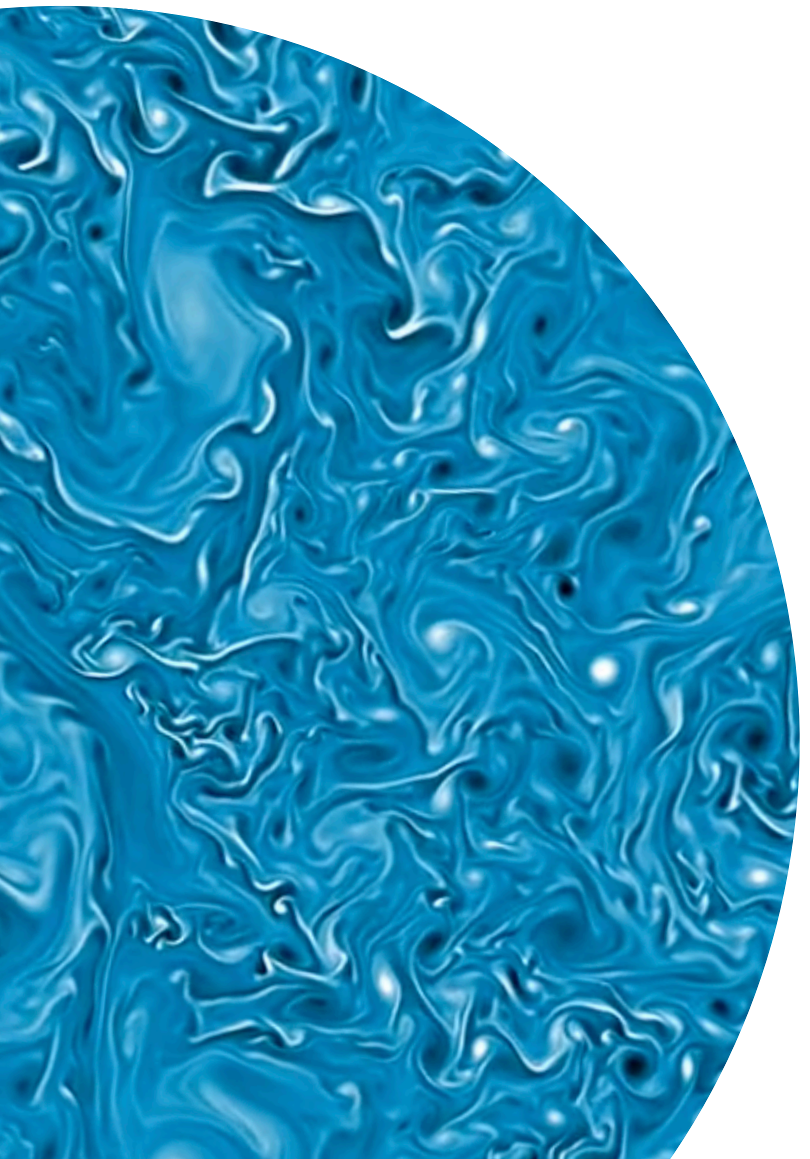
Grenoble | 29 May 2024

Towards AI-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



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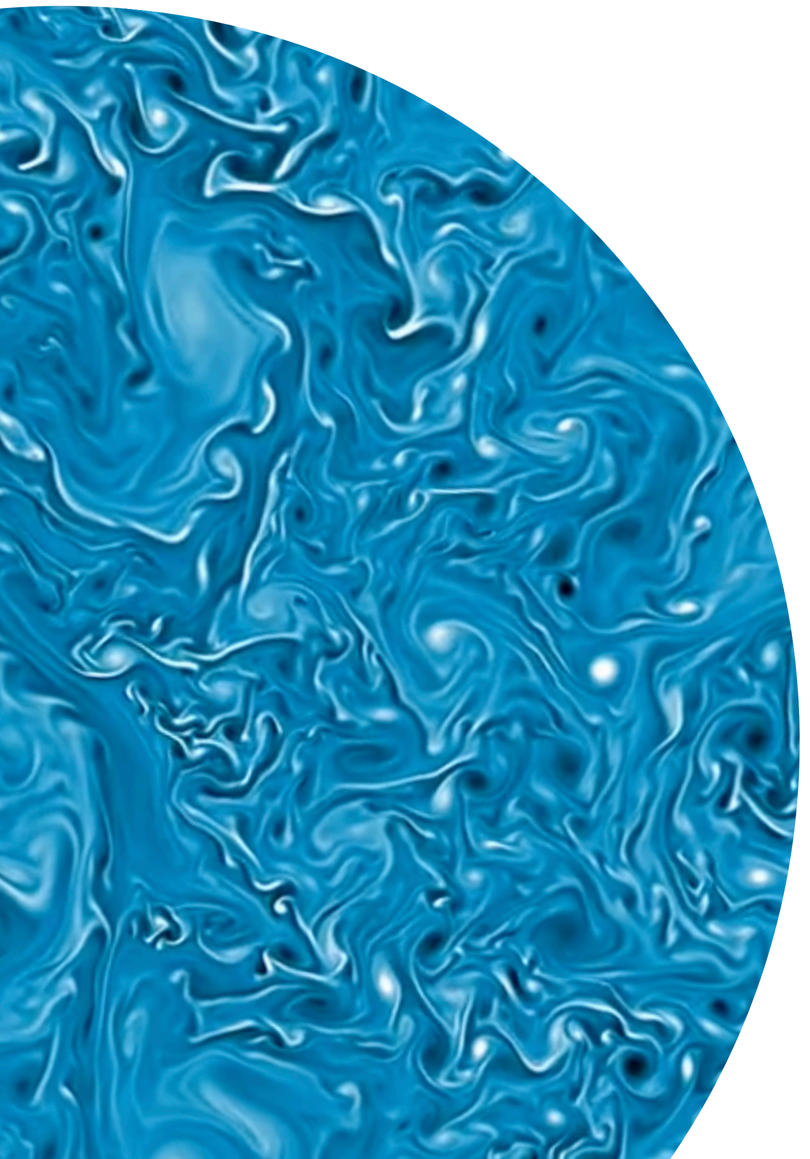
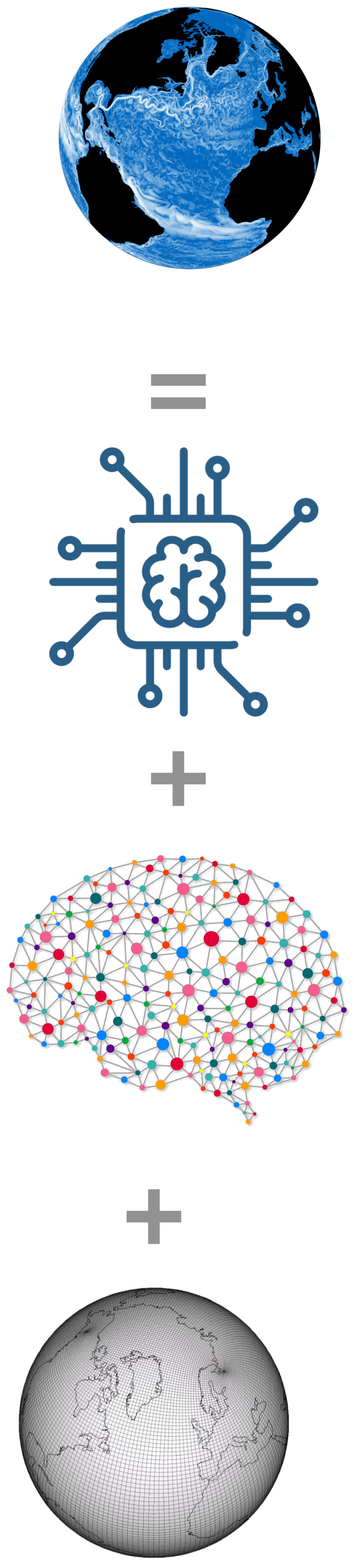


Objectives of this talk

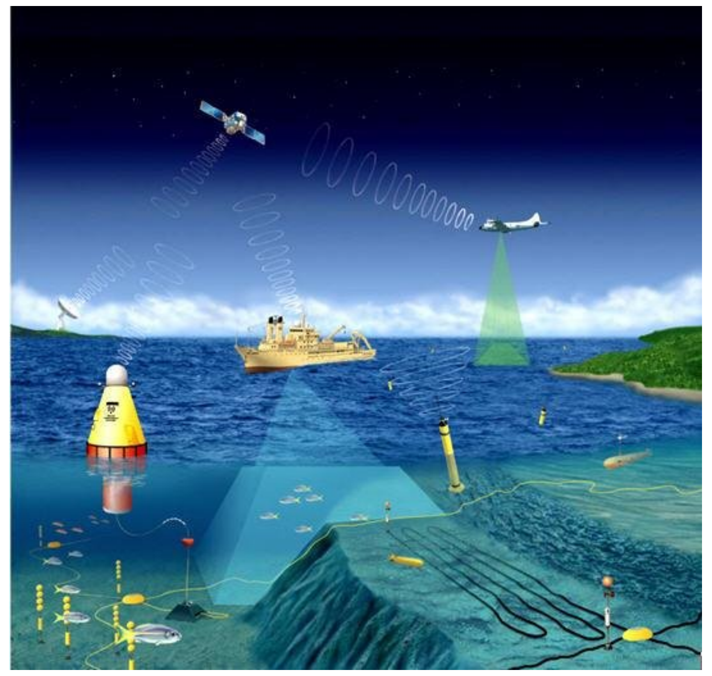


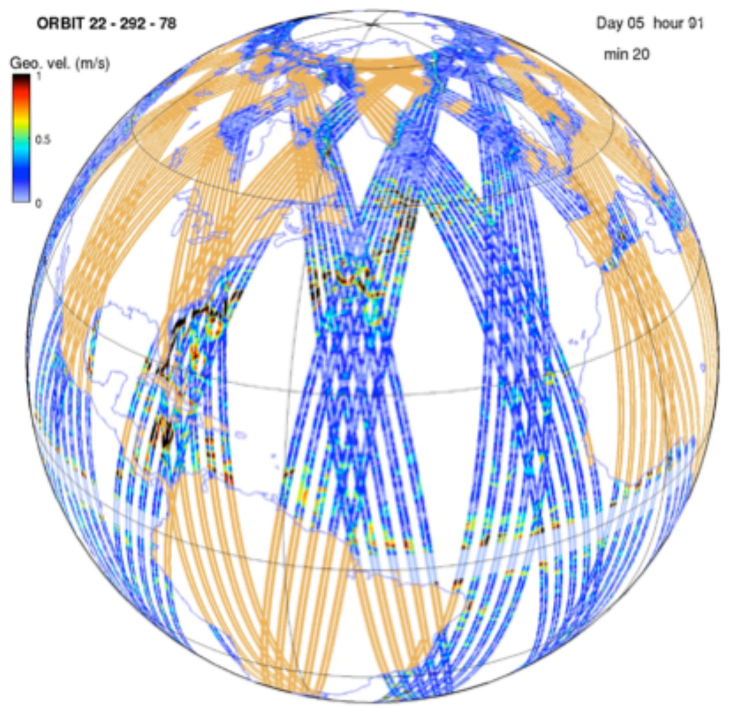
- Illustrate why we explore **augmenting models** with ML
- Illustrate **how this is done** in practice today
- Advocate that a **deep recast** of our models is needed
- Discuss some steps towards **AI-native hybrid** models

New toys in the oceanographer's toolbox

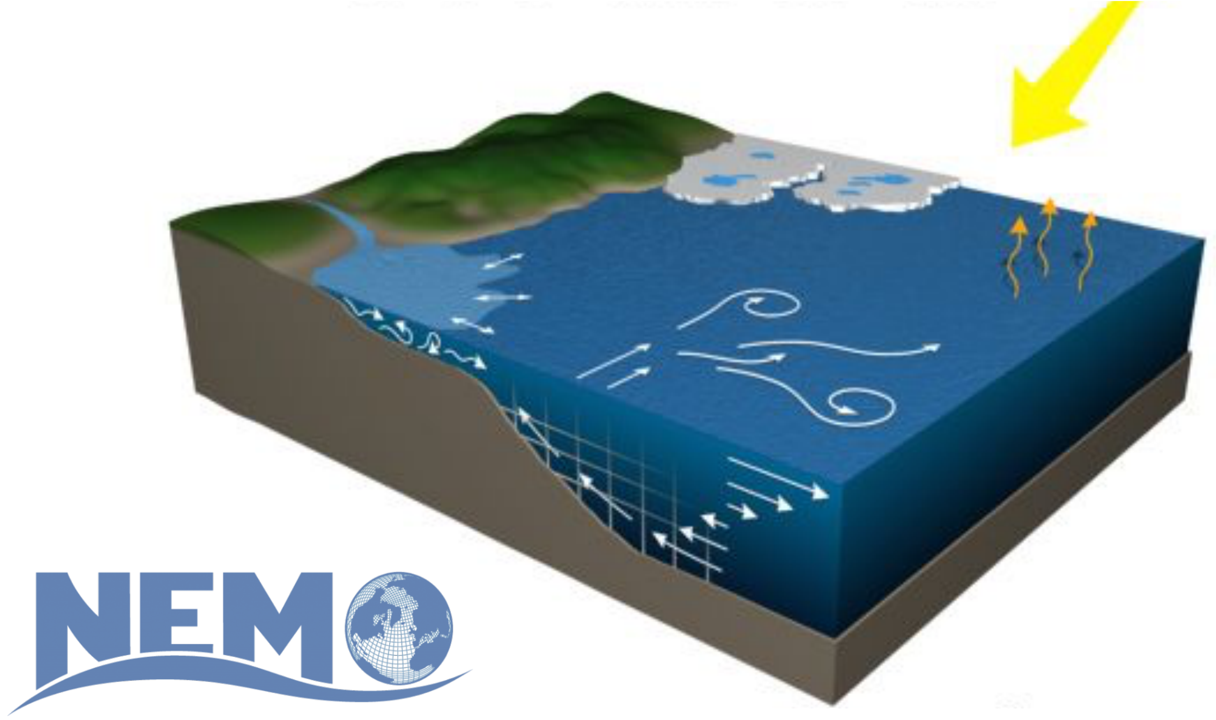
Computational oceanographer's toolbox

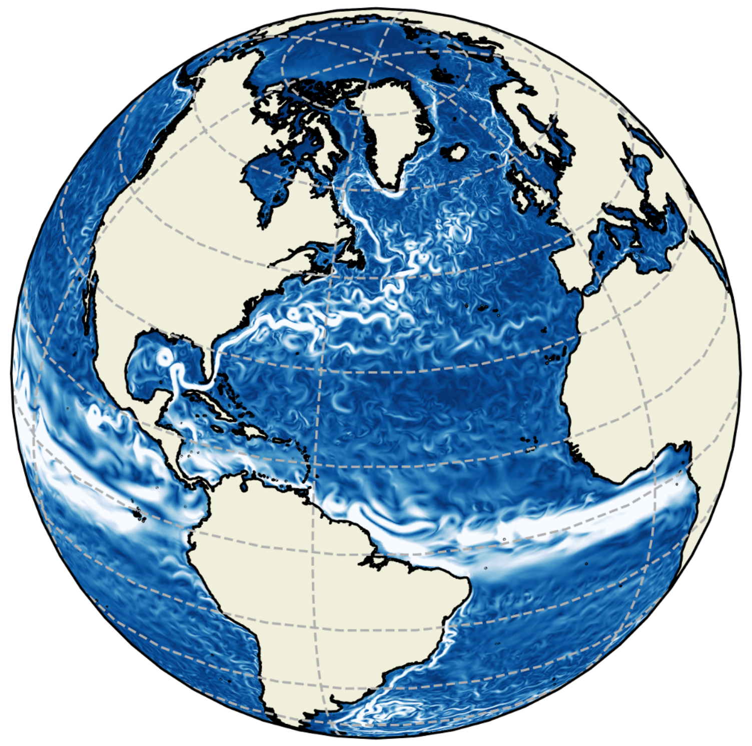
Observations
(in situ/satellite)



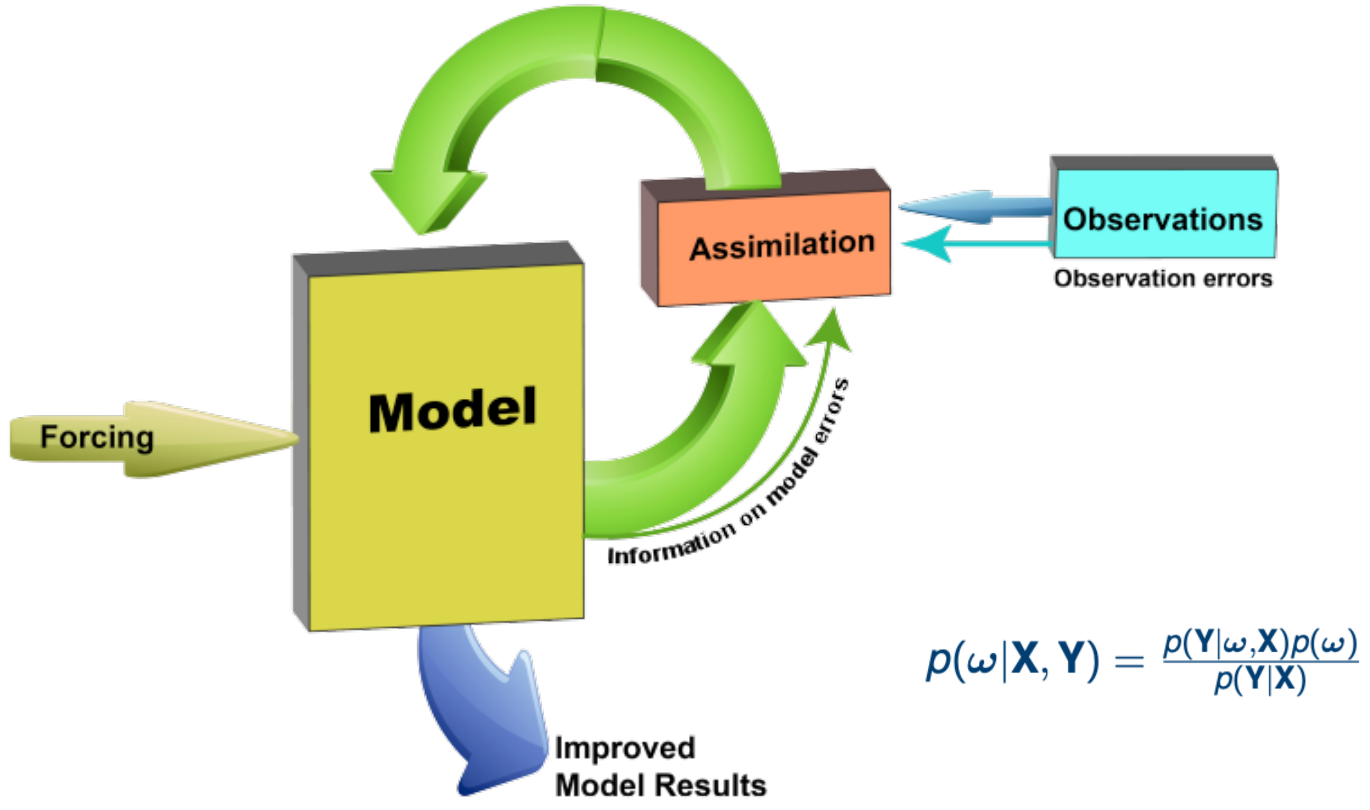


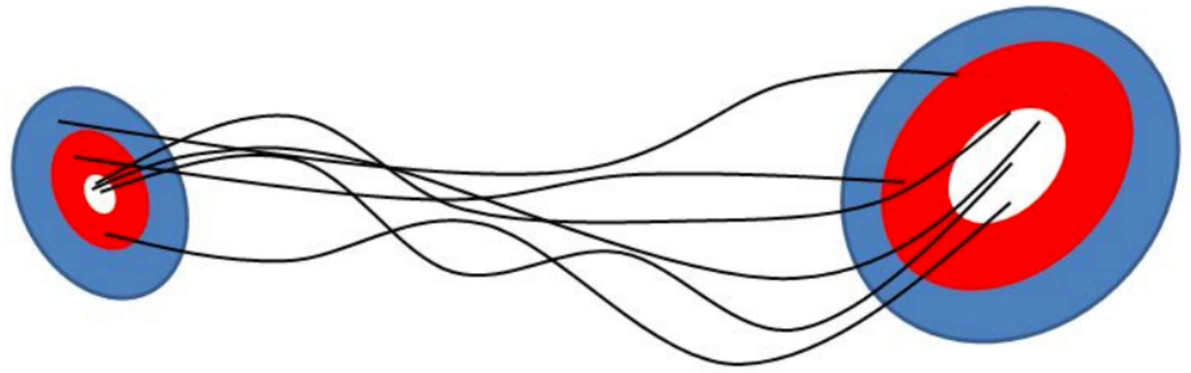
Physical models
(ocean circulation models)





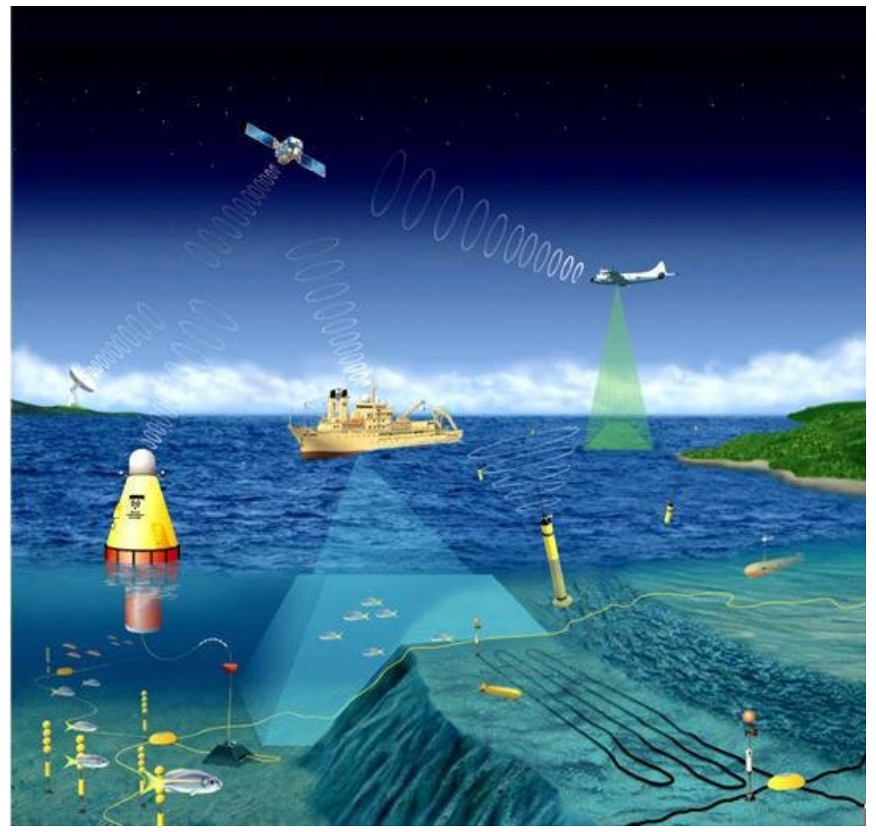
Inverse methods
(data assimilation)



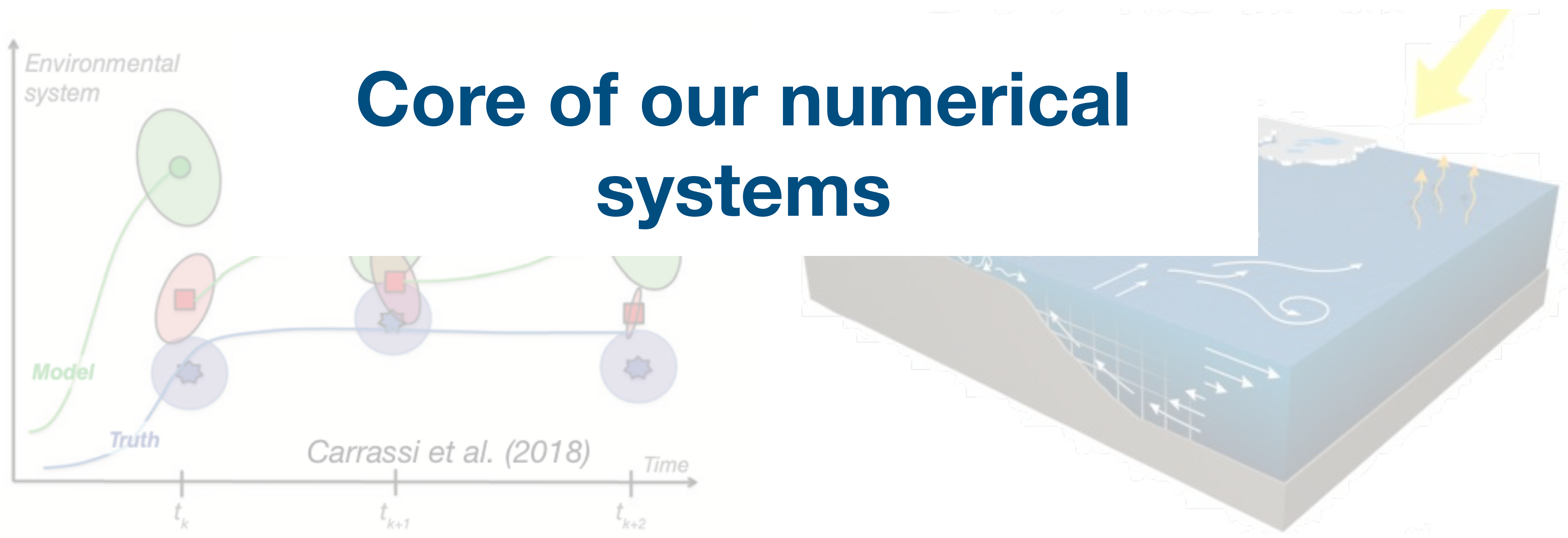


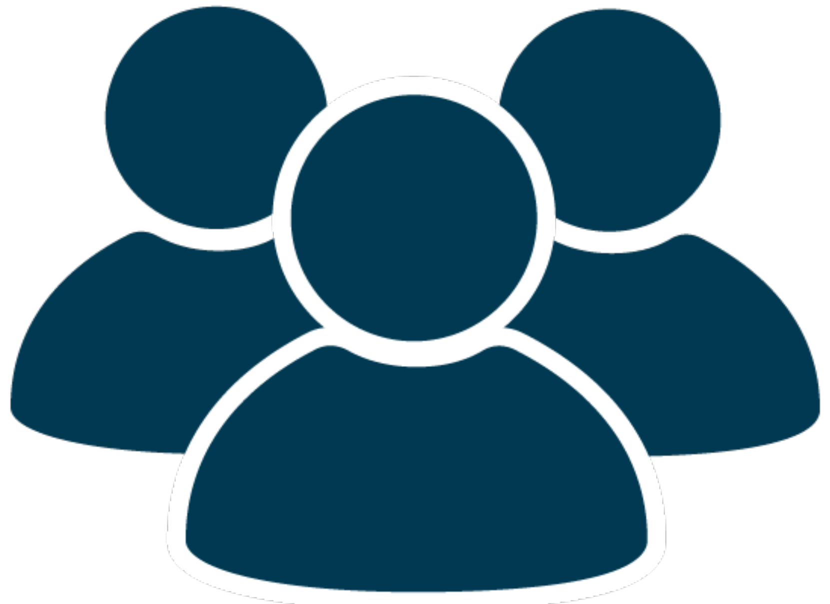
Tools for understanding but also monitoring and forecasting ocean circulation

How AI is affecting our numerical systems



Core of our numerical systems





Observations → **Data assimilation** → **Physics-based forecast** → **Post-processing, dissemination**

Upstream

Downstream

denoising, inpainting
parameter retrieval
quality control

AI, machine learning & data-driven approaches

data fusion,
tailored services
data mining

AI-based ocean forecasting

COMING UP

MANUSCRIPT 1

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

1 Introduction

Ocean forecasting is critically important for many marine activities. At present, the leading GOFSs (e.g. Mercator Ocean Physical SYstem (PSY4) and Real-Time Ocean Forecast System (RTOFS)) use physics-driven models in fluid mechanics and thermodynamics to predict future ocean motion states and phenomena based on current ocean conditions [1]. The GOFSs adopt numerical methods that rely on supercomputers to solve the partial differential equations of the physical models. Due to their desirable performance, they are operationally run in different countries worldwide. However, numerical forecasting methods are usually computationally expensive and slow. For example, a single forecasting simulation in the numerical GOFSs may take hours on a supercomputer with hundreds of computational nodes [2]. Besides, improving the forecasting accuracy of these methods is exceedingly challenging because they heavily rely on the human cognitive abilities in understanding the physical laws of the ocean environment [3].

With the recent advances of Artificial Intelligence (AI) techniques, deep learning methods have been widely applied in various prediction/forecasting tasks of different fields and achieved great success. Particularly, some data-driven AI models have shown the potential in atmosphere weather forecasting like *Pangu-Weather* [4] and *GraphCast* [5]. They have achieved comparable or even better prediction results in global medium-range weather forecasting than current leading numerical weather prediction (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 rules of weather changing, without introducing the prior knowledge of physics mechanisms.

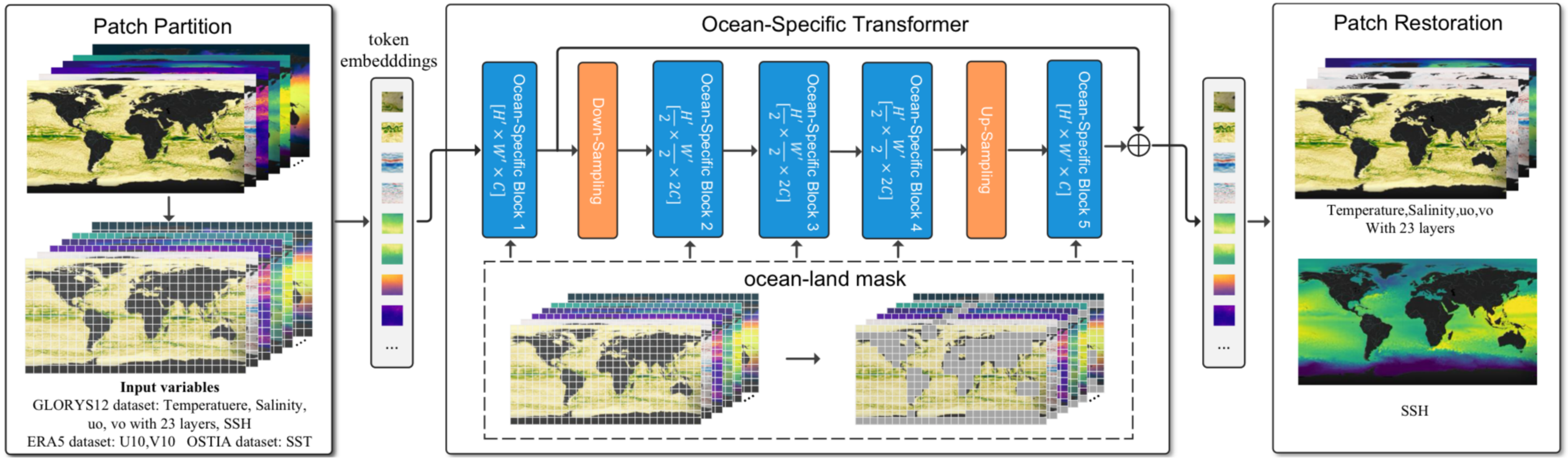
Although data-driven models have achieved promising results in atmosphere weather forecasting, how to build a more accurate and efficient data-driven ocean forecasting model remains an open research issue due to the following

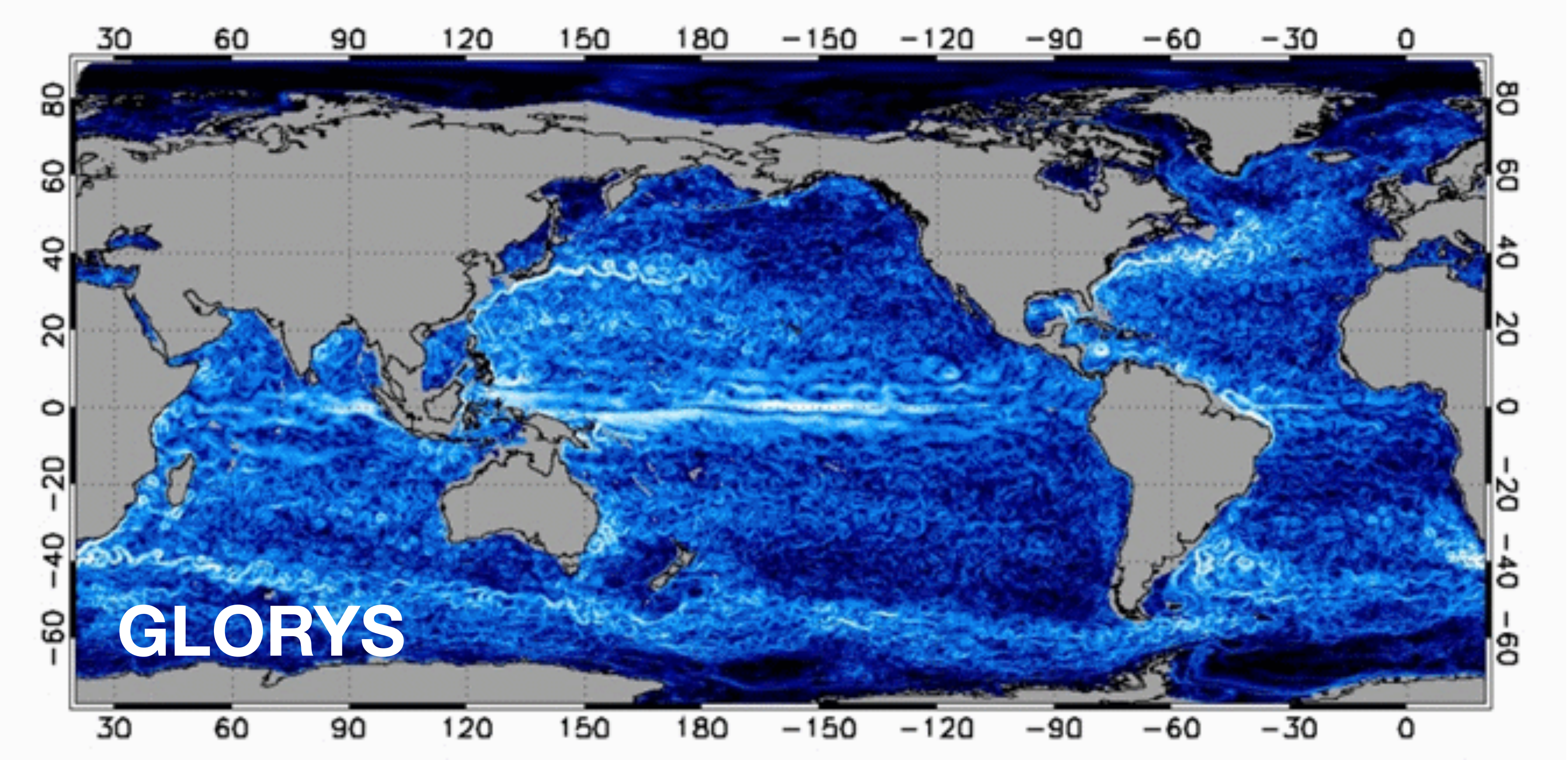
- *Xiang Wang, Pinqiang Wang, Huizan Wang, Junxing Zhu, Jianbo Xu, Senliang Bao, Ciqiang Luo, Yi Han, Weimin Zhang, Kaijun Ren, Kefeng Deng, and Junqiang Song are with the College of Meteorology and Oceanography, National University of Defense Technology, Changsha 410073, China.*
- *Renzhi Wang, Senzhang Wang and Jun Yin are with the School of Computer Science and Engineering, Central South University, Changsha 410083, China.*
- *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.*
- *Guihua Wang is with the Department of Atmospheric and Oceanic Sciences, Fudan University, Shanghai 200438, China.*
- *Ziqing Zu, Key Laboratory of Marine Hazards Forecasting, National Marine Environmental Forecasting Center, Ministry of Natural Resources, Beijing 100081, China.*
- *Guihua Wang, Huizan Wang, Senzhang Wang, and Weimin Zhang are the corresponding authors.*

arXiv:2402.02995v2 [physics.ao-ph] 8 Feb 2024

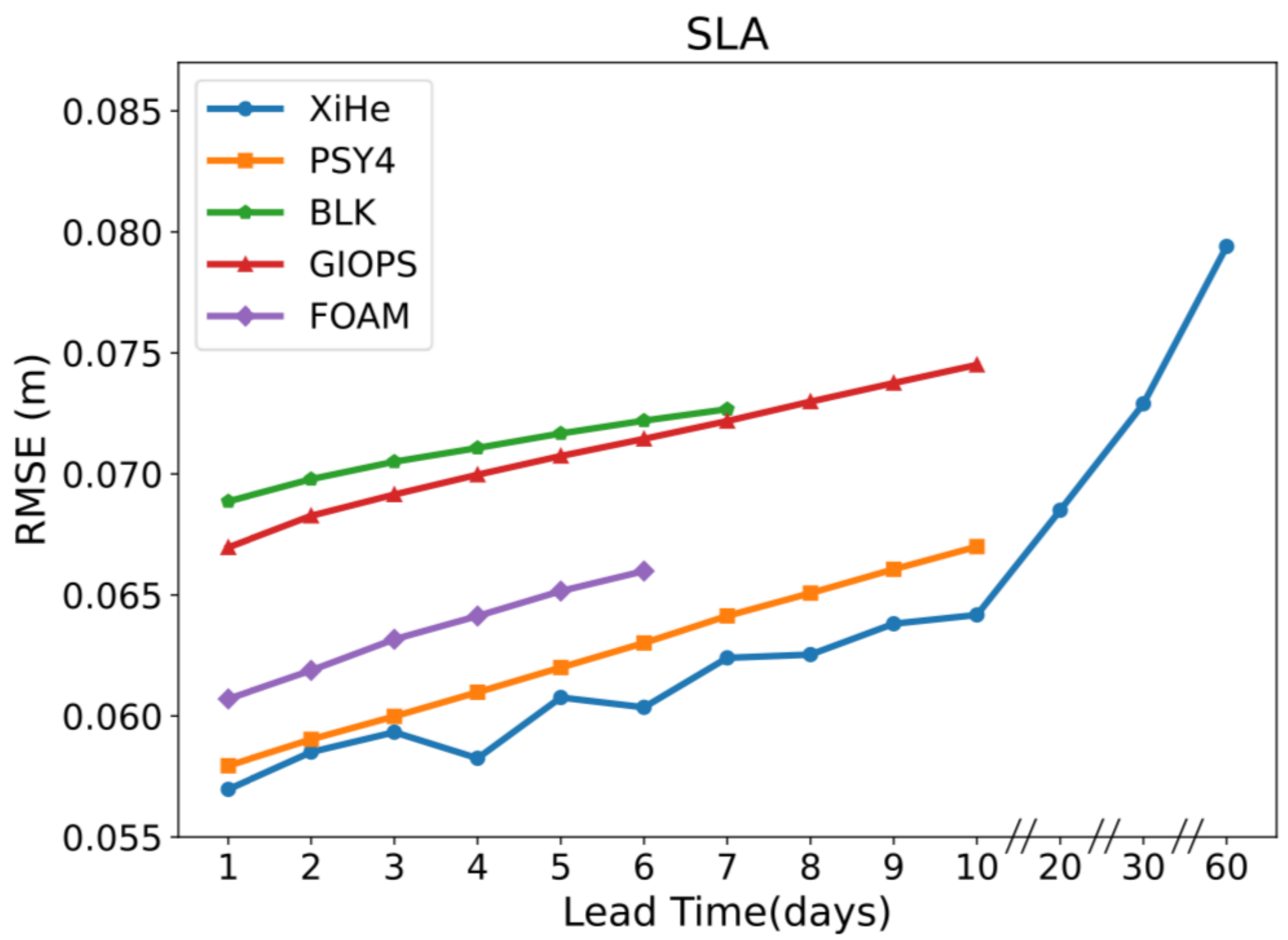
https://arxiv.org/abs/2402.02995

Wang et al. (2024)





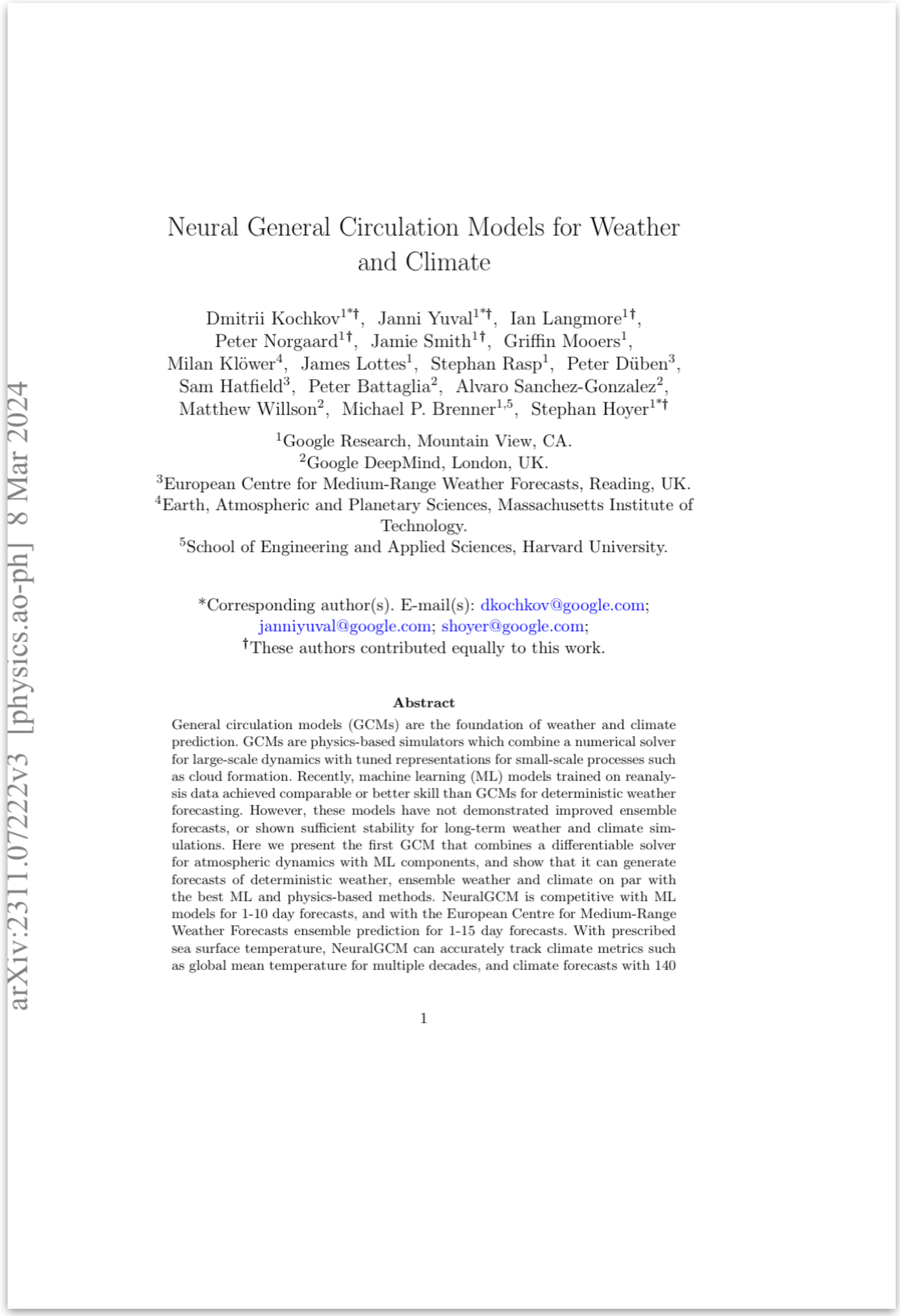
Trained from ocean reanalyses



Short term forecast skill

COMING UP

AI-native hybrid geoscientific models



arXiv:2311.07222v3 [physics.ao-ph] 8 Mar 2024

Neural General Circulation Models for Weather and Climate

Dmitrii Kochkov[1*†], Janni Yuval[1*†], Ian Langmore[1†], Peter Norgaard[1†], Jamie Smith[1†], Griffin Mooers[1], Milan Klöwer[4], James Lottes[1], Stephan Rasp[1], Peter Düben[3], Sam Hatfield[3], Peter Battaglia[2], Alvaro Sanchez-Gonzalez[2], Matthew Willson[2], Michael P. Brenner[1,5], Stephan Hoyer[1*†]

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

*Corresponding author(s). E-mail(s): dkochkov@google.com; janniyuval@google.com; shoyer@google.com;
†These authors contributed equally to this work.

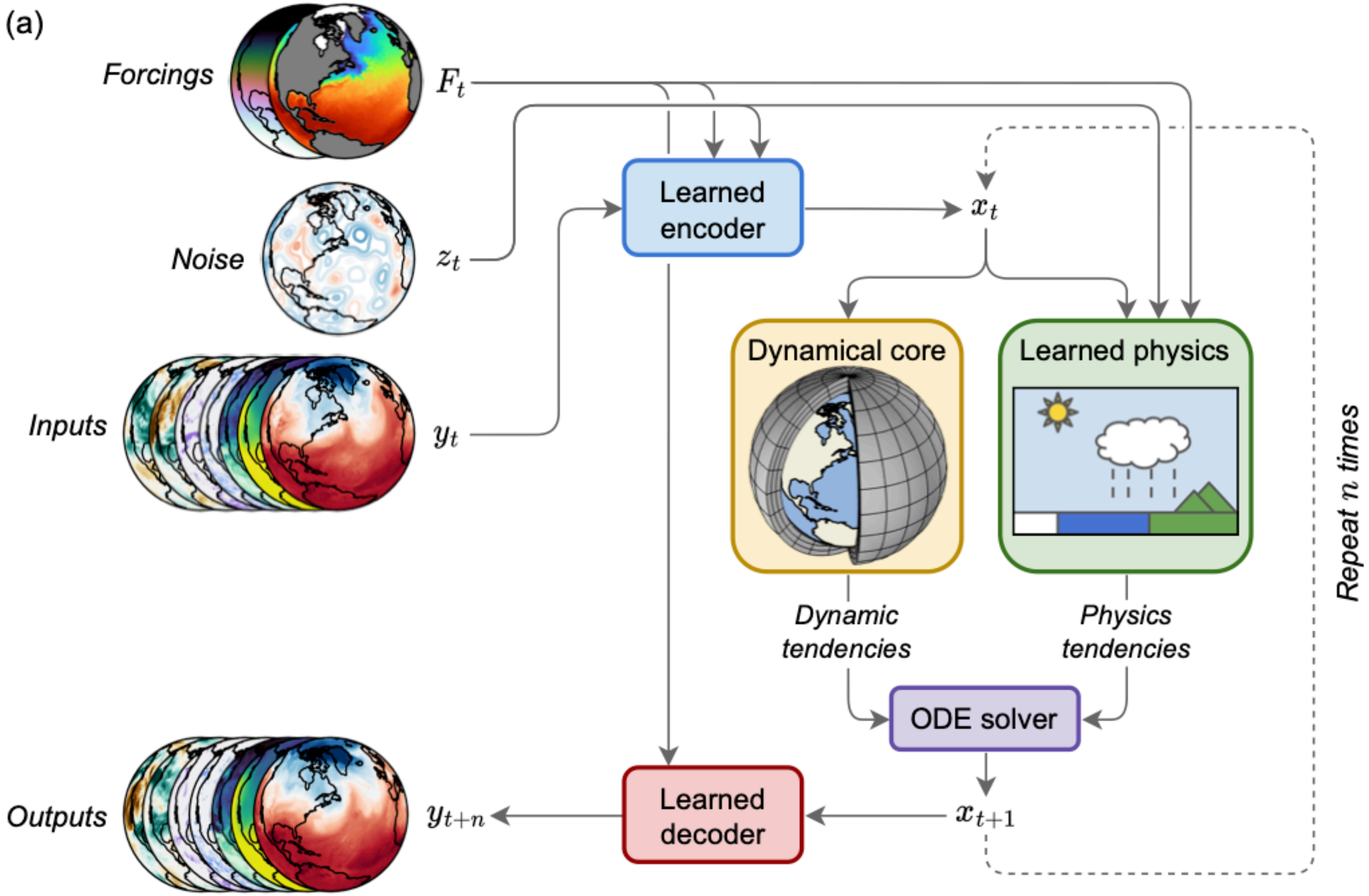
Abstract

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

https://arxiv.org/abs/2311.07222

Kochkov et al. (2024)



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

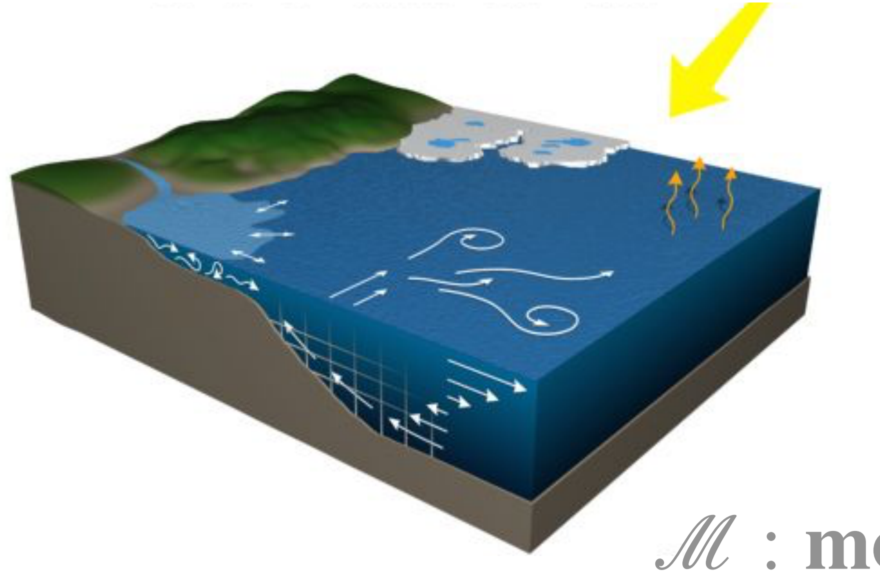
https://github.com/google-research/neuralgcm

Hybrid models combining physics and ML

Augmenting ocean models with ML components

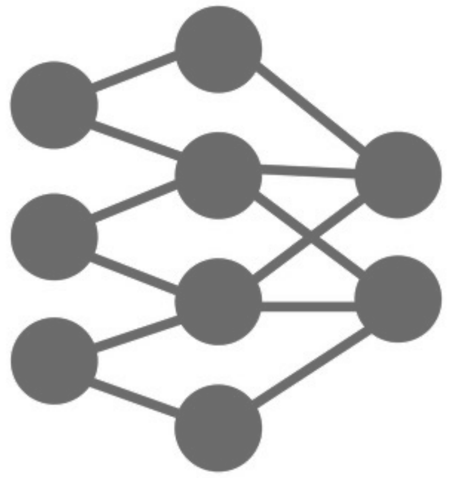
Input

step n



$\mathscr{M}$: **model**

+



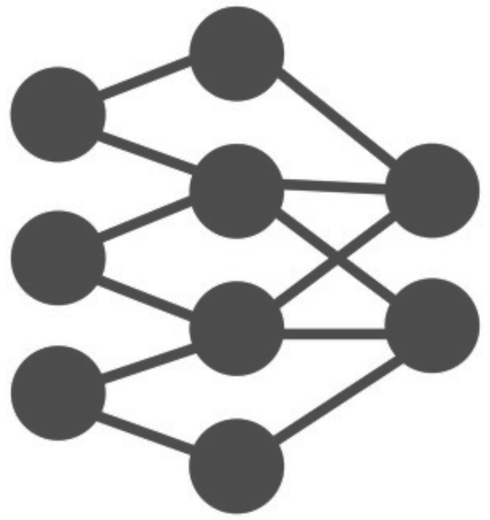
θ : **parameters**

step n+1

Output

The model is augmented with a trainable component

with



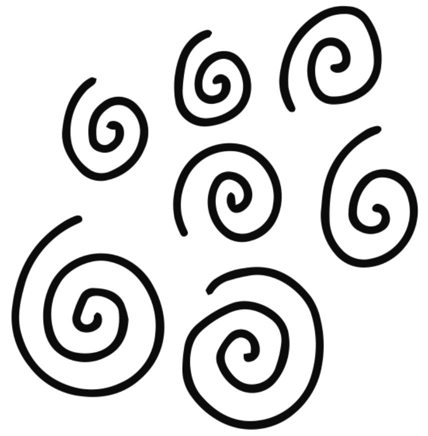
θ : **parameters**

trained to minimise :

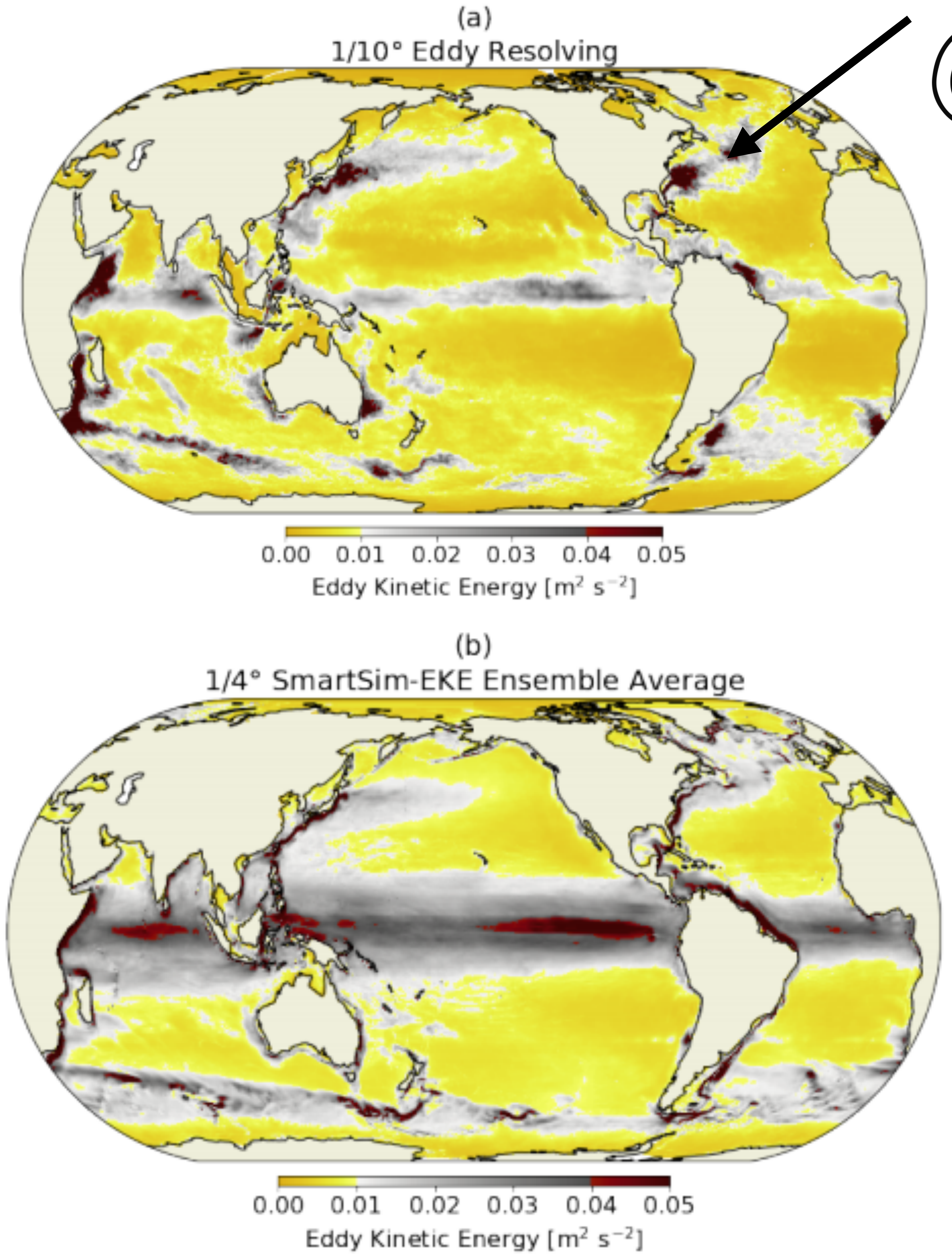
$$\mathscr{L}(\theta) = \textbf{training objective}$$

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

ML for ocean models subgrid physics (1/2)



ocean
macro-turbulence



Partee et al. (2022)

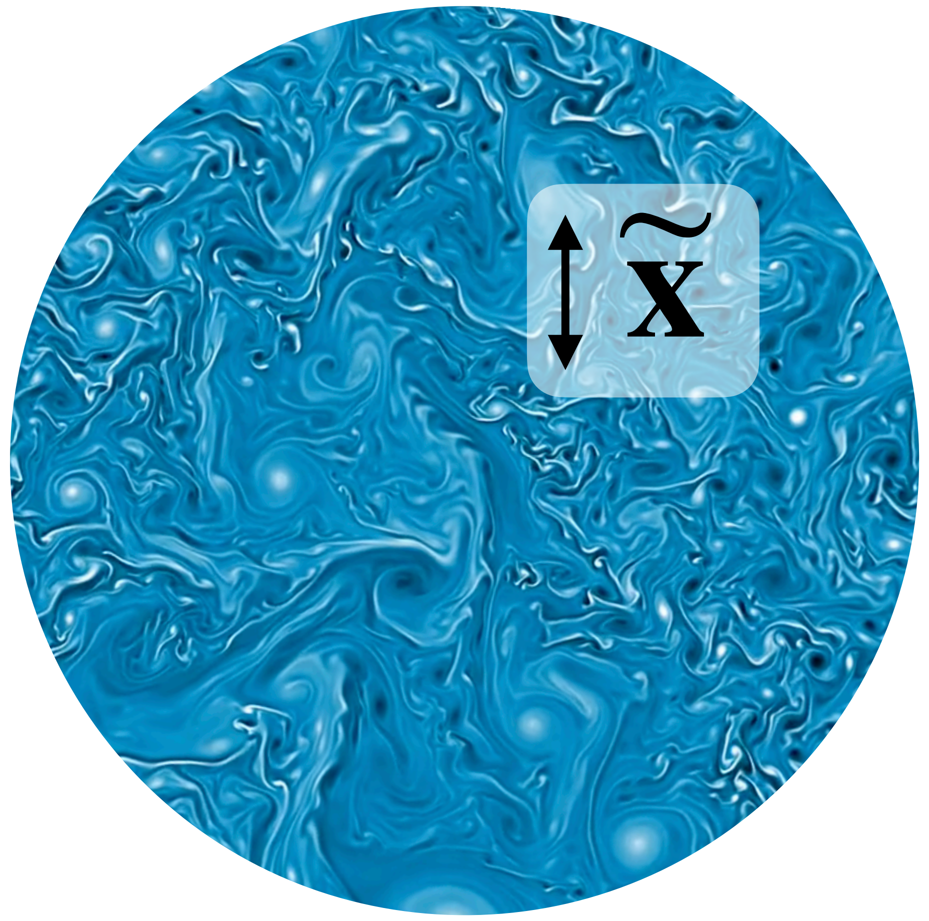
- missing terms from resolved quantities
- closures for turbulent processes
- leveraging hi-res/process model data
- encoded as closed forms or ML models
- a very active field (5-10 papers / months)

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)



Dynamical system

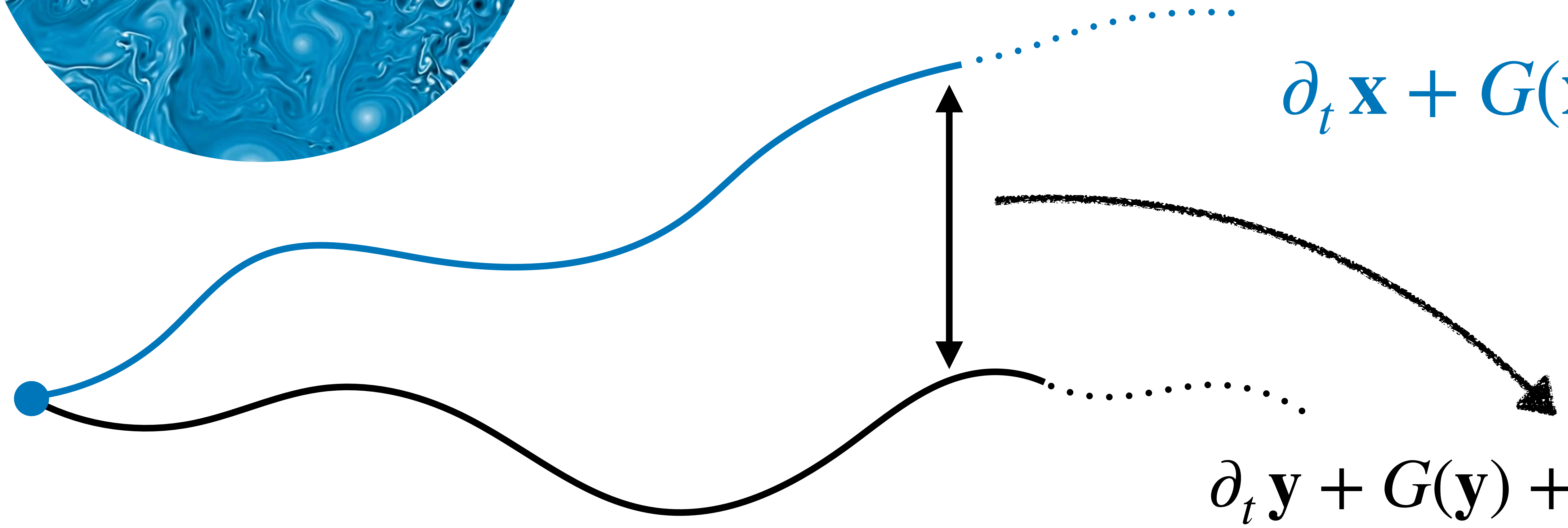
$$\partial_t \mathbf{x} + \mathscr{L}\,\mathbf{x} + \mathscr{N}(\mathbf{x}) = 0$$

Resolved equations

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

Subgrid closure

$$\mathscr{M}(\tilde{\mathbf{x}}) \simeq \mathscr{N}(\tilde{\mathbf{x}}) - \widetilde{\mathscr{N}(\mathbf{x})}$$

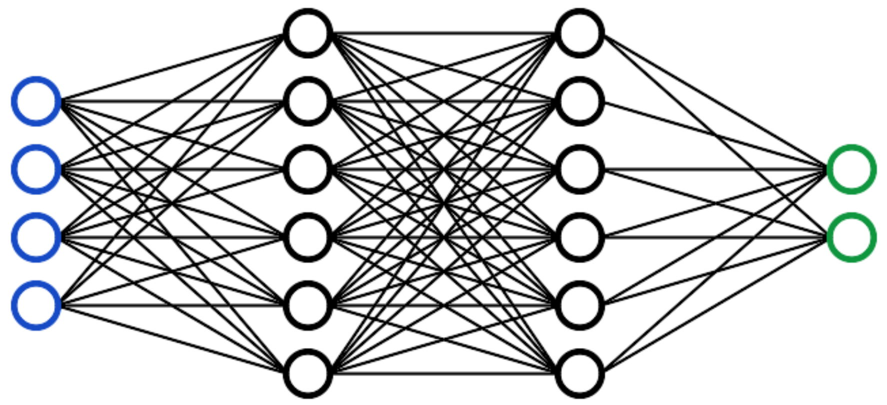


$$\partial_t \mathbf{x} + G(\mathbf{x}) = 0$$

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

Learning the mapping

$$\tilde{\mathbf{x}}(t) \rightarrow \mathscr{M}(\tilde{\mathbf{x}}(t))$$



θ : **parameters**

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

Frezat et al. (2023)

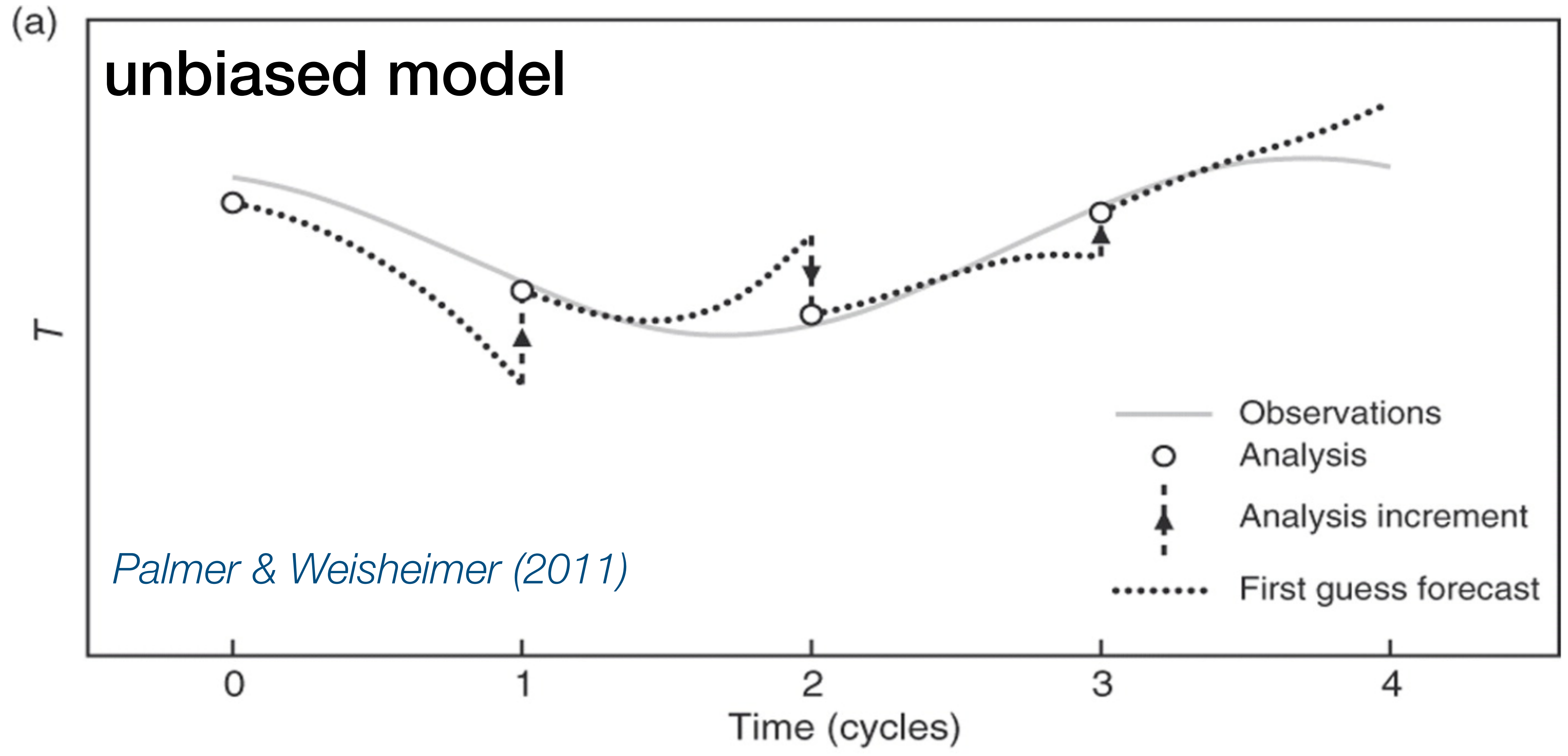
Gradient-free training

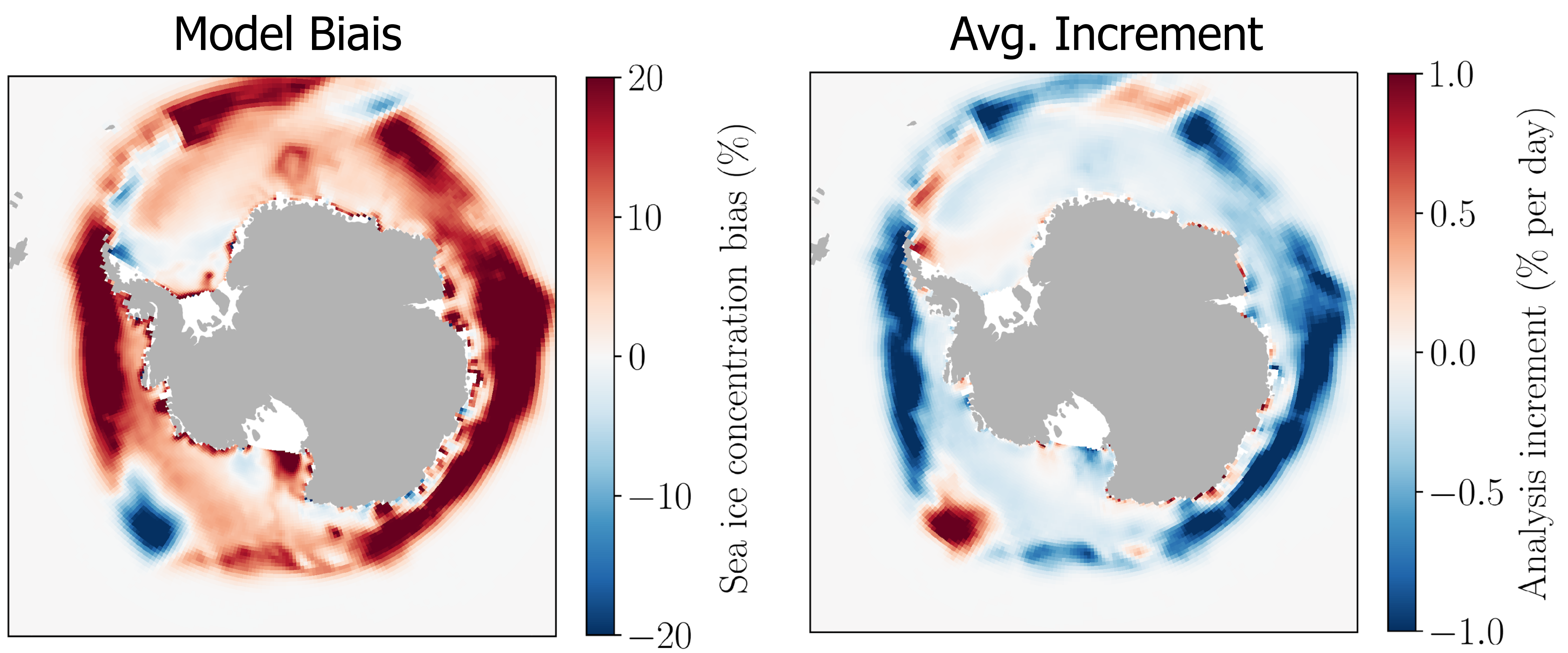
training model emulator
for approx. gradient
wrt NN. parameters

Performance, stability

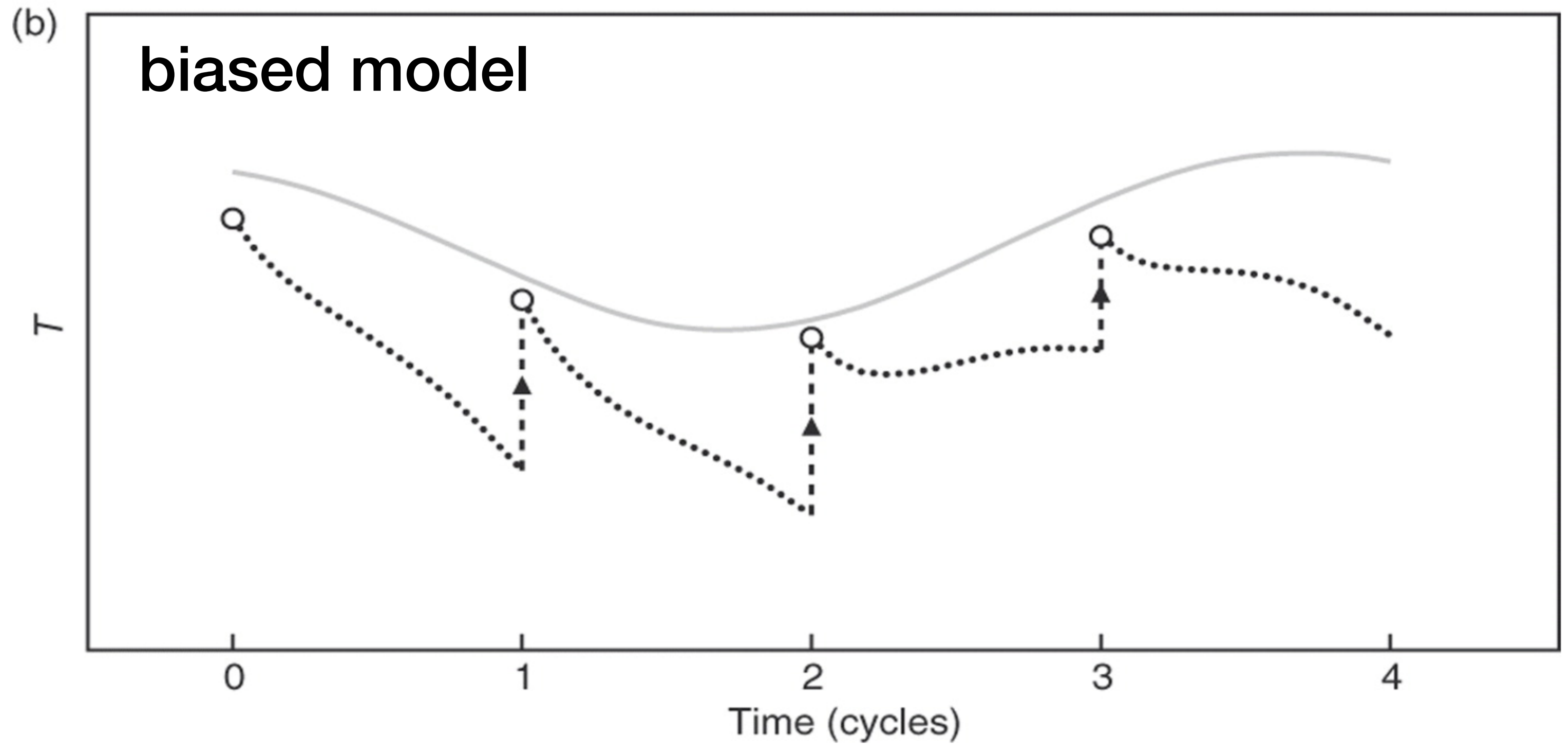
Generalisation, interpretability

Learning model error from DA increments (1/3)





Gregory et al. (2023)

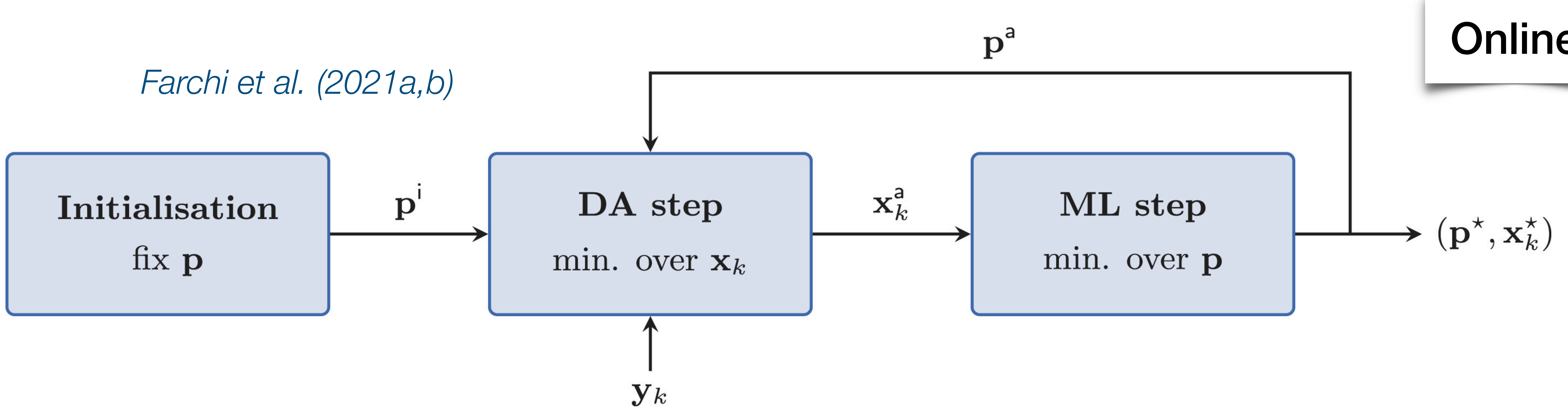


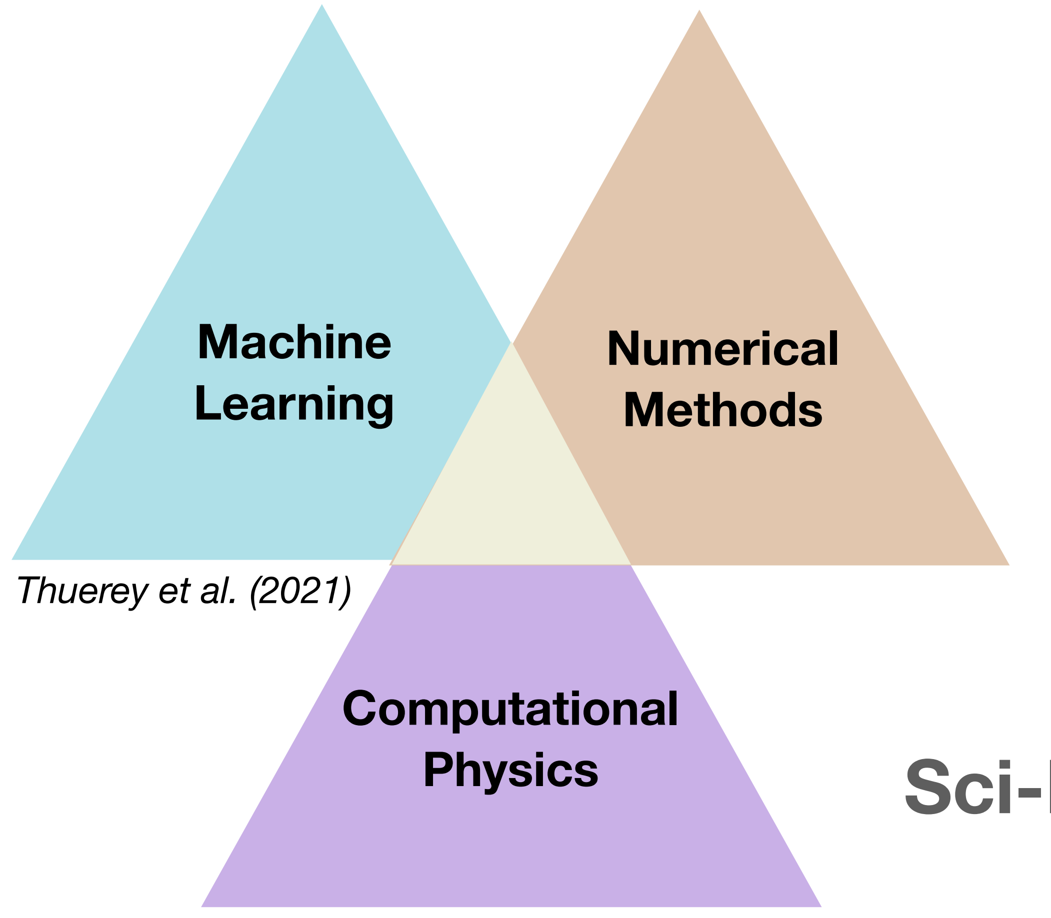
- w/ unbiased observations, analysis increments compensate for model biais
- estimating state-dependent bias corrections (Leith, 1978; Saha, 1992; DelSole and Hou, 1999)
- state-dependent biais corrections provide a representation of model errors

Learning model error from DA increments (2/3)

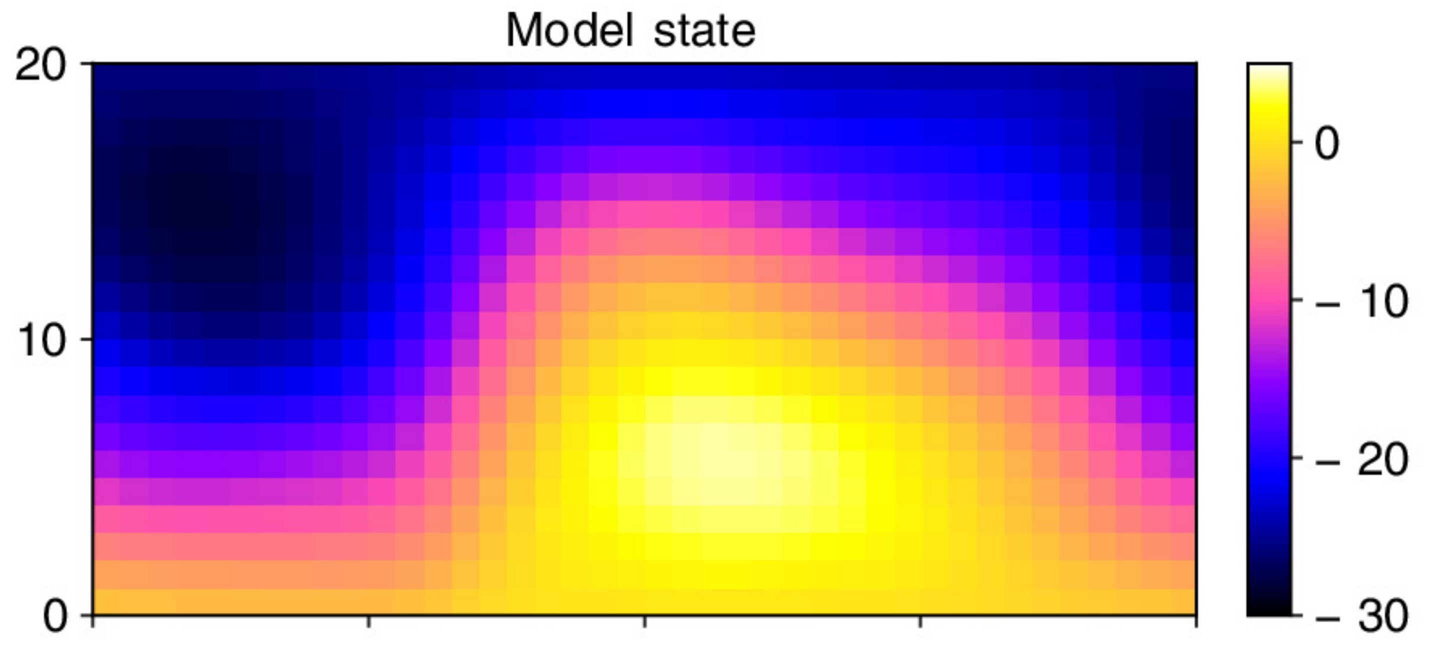
Farchi et al. (2021a,b)

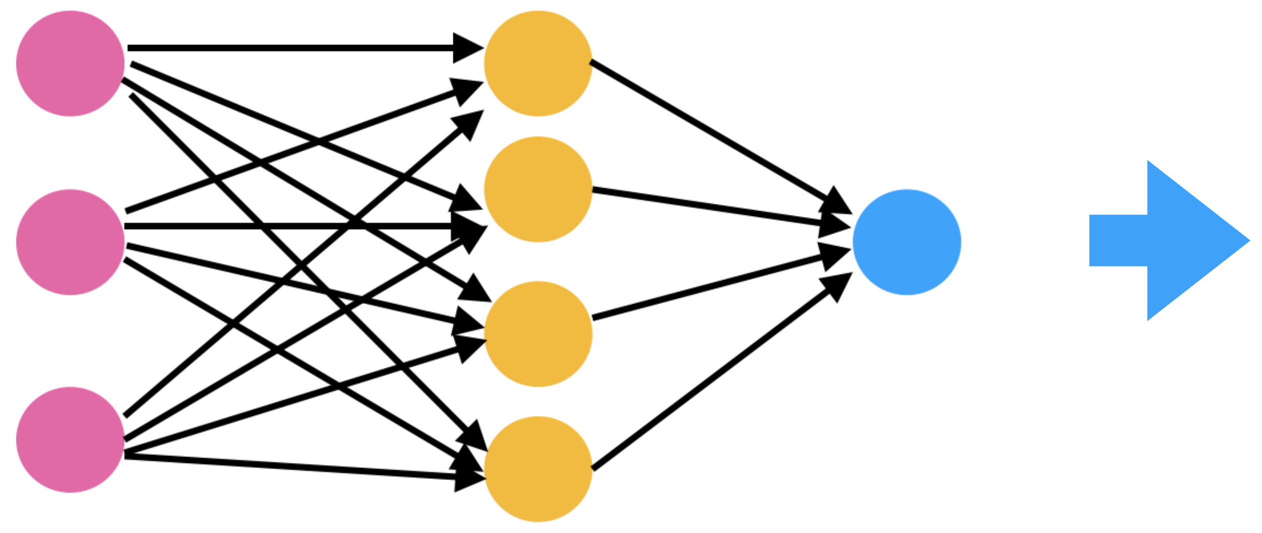
Online

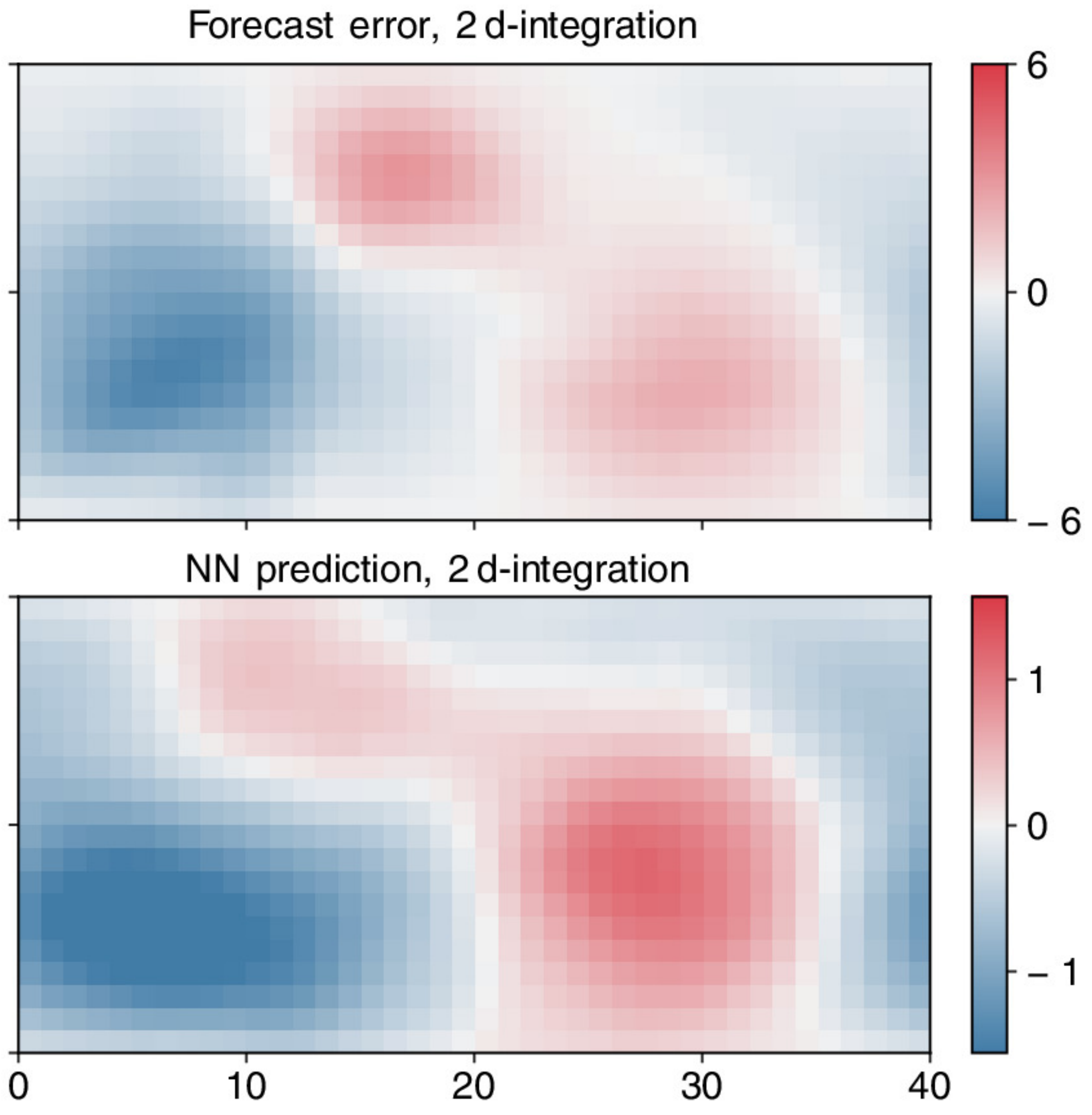




Sci-ML





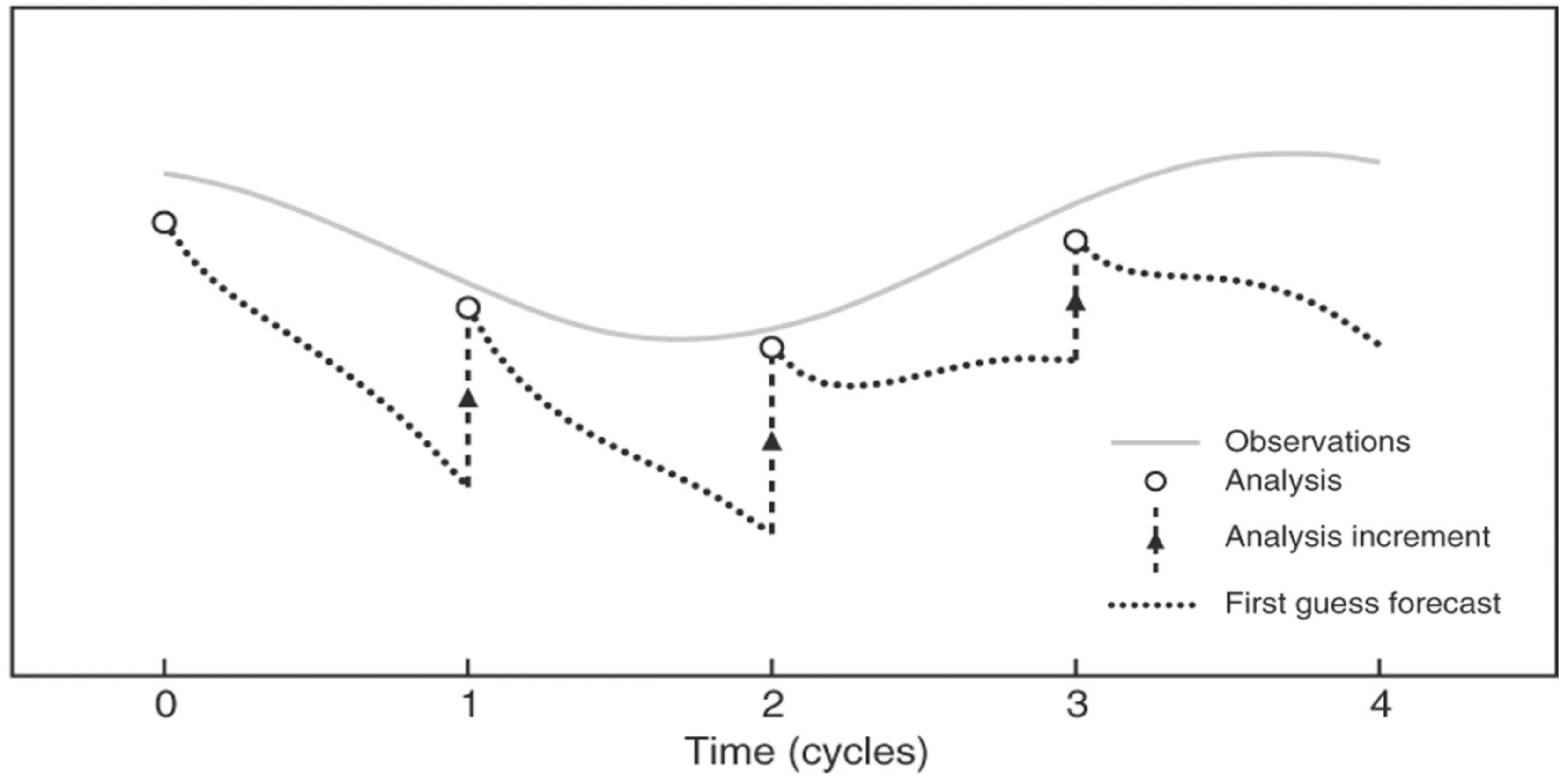


Online estimation of model errors w/ a joint DA-ML 4DVAR (weak)

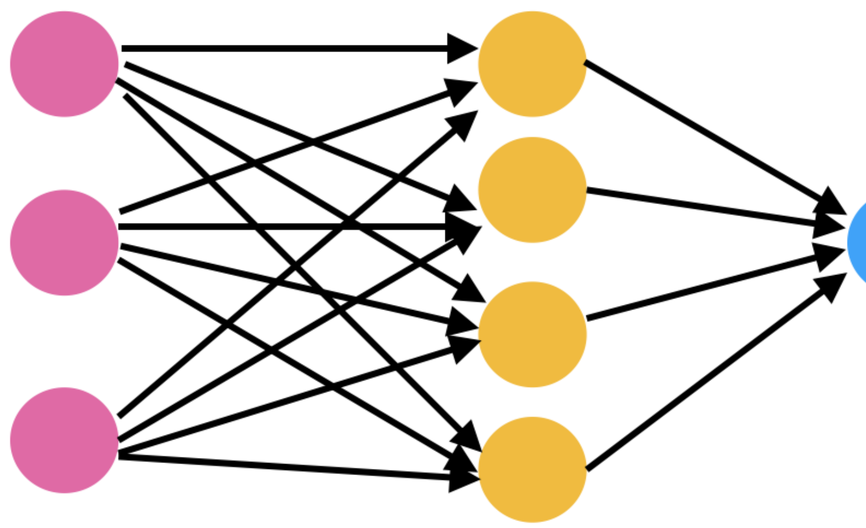
- renewed interest in biais corrections for DA systems over recent years
- joint DA-ML frameworks for estimating model errors (in idealised settings)
- iterative online training of NN with DA

(Farchi et al. 2021a,b; 2023; Brajard et al. 2021; Frezat et al. 2022)

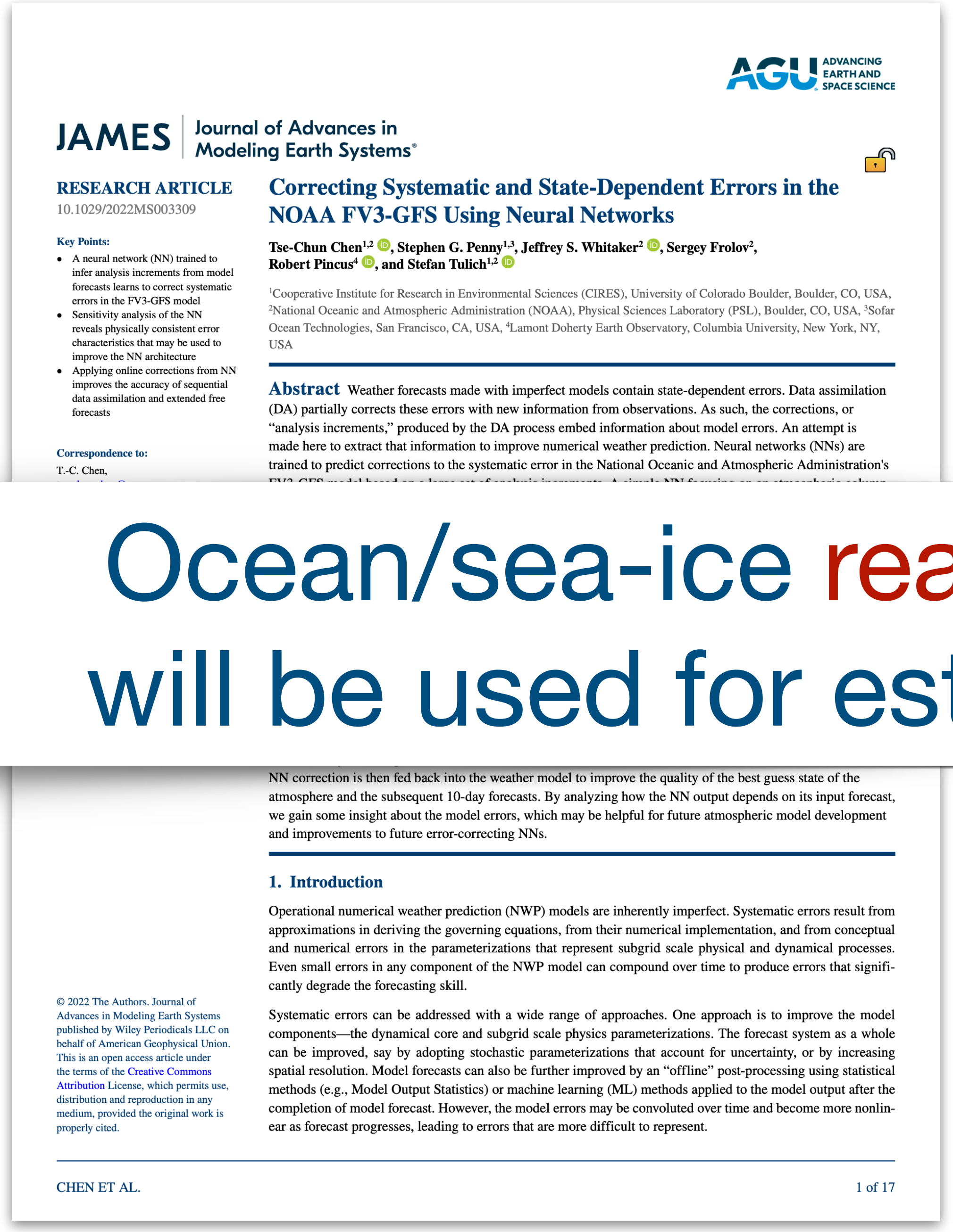
Learning model error from DA increments (3/3)



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


JAMES Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1029/2022MS003309

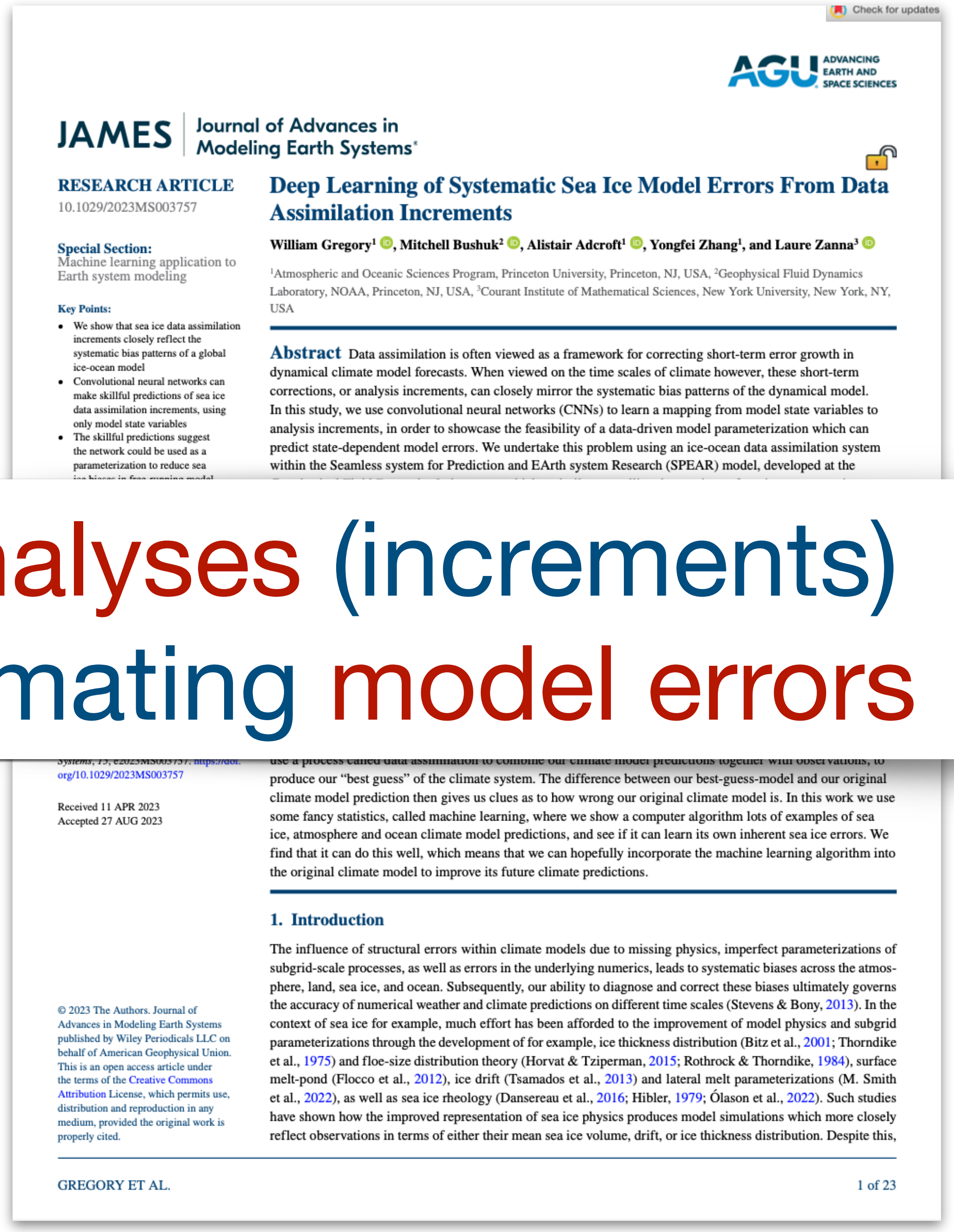
Correcting Systematic and State-Dependent Errors in the NOAA FV3-GFS Using Neural Networks

Tse-Chun Chen, Stephen G. Penny, Jeffrey S. Whitaker, Sergey Frolov, Robert Pincus, and Stefan Tulich

1. Introduction

CHEN ET AL. 1 of 17

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


JAMES Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1029/2023MS003757

Deep Learning of Systematic Sea Ice Model Errors From Data Assimilation Increments

William Gregory, Mitchell Bushuk, Alistair Adcroft, Yongfei Zhang, and Laure Zanna

1. Introduction

GREGORY ET AL. 1 of 23

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

Ocean/sea-ice reanalyses (increments) will be used for estimating model errors

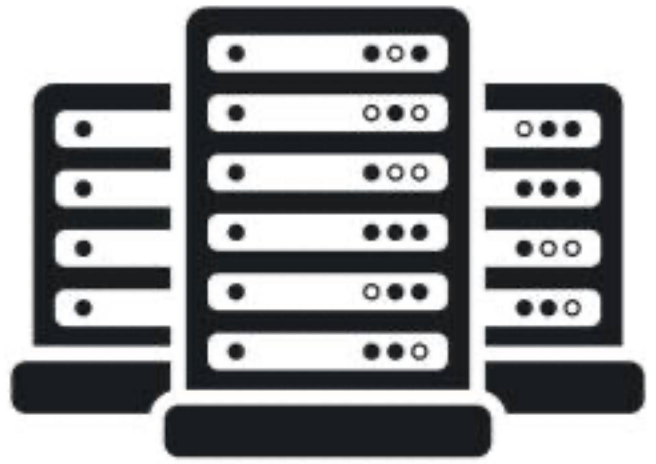
(Bonavita and Laloyaux, 2020; Watt-Meyer et al., 2021; Chen et al., 2022; Gregory et al. 2023; Chapman and Berner 2023)

Hybrid modelling with existing codes

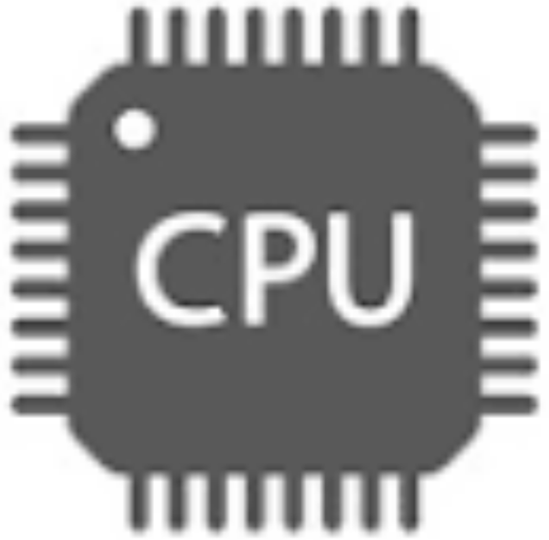
Interfacing ocean models with DL frameworks (1/3)

stable, robust, low abstraction languages

+



supercomputers

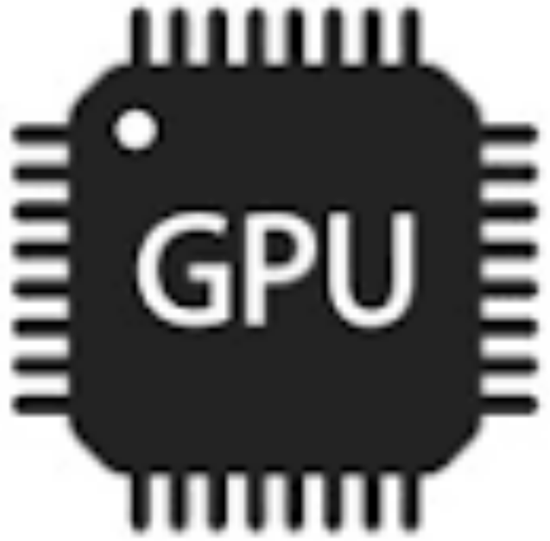


runs only on CPUs

high abstraction, fast evolving languages

+

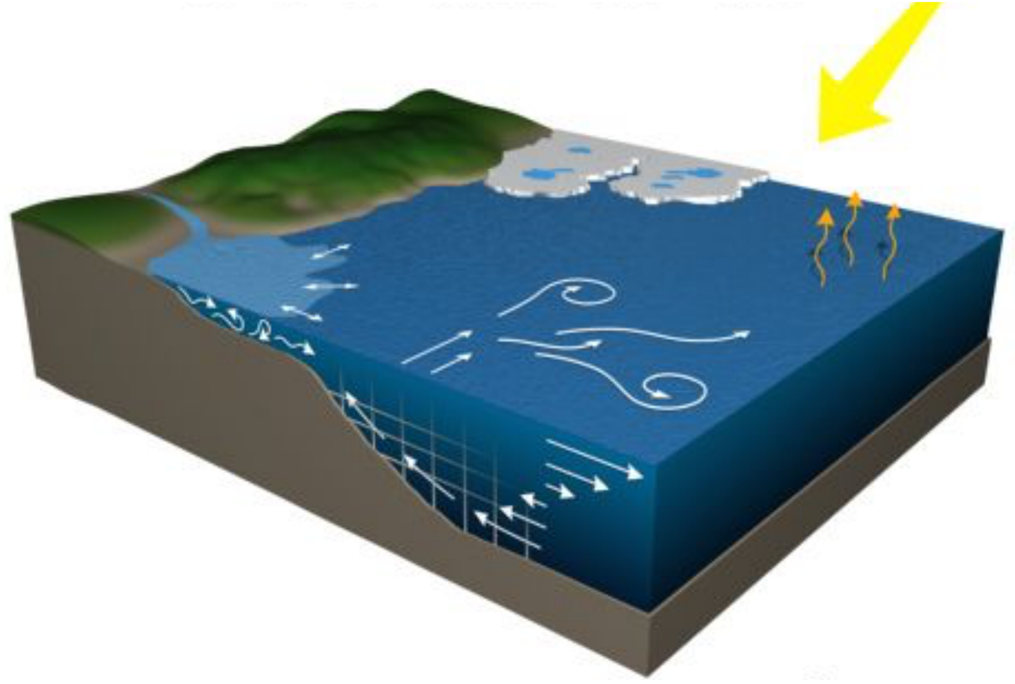
cloud ready

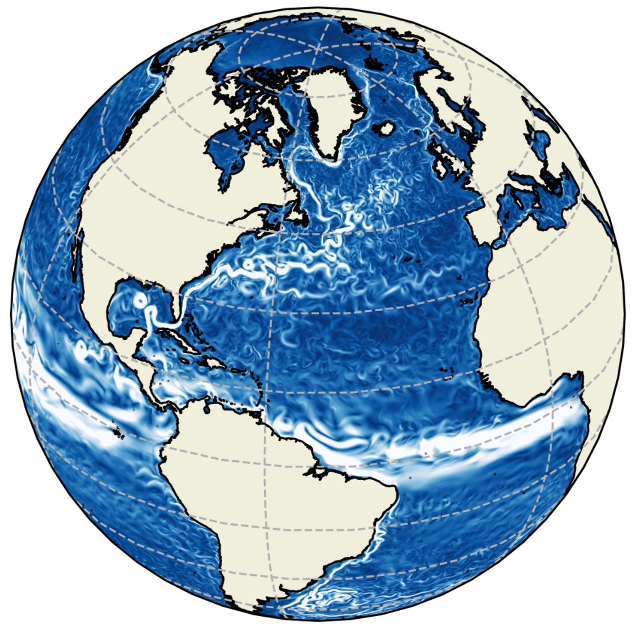


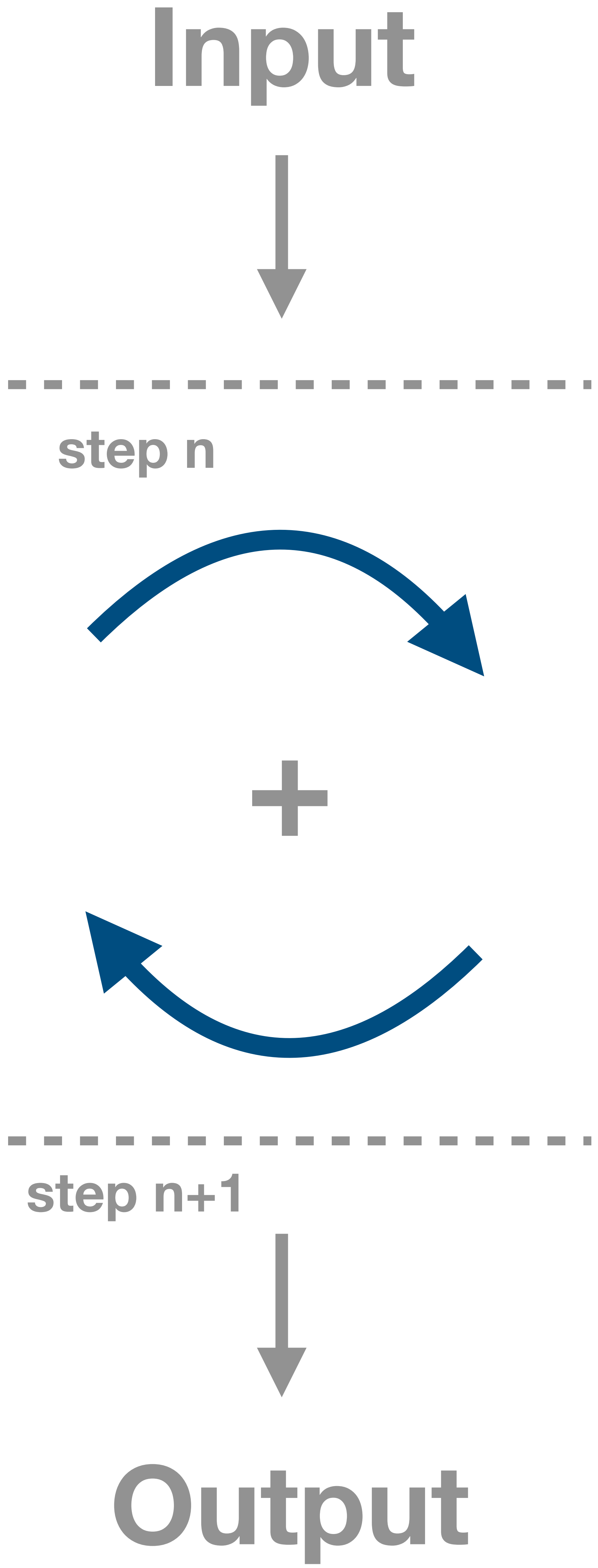
natively runs on GPUs

Interfacing ocean models with DL frameworks (2/3)

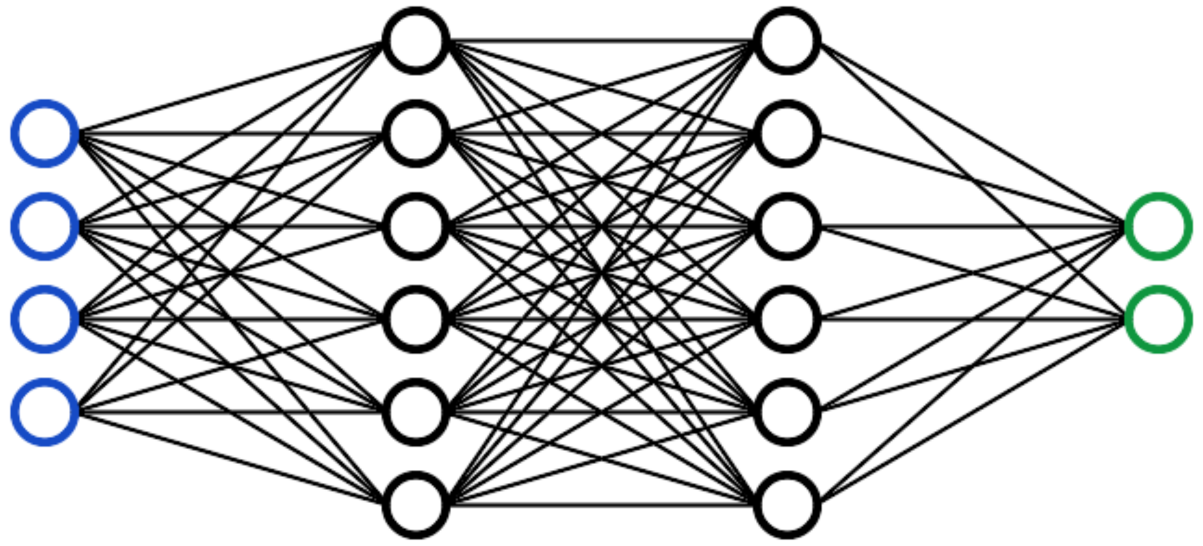
Ocean circulation models



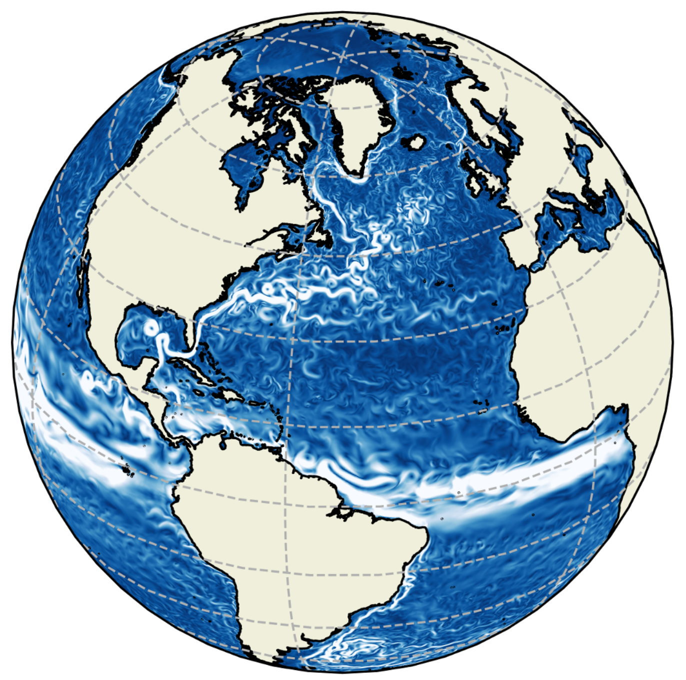


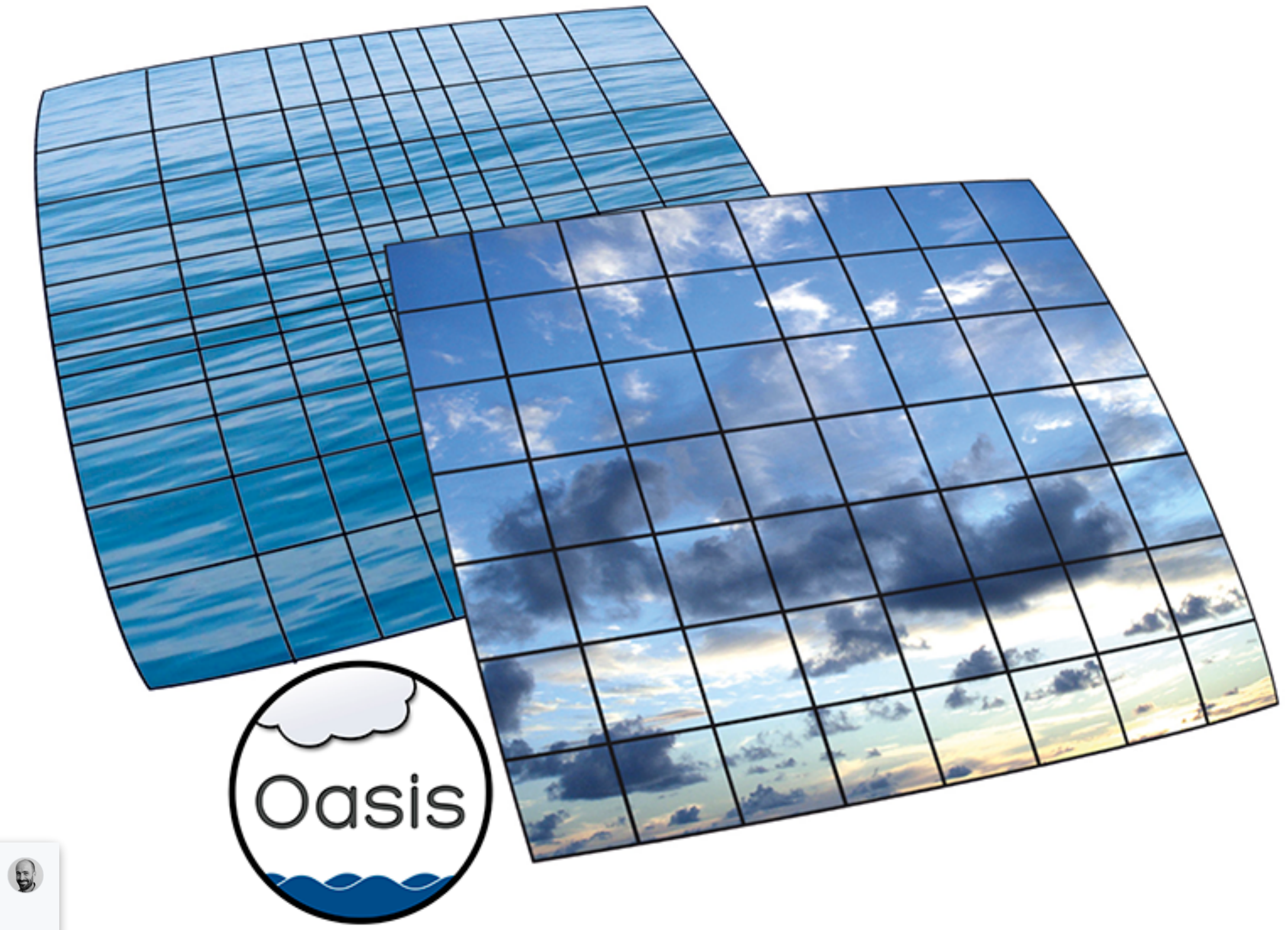


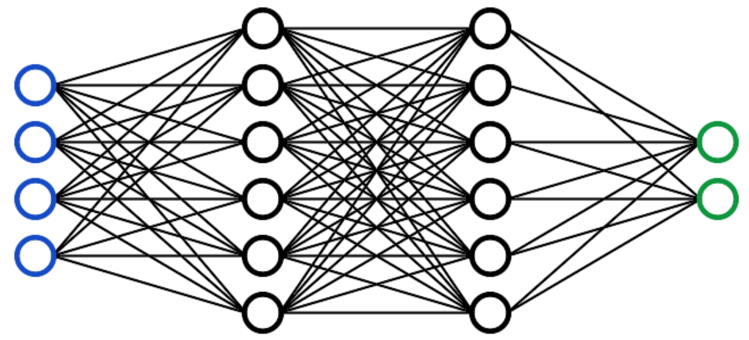
Trainable components
(closures, error corrections)

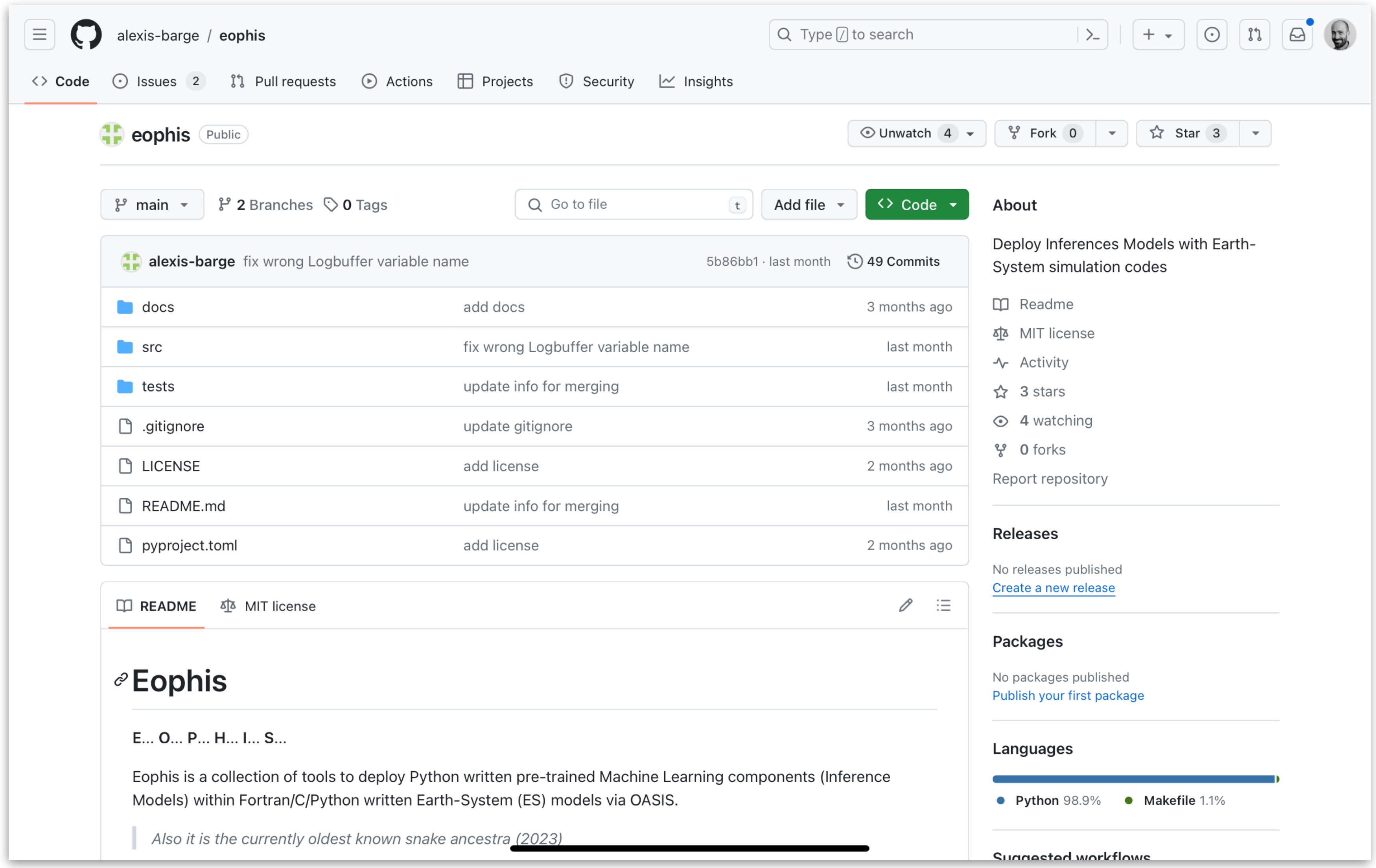


Interfacing ocean models with DL frameworks (3/3)









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

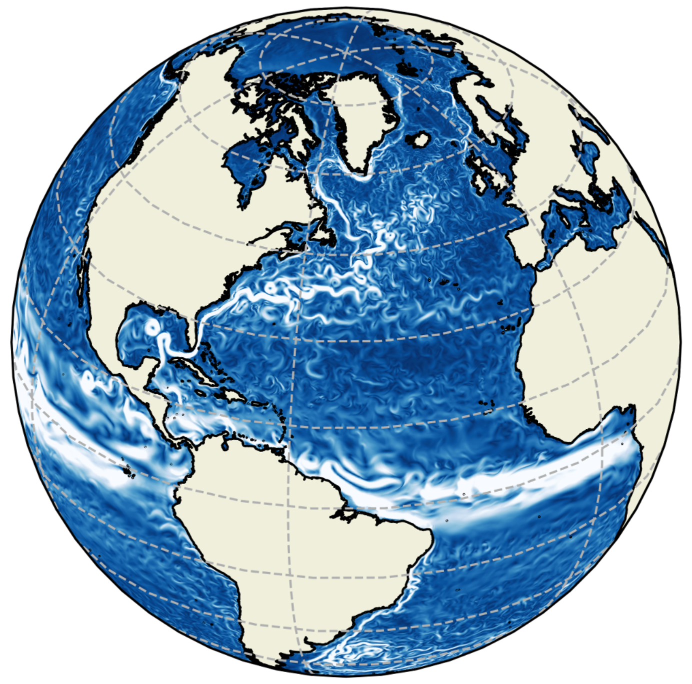
A. Barge

Work by Alexis Barge at IGE

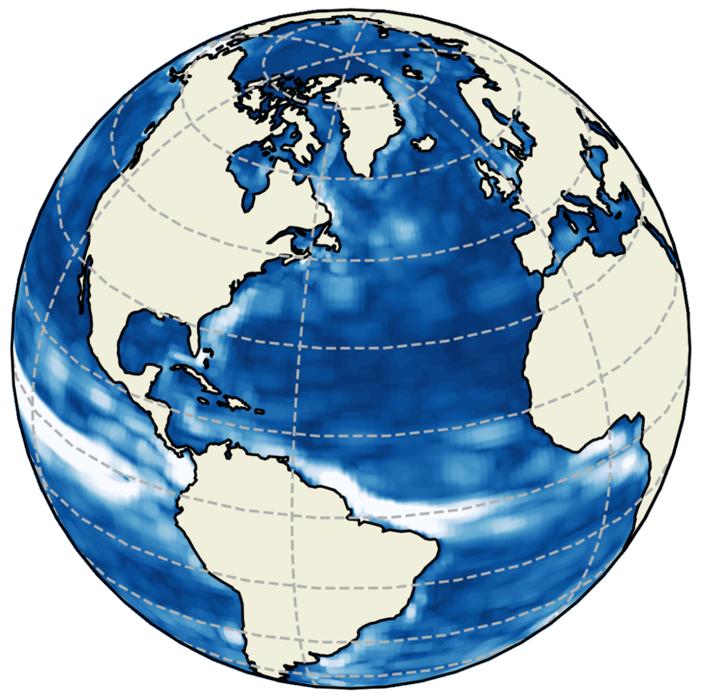
- OASIS : exchange of 3D data between different codes
- Eophis : simplified deployment of ML models w/ OASIS
- Requires some change to the NEMO code
- Key : portability, domain decomposition

ML for ocean macro-turbulence

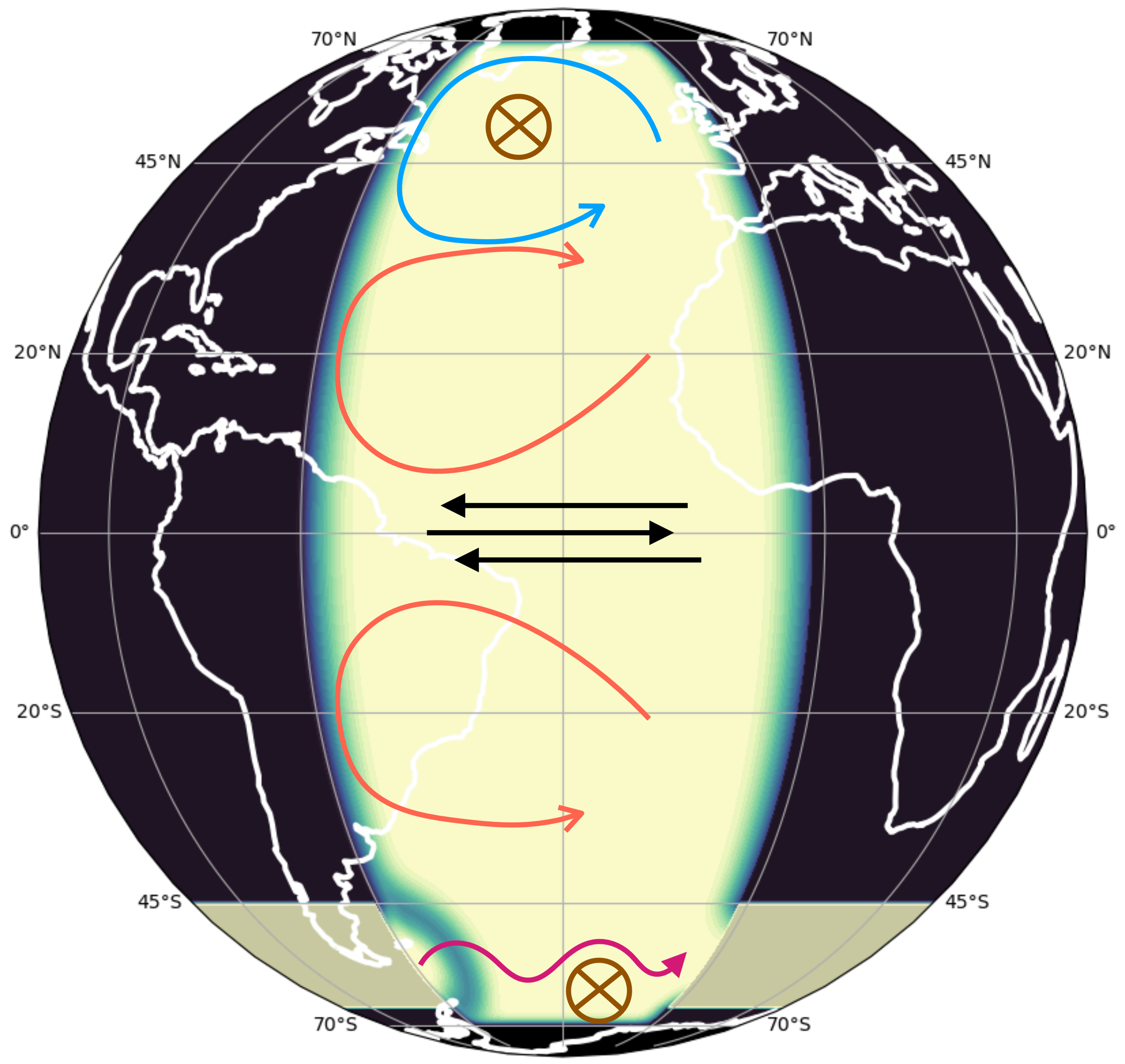
Target NEMO configurations



NEMO-eORCA025



NEMO-eORCA1



DINO : Diabatic Neverworld

Light-weight test-bed

resolutions ~ 1°, 1/4°, 1km

D. Kamm

E. Meunier

J. Deshayes

On-going work :

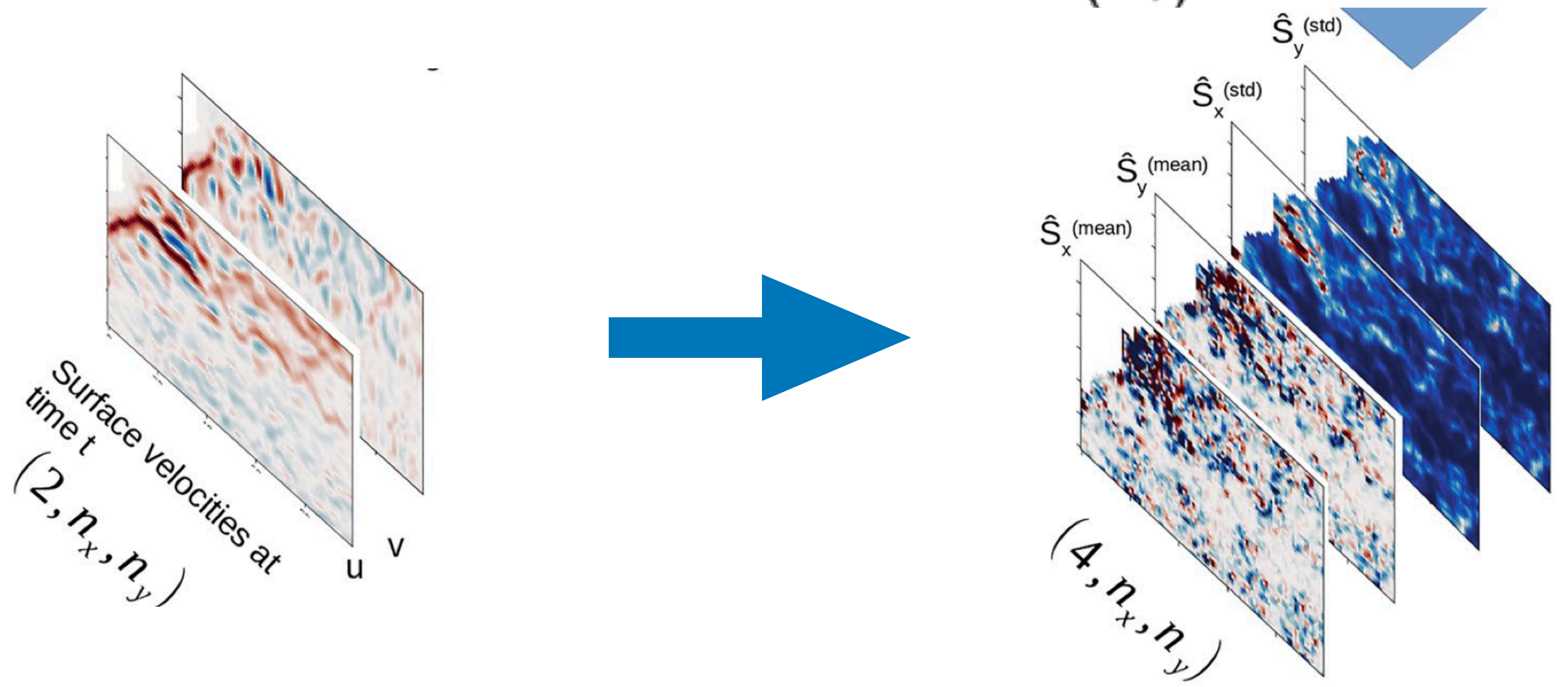
Subgrid momentum forcing due to mesoscale eddies

Work by D. Kamm, E. Meunier, A. Barge

Collaboration through M2LINES project

$$\frac{\partial \bar{\mathbf{u}}_k}{\partial t} + \frac{f+\bar{\zeta}_k}{\bar{h}_k}\hat{\mathbf{z}}\times \bar{h}_k\bar{\mathbf{u}}_k + \nabla\bar{K}_k + \nabla\bar{M}_k = \bar{\mathbf{F}}_k + \mathbf{S}_k$$

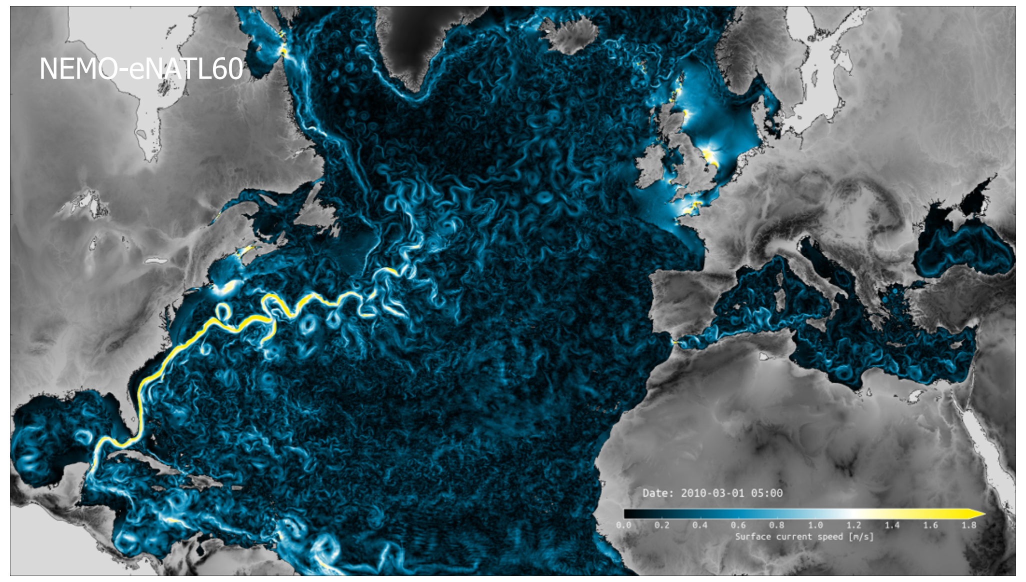
$$\mathbf{S}_k = \begin{pmatrix}S_{kx}\\ S_{ky}\end{pmatrix} = (\bar{\mathbf{u}}_k\cdot\nabla)\bar{\mathbf{u}}_k - \overline{(\mathbf{u}_k\cdot\nabla)\mathbf{u}_k}$$



Guillaumin and Zanna 2021 https://doi.org/10.1029/2021MS002534

Zhang et al. 2023 https://doi.org/10.1029/2023MS003697

Training from realistic ocean models

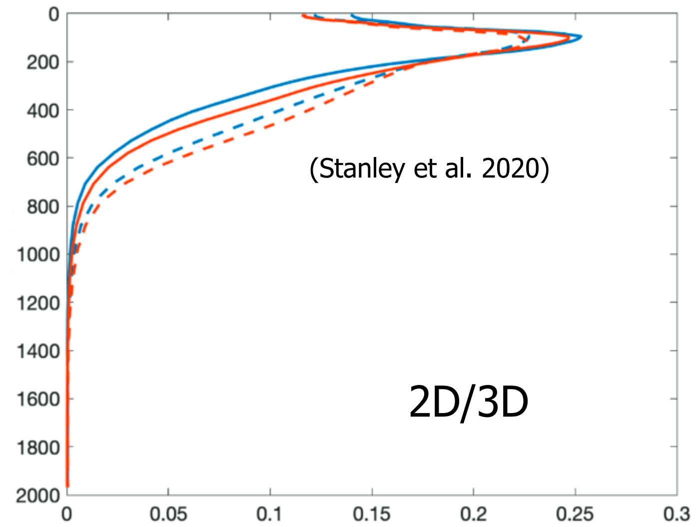


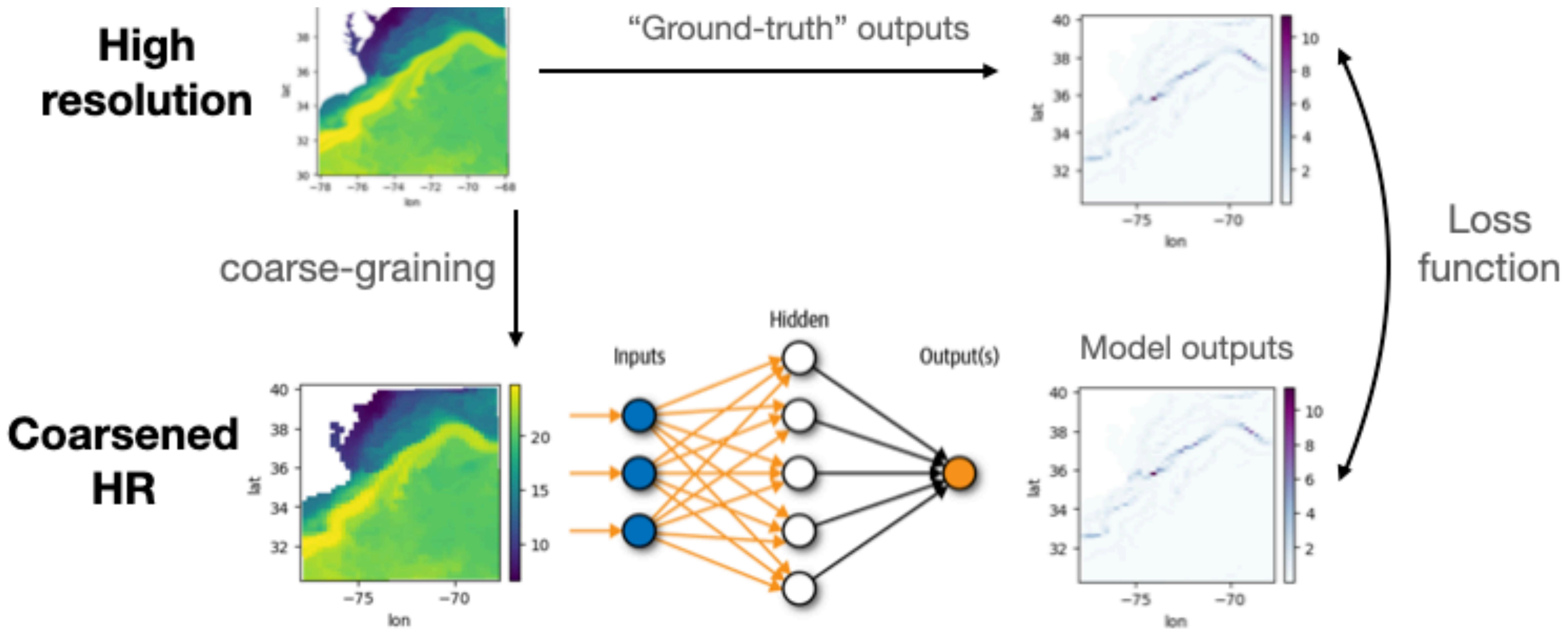
- geometry, grid, coastlines
- heterogeneous regimes
- optimal coarse graining
- data structure / orchestration

sub-mesoscale
temperature variance

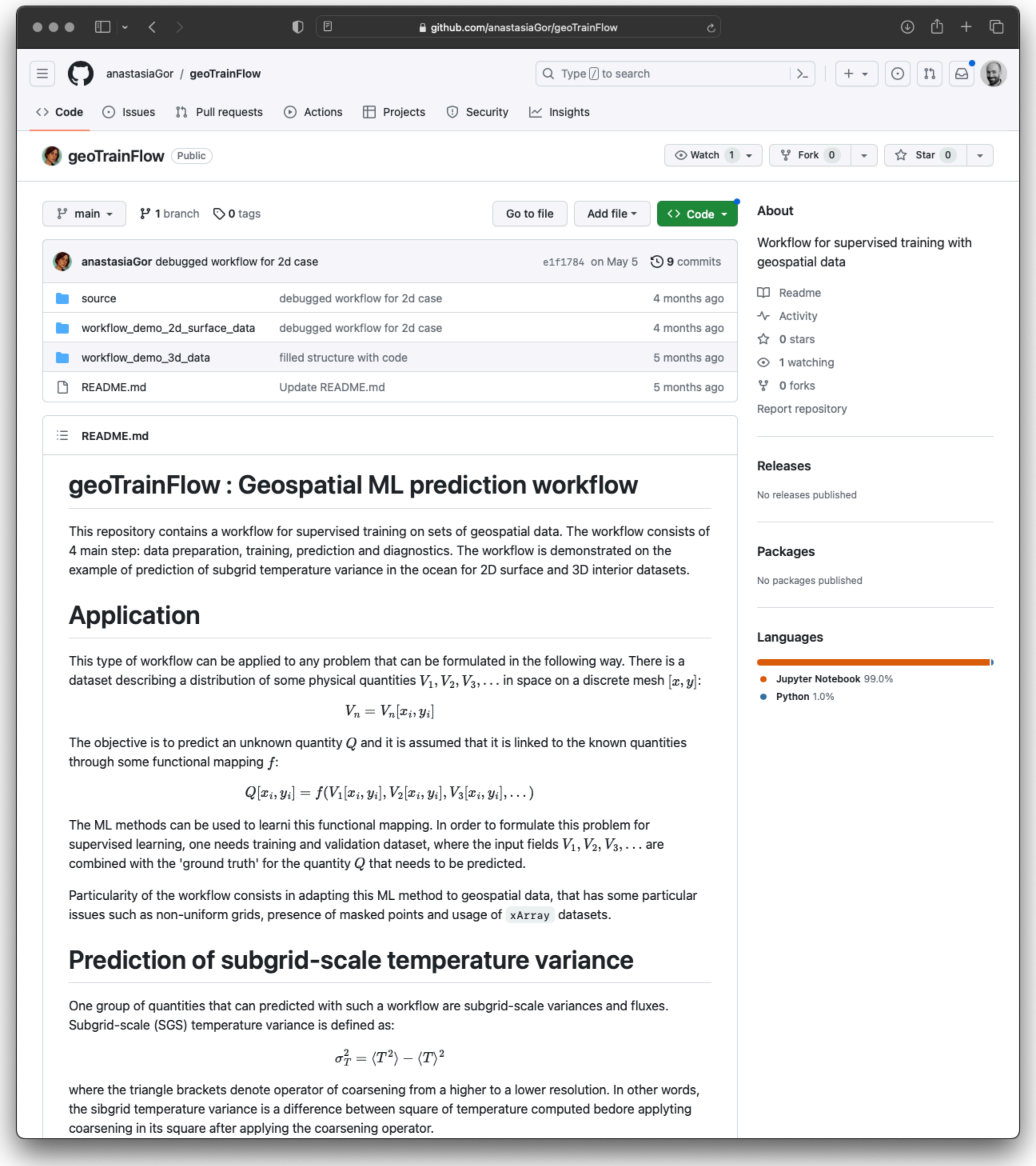
$$\sigma_T^2 = \langle T^2 \rangle - \langle T \rangle^2$$

w/ simple baseline (eq. state)



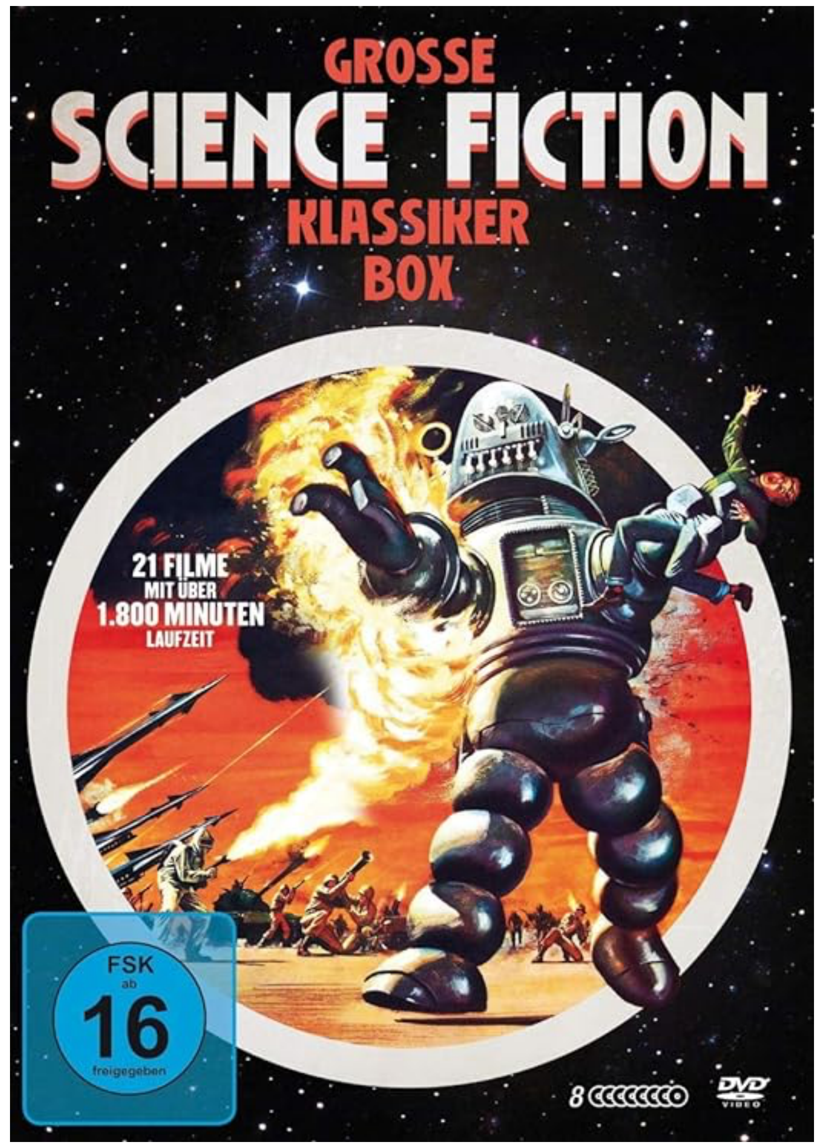


Problem formulation



GeoTrainFlow training pipeline

A. Gorbunova

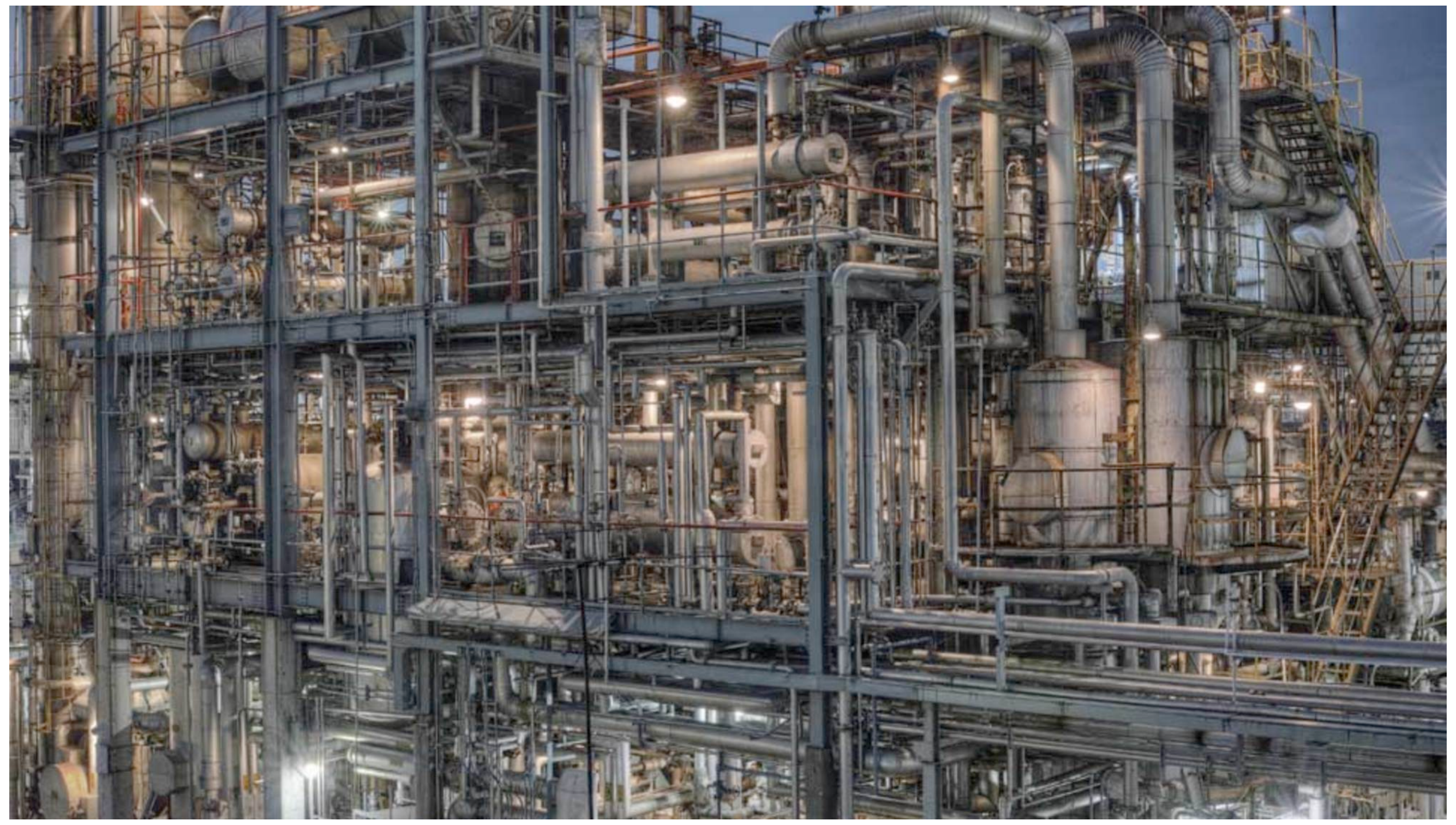


The need for AI-native hybrid models

Avoid having to bridge the technological gap

stable, robust, low abstraction languages

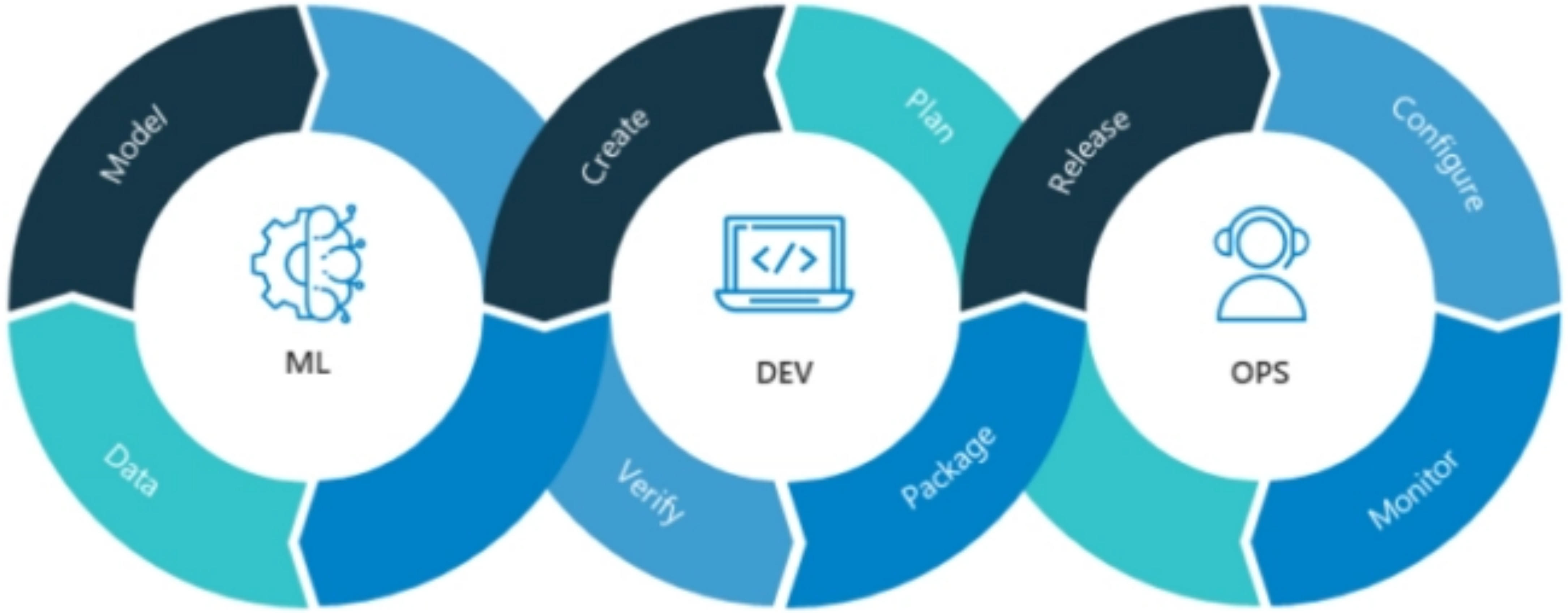
+



Less robust software design (APIs)

high abstraction, fast evolving languages

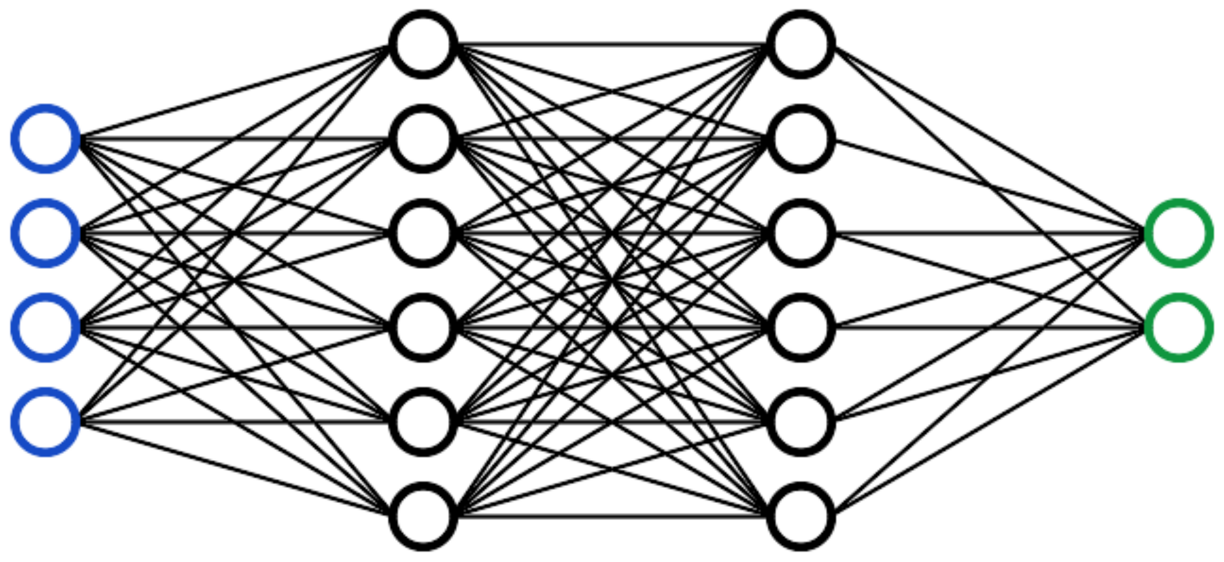
+



Clean APIs and MLOPs

Training ML components for physical models

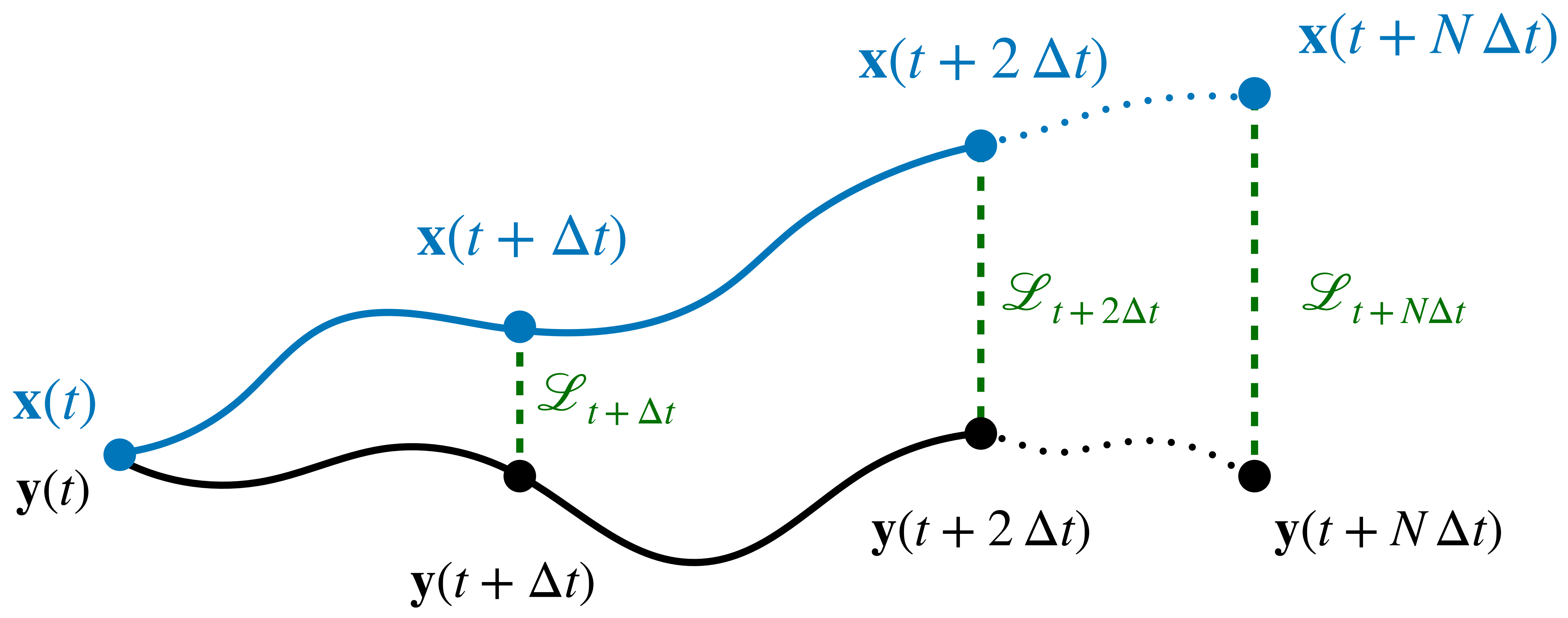
offline learning



mapping $\overline{\mathbf{x}} \rightarrow \overline{\mathcal{N}(\mathbf{x})}$

at fixed time t

online learning



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

along a trajectory

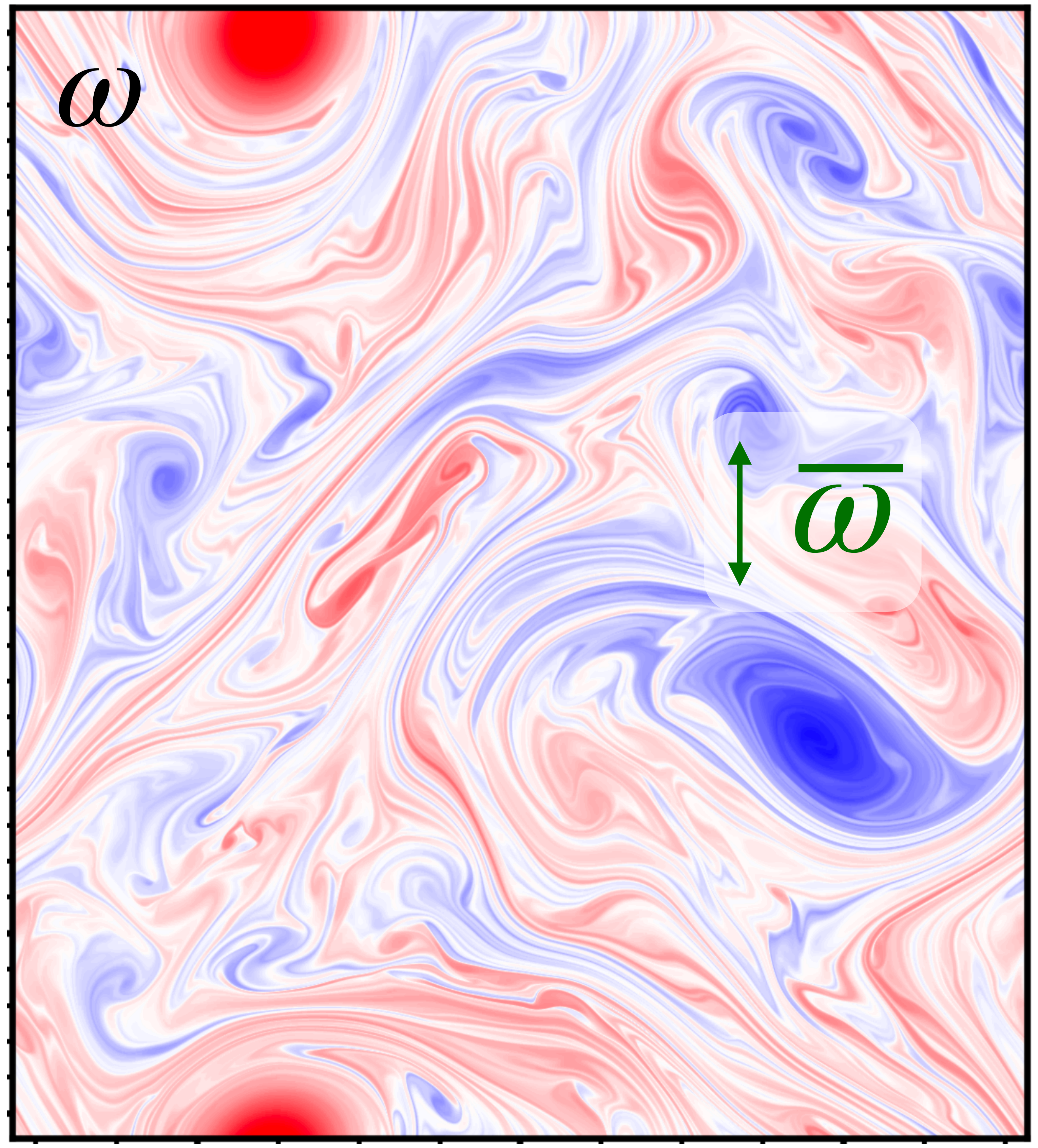
(a.k.a : a posteriori, solver-in-the-loop, end-to-end)

Frezat et al. 2022, JAMES

How does online training affects : performance, stability, generalisation

ML closure for ocean macro-turbulence (1/3)

$$\partial_t \omega + J(\psi, \omega) = \nu \nabla^2 \omega - \mu\omega - \beta \partial_x \psi + F$$



See e.g. Graham and Ringler (2013)

$$\omega = \nabla^2 \psi$$

vorticity

$$\mathbf{u} = (-\partial_y \psi, \partial_x \psi)$$

velocity

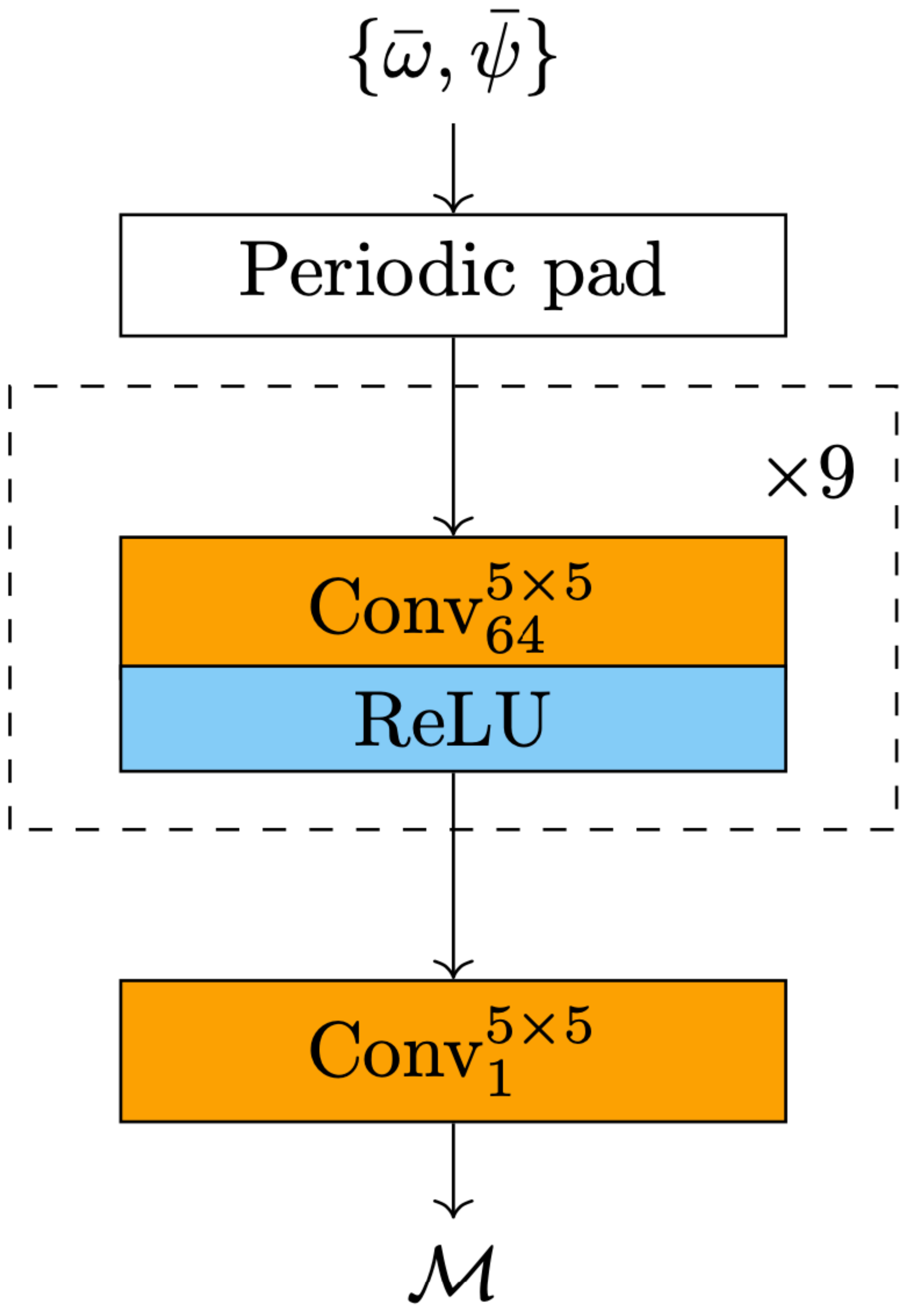
Filtering $\quad \overline{\omega} := \int \omega(\mathbf{x}') G(\mathbf{x} - \mathbf{x}') \mathrm{d}\mathbf{x}'$

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

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

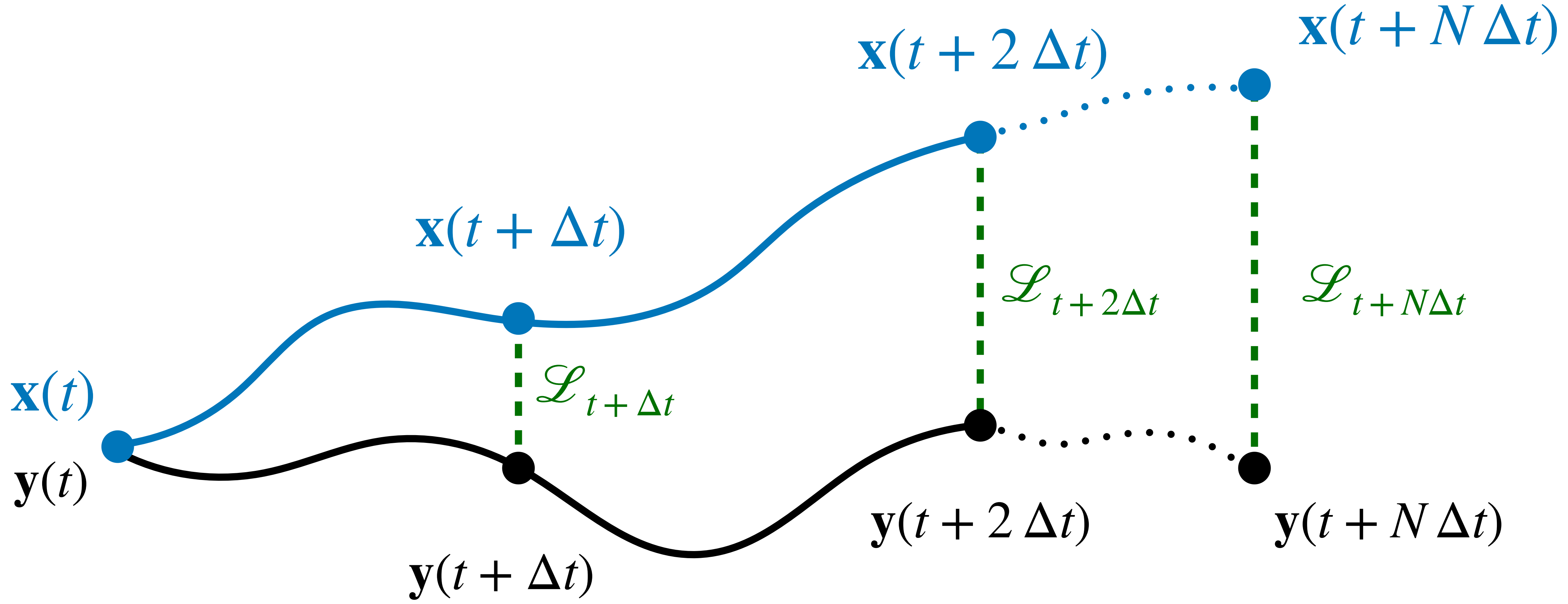
Closure pbm $\quad R(\psi, \omega) \simeq \mathscr{M}_\theta^{NN}(\bar{\psi}, \bar{\omega})$

ML closure for ocean macro-turbulence (2/3)



Loss for <u>a priori</u> training

$$\mathscr{L}_{\text{prio}}(\mathscr{M}) := \frac{1}{S}\sum_{i=1}^{S}\left(R(\psi,\omega)_i - \mathscr{M}(\bar{\psi}_i, \bar{\omega}_i)\right)^2$$

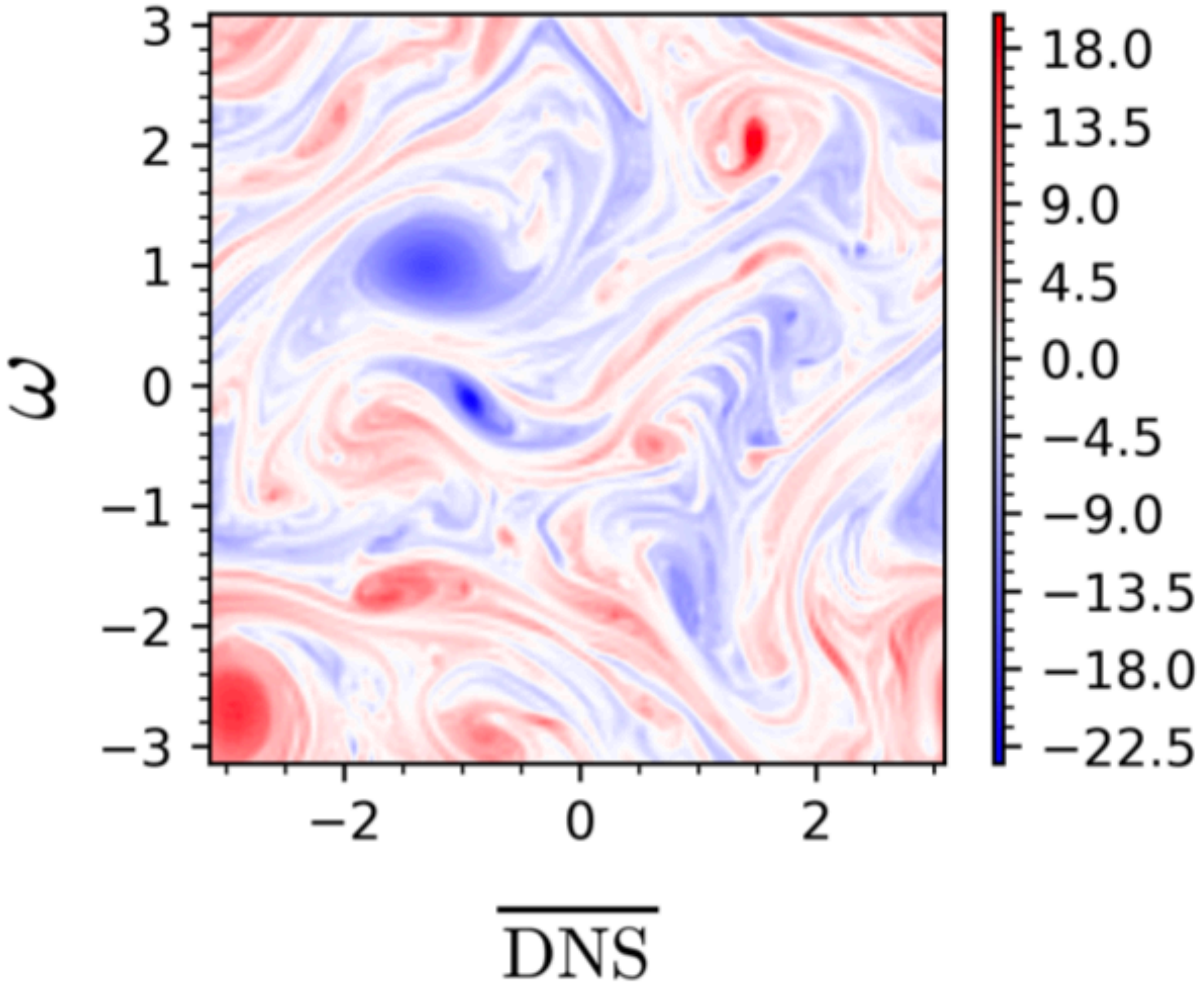


Loss for <u>a posteriori</u> training

$$\mathscr{L}_{\text{post}}(\mathscr{M}) := \frac{1}{N}\sum_{i=1}^{N}\left(\mathscr{T}(\omega(i\Delta t)) - \bar{\omega}(i\Delta t)\right)^2$$

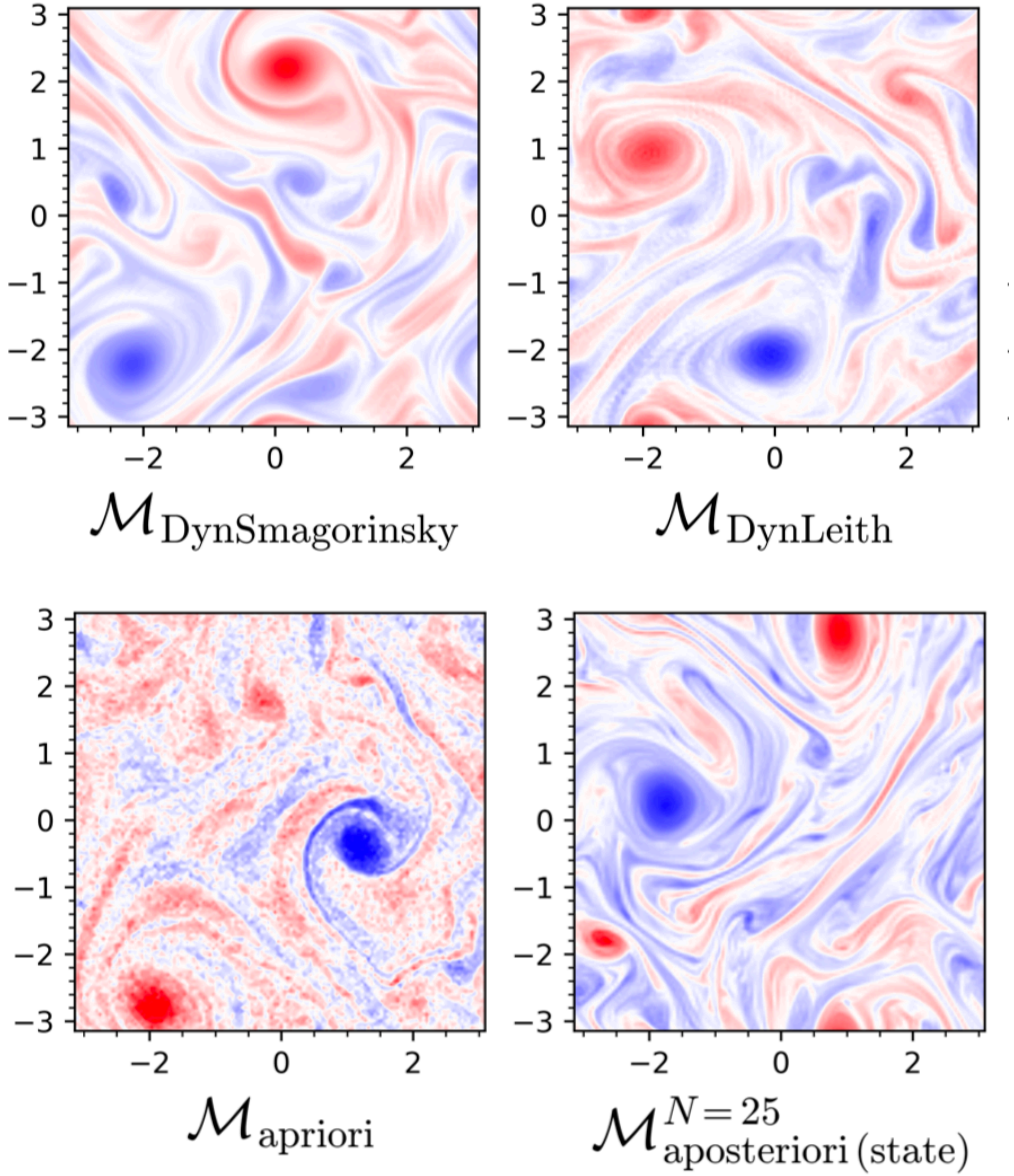
ML closure for ocean macro-turbulence (3/3)

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

$$\underset{\theta}{\arg\min}\, \mathscr{L}(\overset{\text{target}}{\mathbf{z}}, \overset{\text{prediction}}{\mathscr{M}(\mathbf{y} \mid \theta)})$$

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

gradient of the loss

For time evolving problems, with

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

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

The gradient of the loss involves

tricky without Automatic Differenciation (AD)

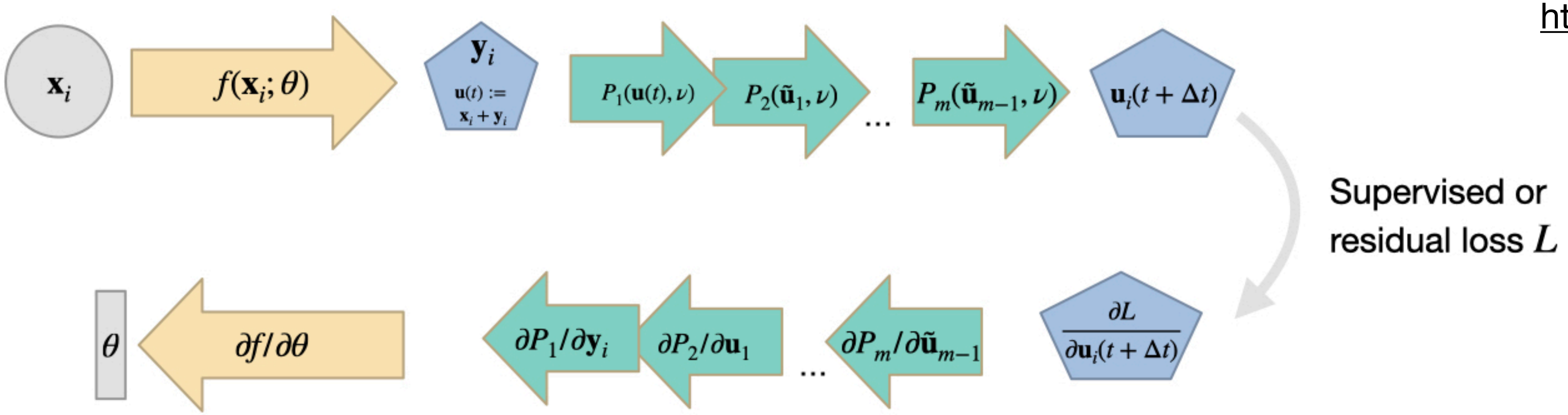
$$\frac{\partial \mathscr{M}}{\partial \theta} \equiv \frac{\partial E}{\partial \theta} = \frac{\partial (E_m \circ \cdots \circ E_1)}{\partial \theta} = \frac{\partial E_m}{\partial E_{m-1}} \cdots \frac{\partial E_2}{\partial E_1}\frac{\partial E_1}{\partial \theta}$$

But AD not available
in ocean models...

Leveraging differentiable programming

See eg Thuerey et al. 2021

https://arxiv.org/abs/2109.05237



specific

languages

- 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

Differentiable numerical
simulations of physical systems

AI-native hybrid geoscientific models

arXiv:2311.07222v3 [physics.ao-ph] 8 Mar 2024

Neural General Circulation Models for Weather and Climate

Dmitrii Kochkov[1*†], Janni Yuval[1*†], Ian Langmore[1†], Peter Norgaard[1†], Jamie Smith[1†], Griffin Mooers[1], Milan Klöwer[4], James Lottes[1], Stephan Rasp[1], Peter Düben[3], Sam Hatfield[3], Peter Battaglia[2], Alvaro Sanchez-Gonzalez[2], Matthew Willson[2], Michael P. Brenner[1,5], Stephan Hoyer[1*†]

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

*Corresponding author(s). E-mail(s): dkochkov@google.com; janniyuval@google.com; shoyer@google.com;
†These authors contributed equally to this work.

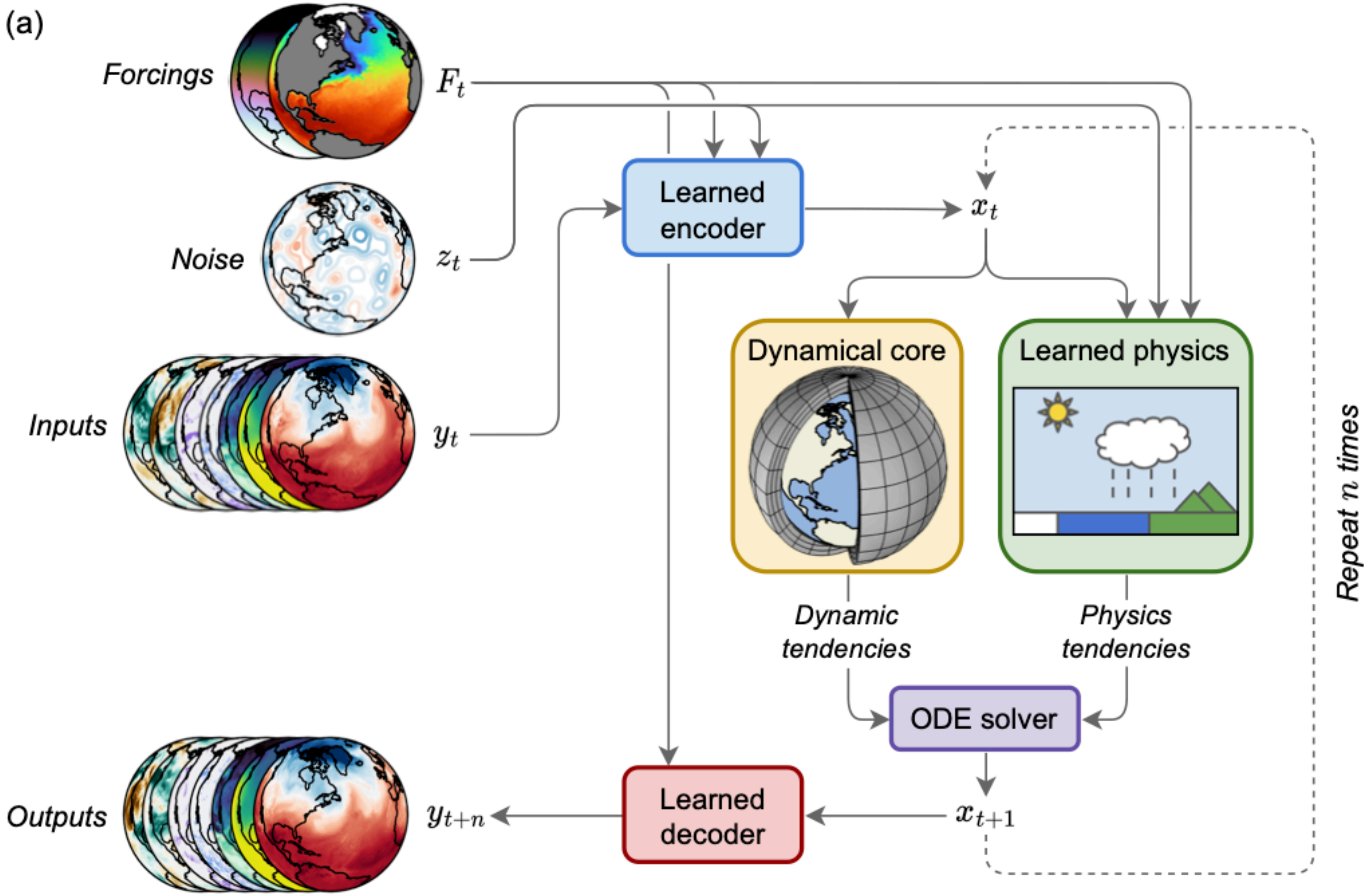
Abstract

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

https://arxiv.org/abs/2311.07222

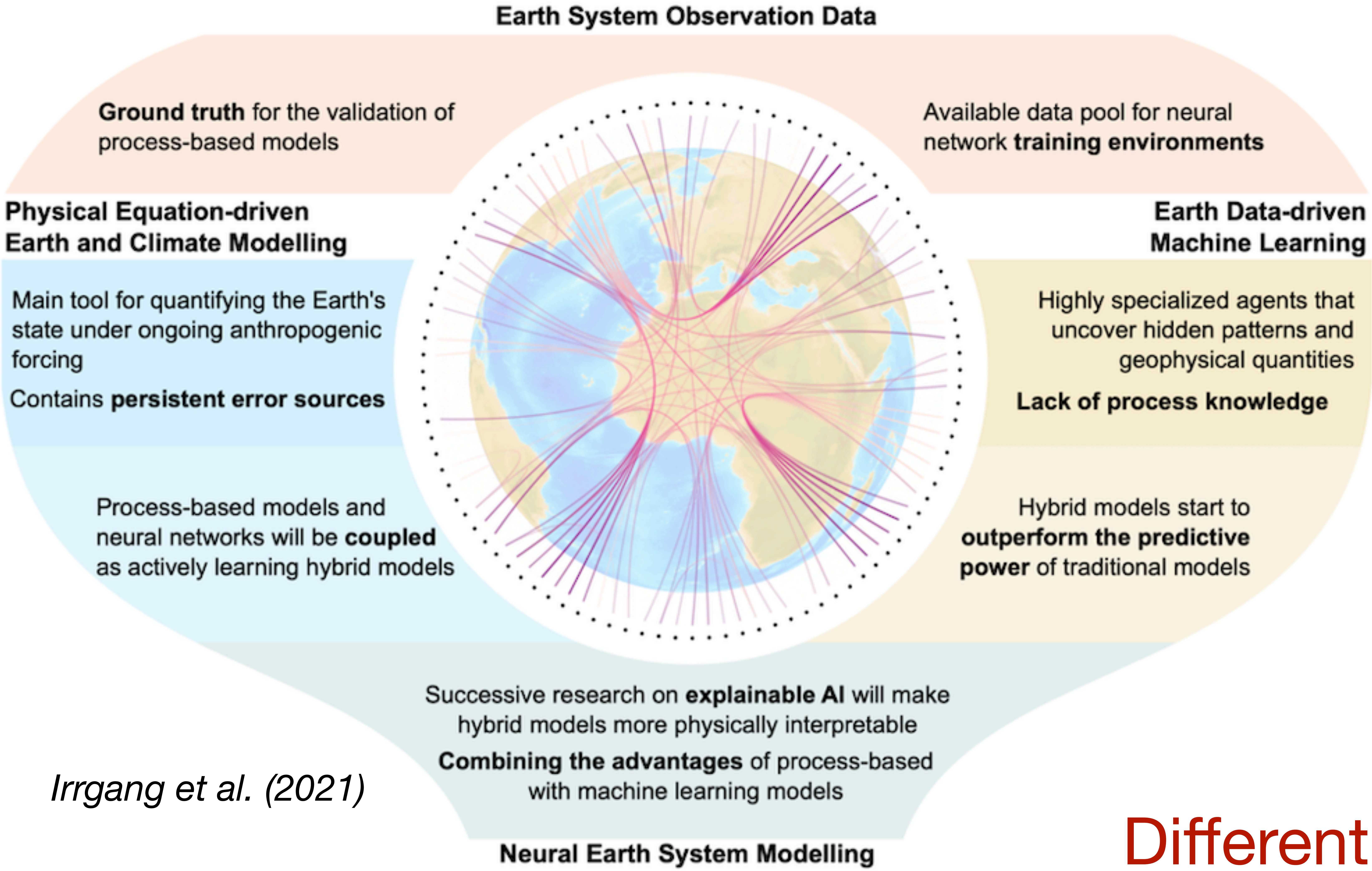
Kochkov et al. (2024)



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

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

AI-native hybrid geoscientific models



Irrgang et al. (2021)

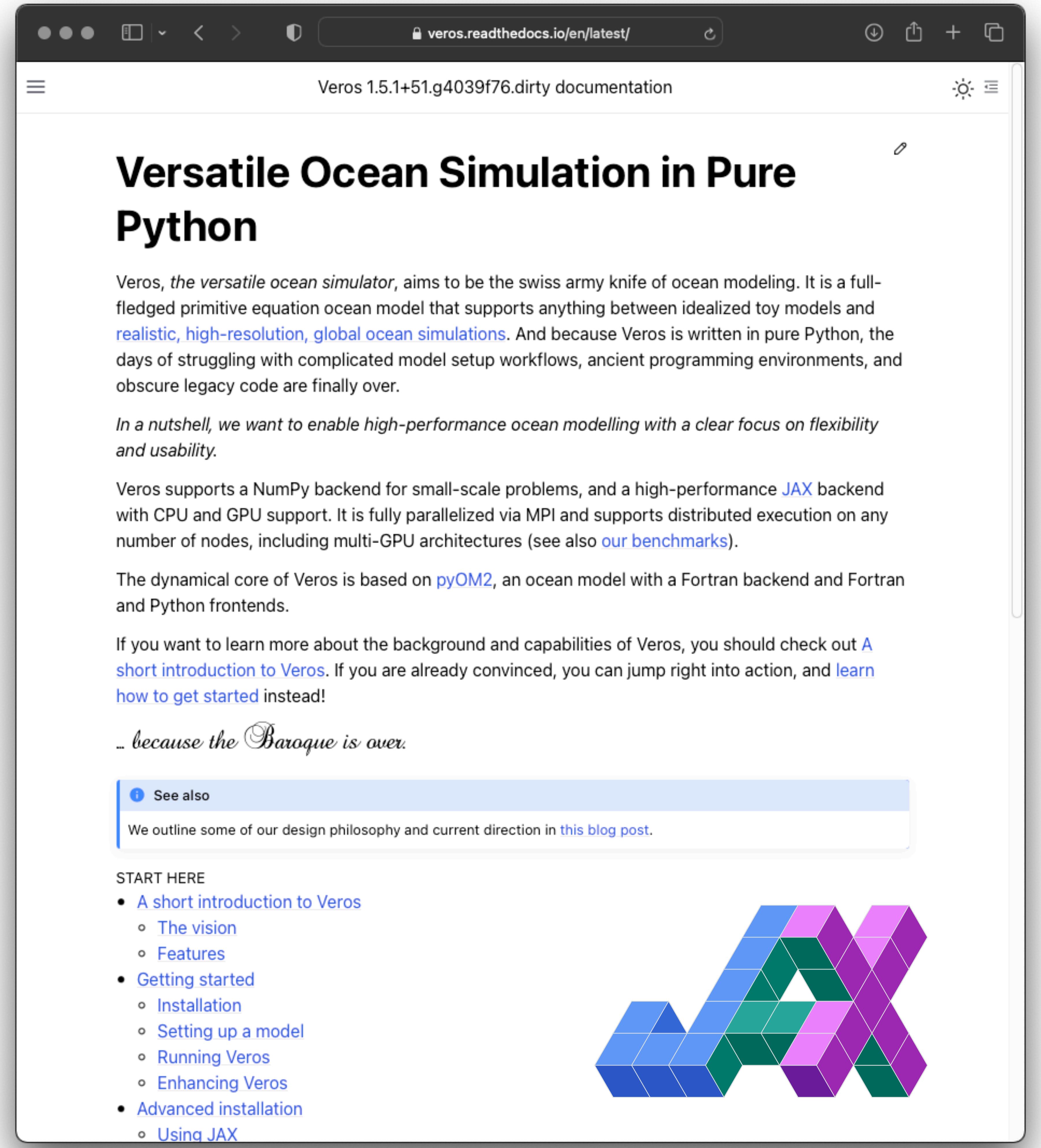
Allowing to optimise
- model parameters
- numerical schemes
- subgrid closures
- …

…and better exploit observations and hi-res simulations

Differentiable programming in earth system models

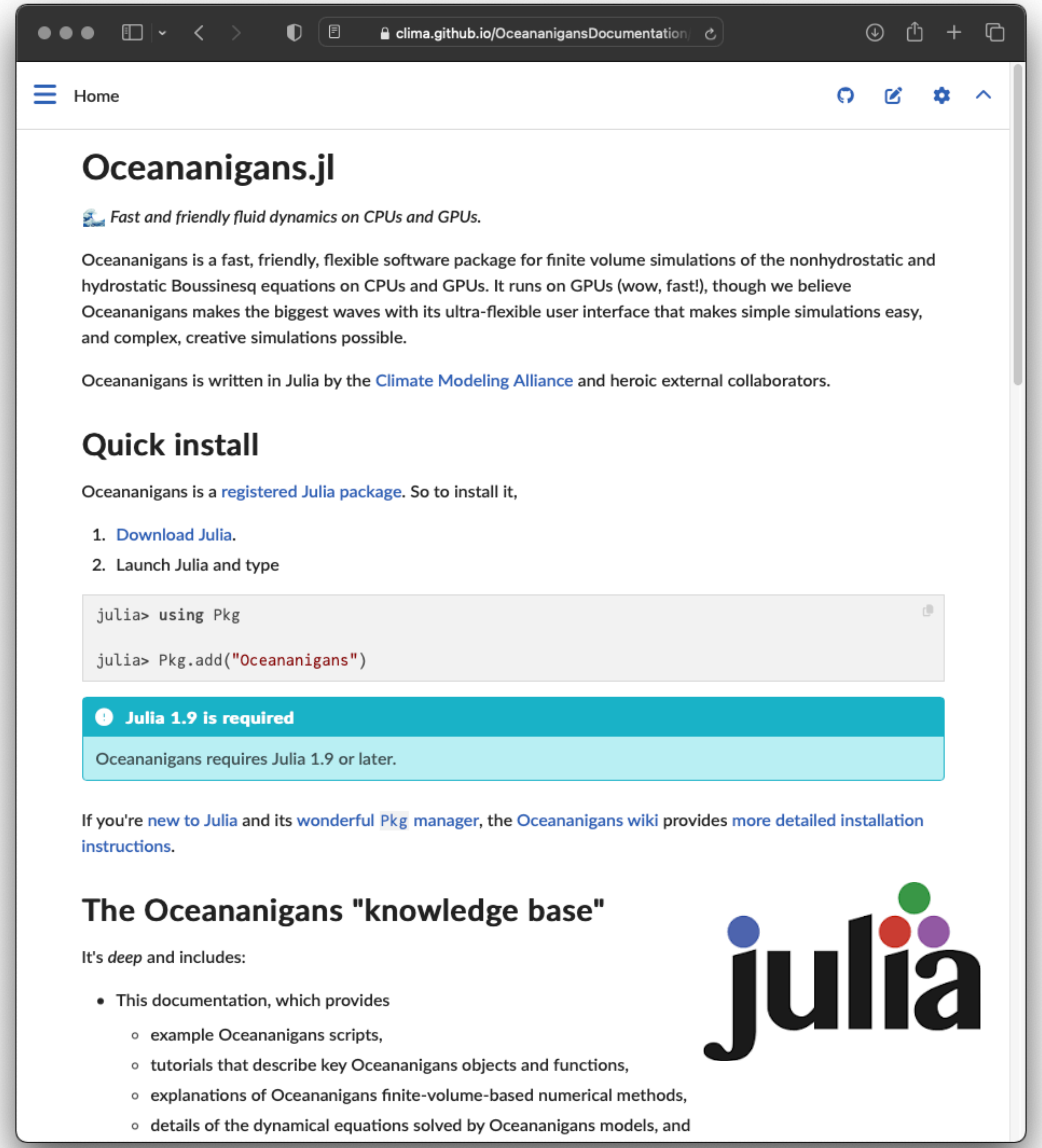
Path towards AI-native hybrid ocean models

The choice of the programming language



Examples
of (almost) **AI-native**
ocean models

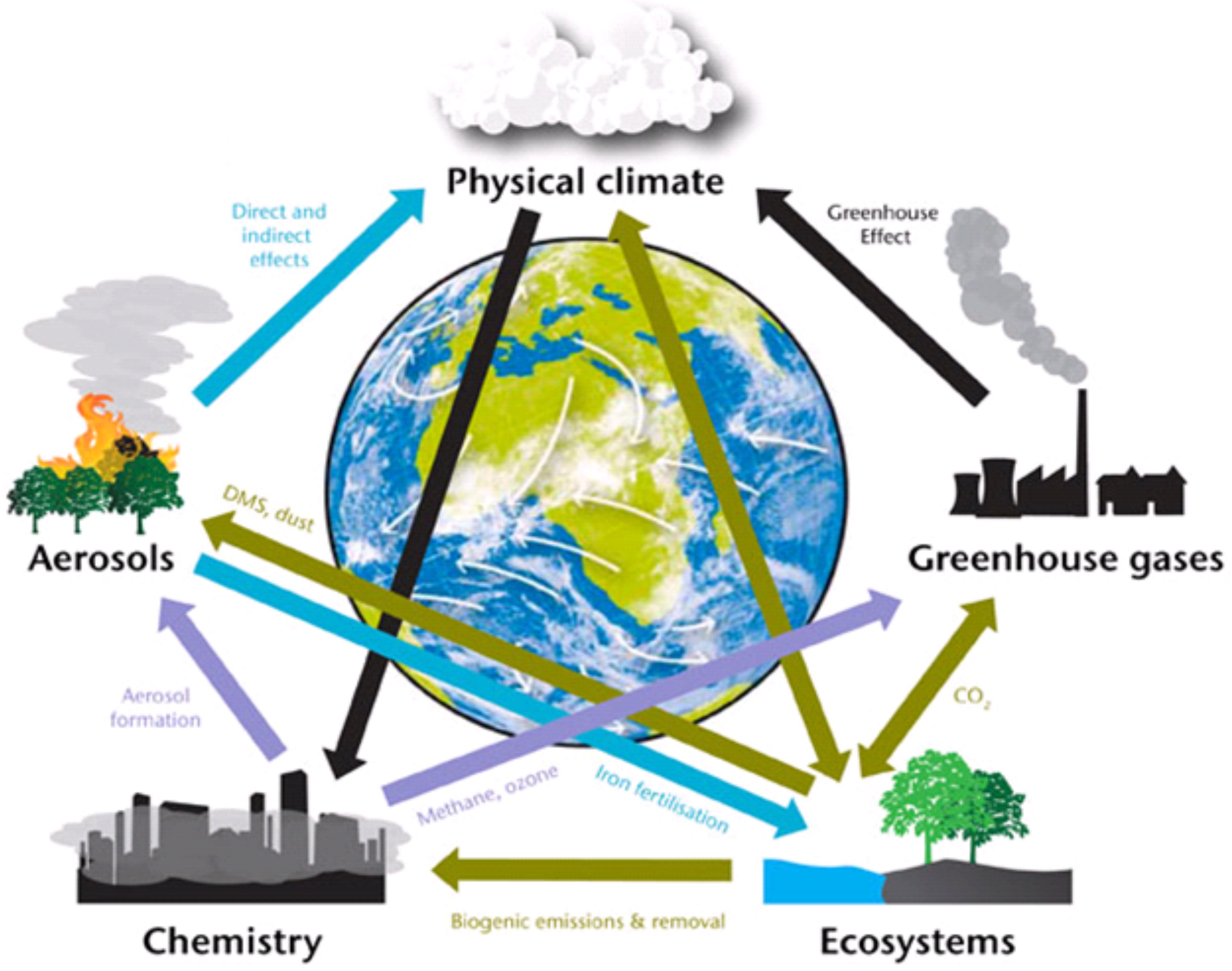
but not fully
AI-ready yet



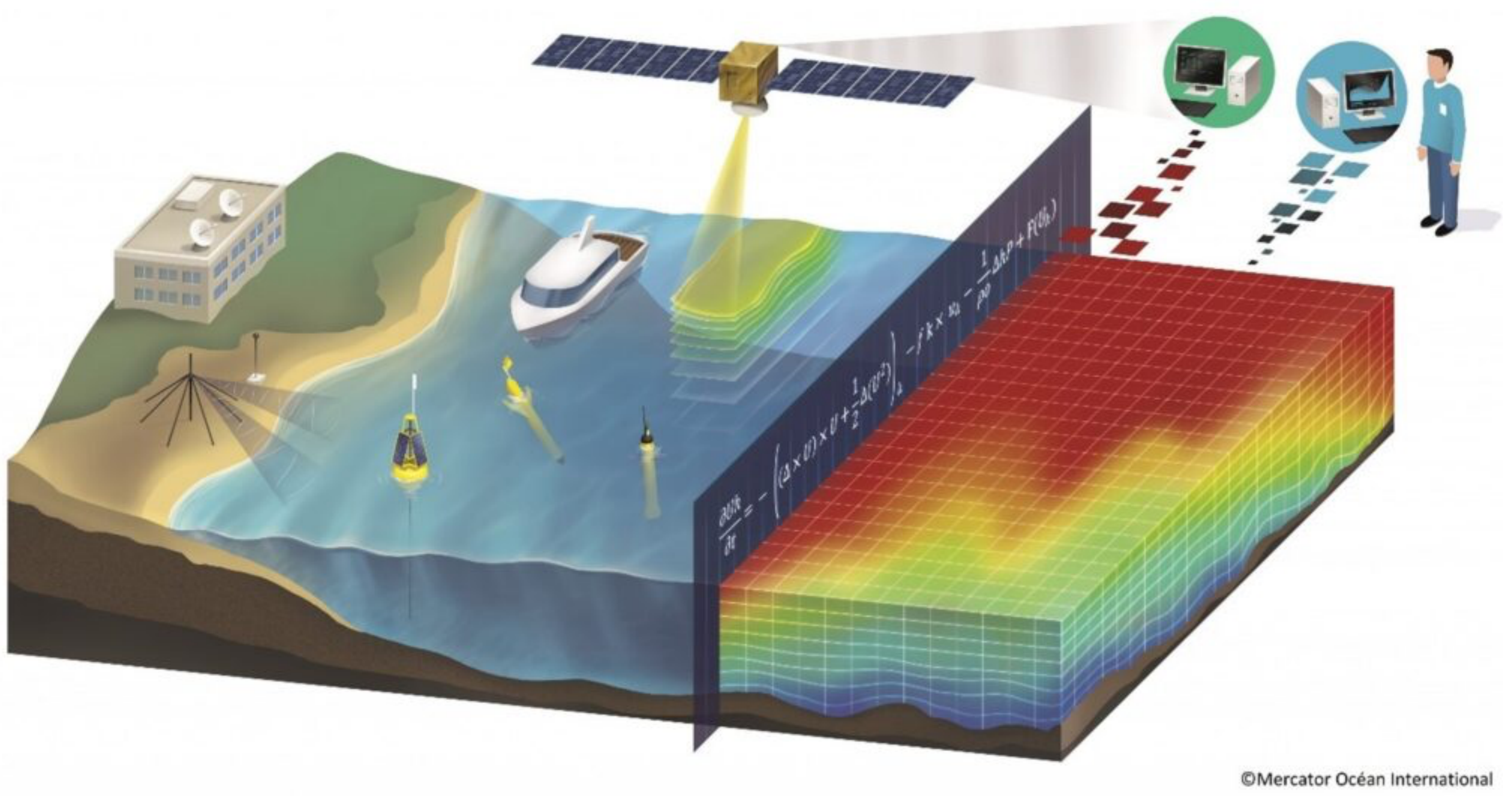
Our Graal : AI-ready, differentiable, fast, high-level abstraction, <u>long-lasting</u>.

Revisiting our systems' APIs

Copernicus
Marine Service



Earth System models
(IPCC)



Operational prediction systems
(Copernicus)

Systems build over decades, based on low level abstraction

No clearly defined APIs for ocean models.

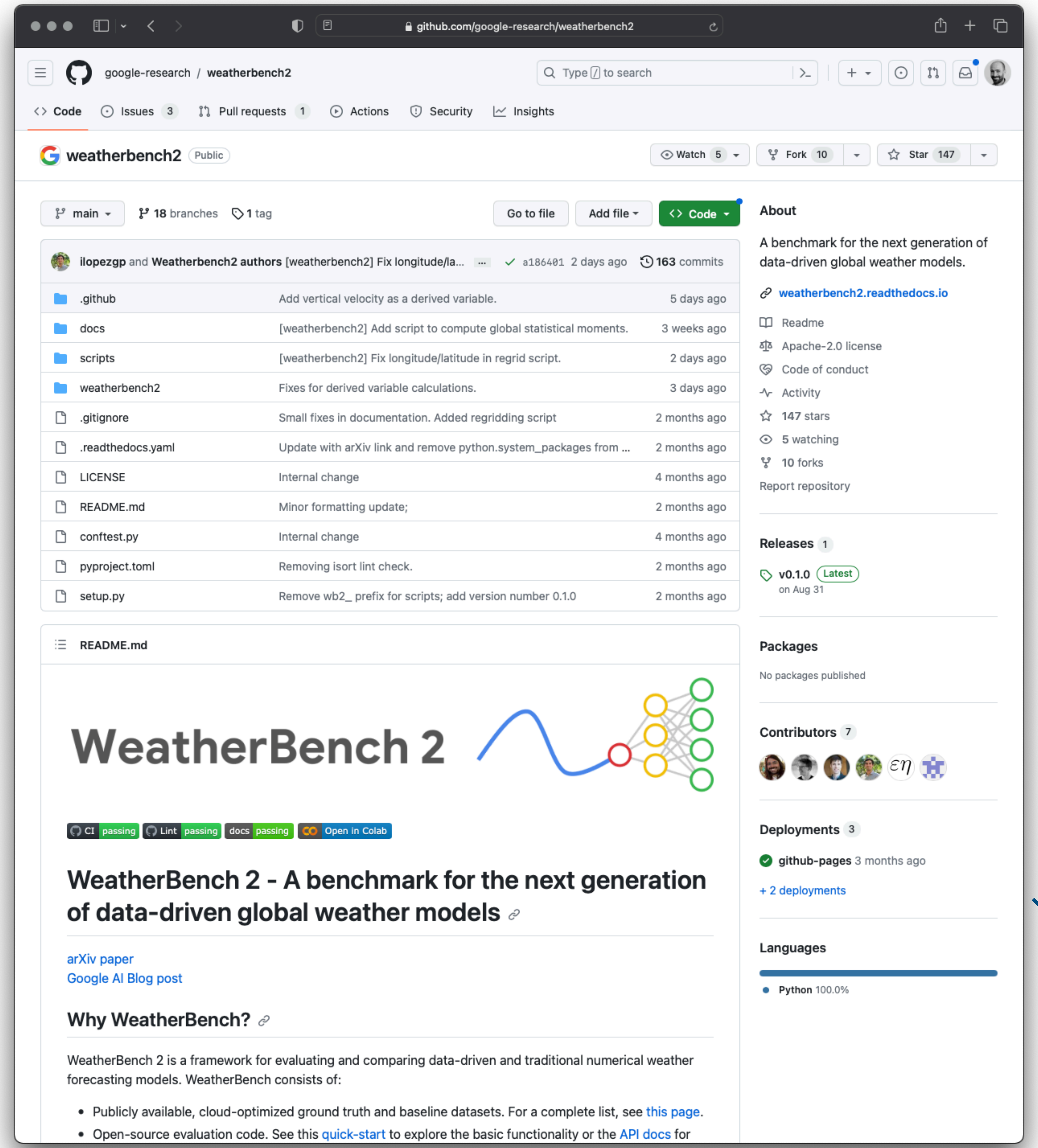
The need for cross-disciplinary efforts

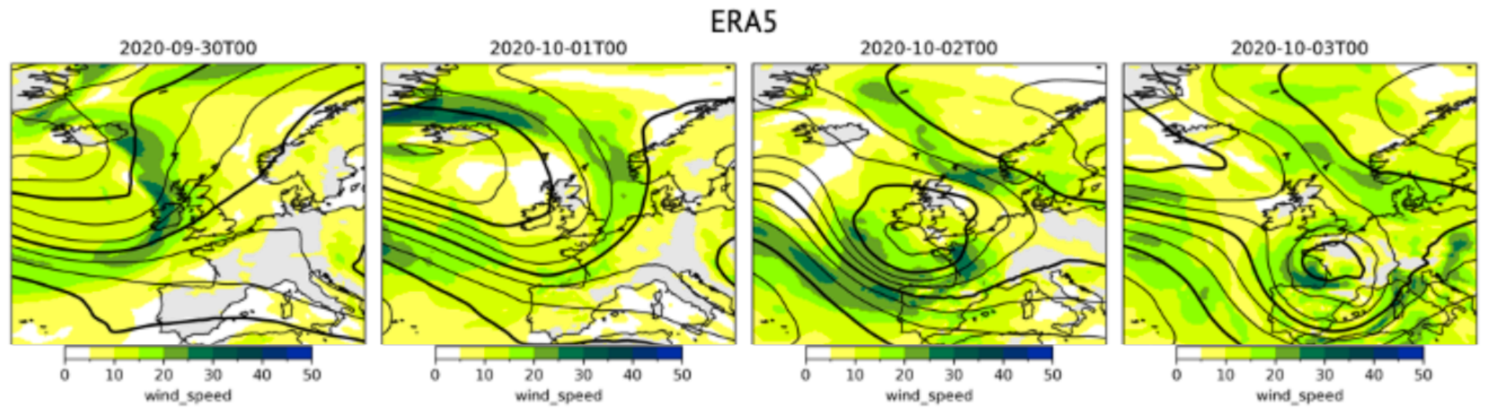
Use cases

Physics **AI** **Computer science** **Applied maths**

Accelerating progress with open benchmarks (1/2)

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





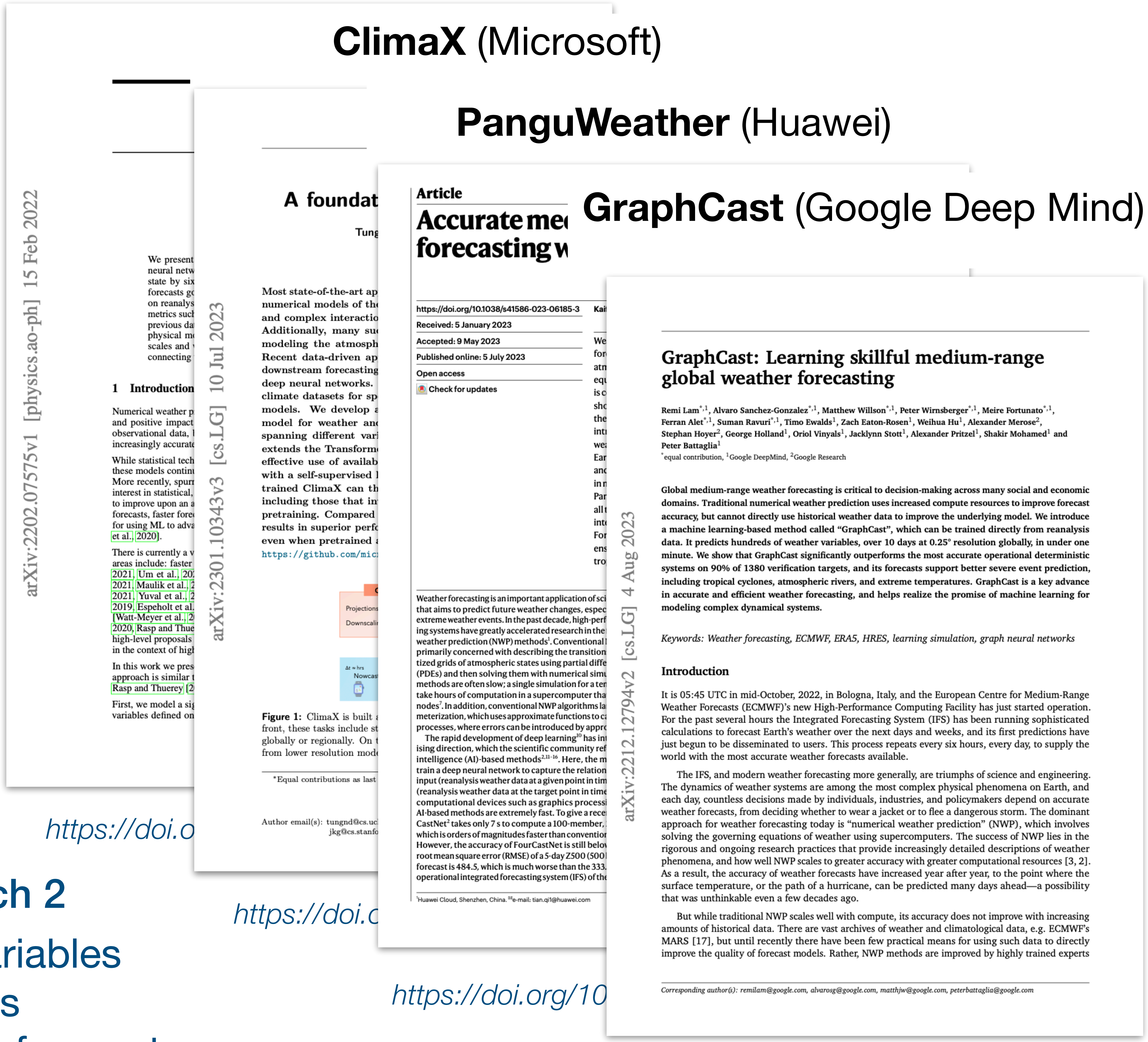
data source : ERA5 reanalysis

Keisler et al. (2022)

ClimaX (Microsoft)

PanguWeather (Huawei)

GraphCast (Google Deep Mind)



https://doi.o

https://doi.c

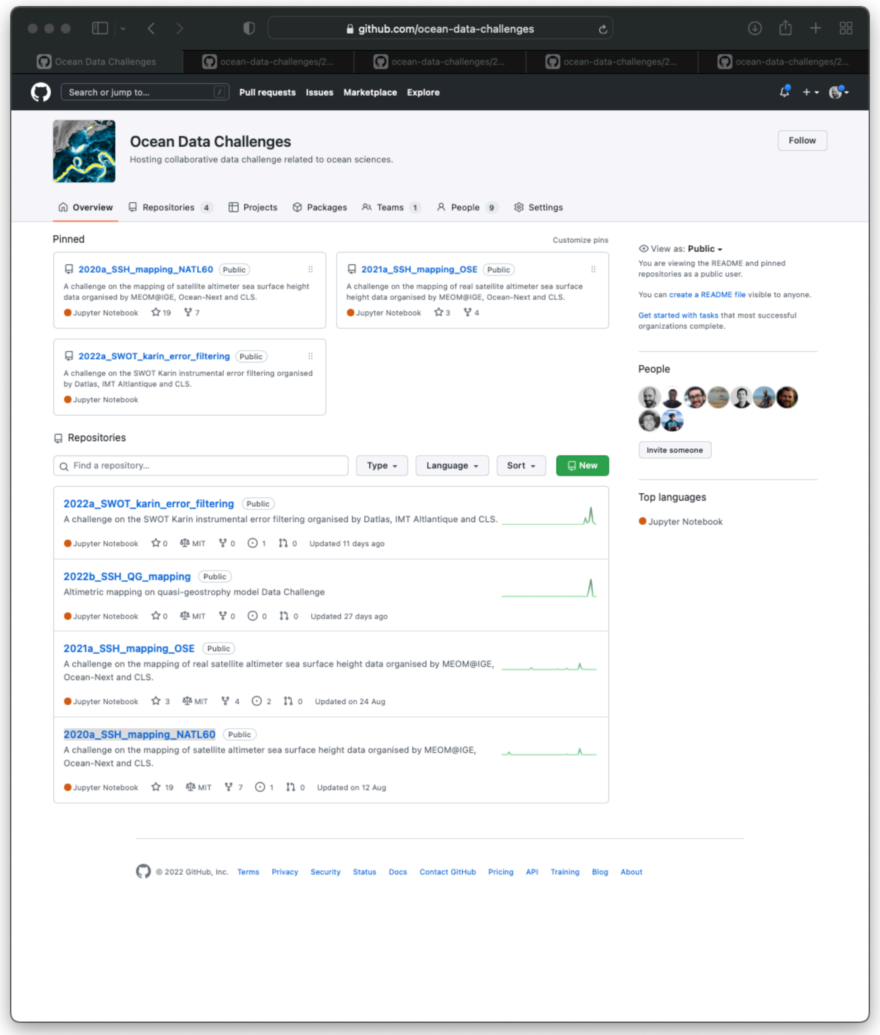
https://doi.org/10

https://doi.org/10.48550/arXiv.2212.12794

WeatherBench 2

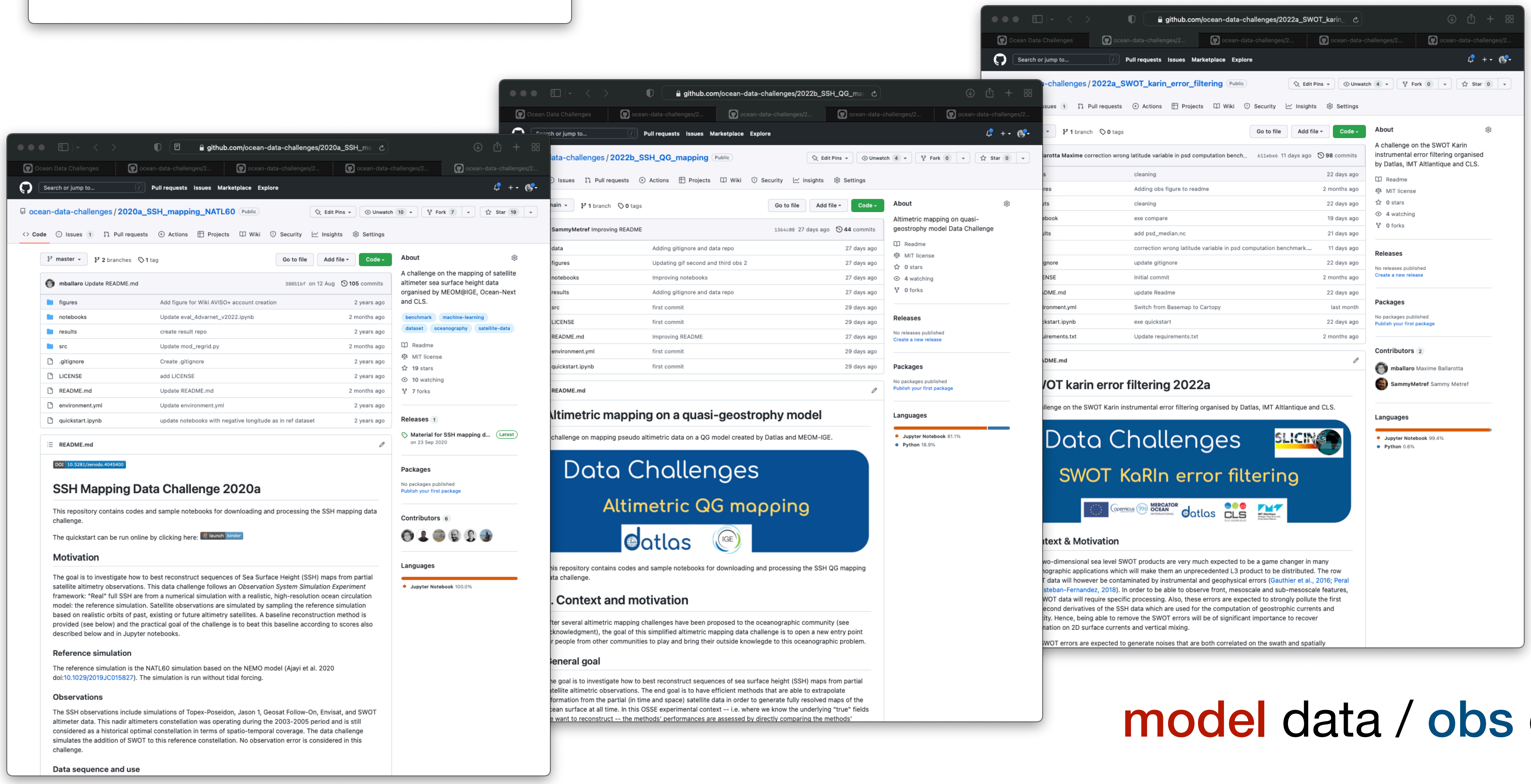
- 3D, more variables
- more metrics
- probabilistic forecasts

Accelerating progress with open benchmarks (2/2)



Collaborative data-challenges

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



model data / obs data

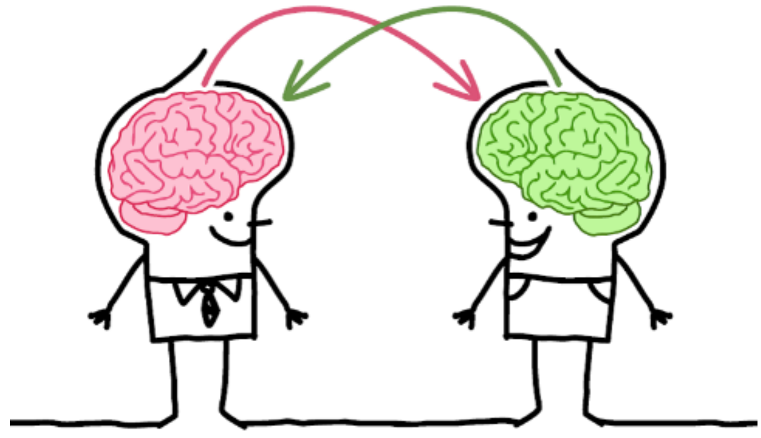
see : https://github.com/ocean-data-challenges/

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 OI 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.ipynb
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.ipynb
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.ipy
duacs 1 swot + 4 nadirs	0.92	0.02	1.22	11.15	Covariances DUACS	eval_duacs.ipynb
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.ipynb
miost 1 swot + 4 nadirs	0.94	**0.01**	1.18	10	Multiscale	
4DVarNet 1 swot + 4 nadirs 🏆	**0.95**	**0.01**	0.82	6.		

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

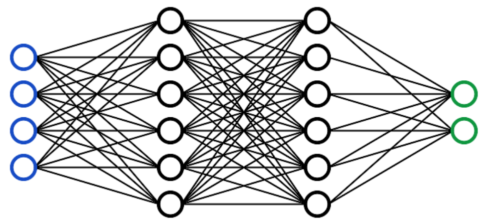
Le Guillou et al. 2021
Febvre et al. 2021
Beauchamp et al. 2022

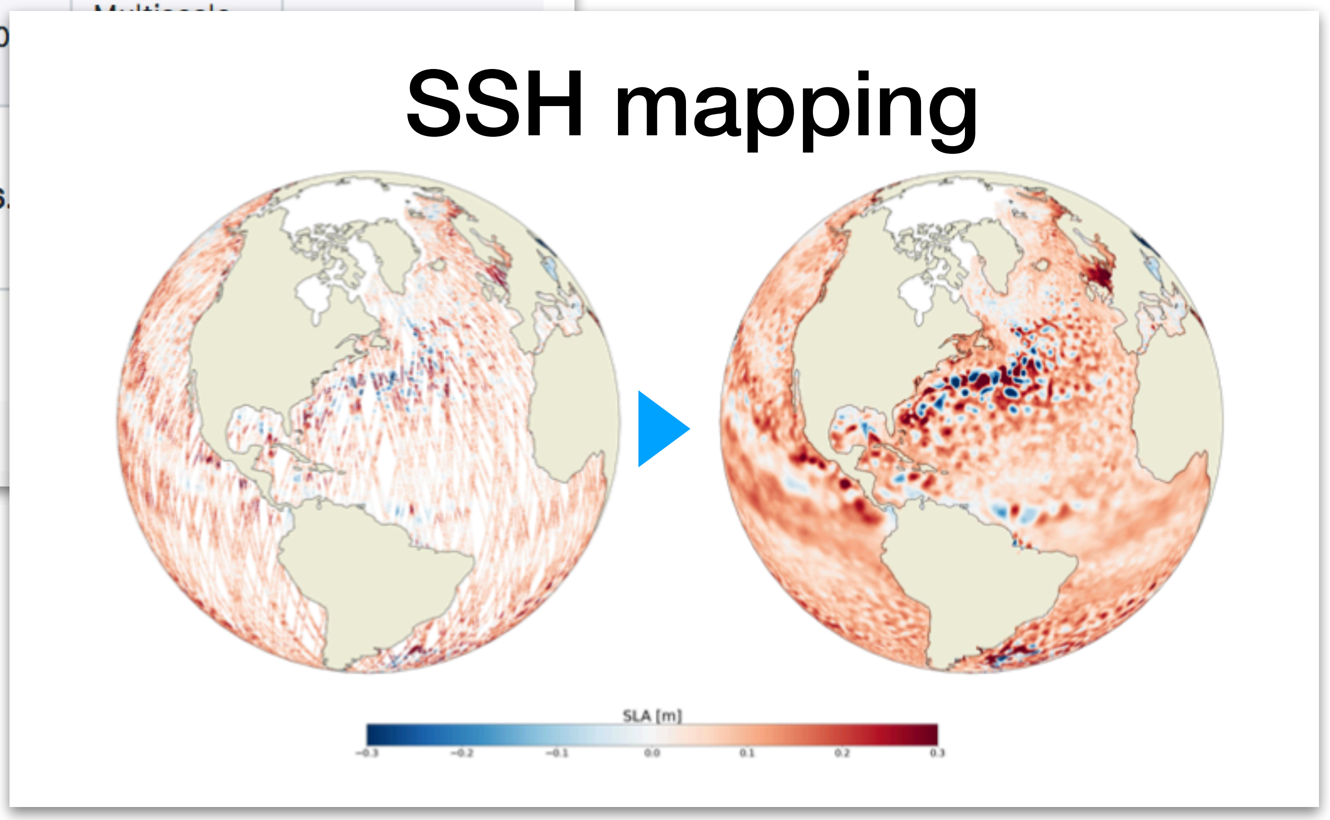


interdisciplinary

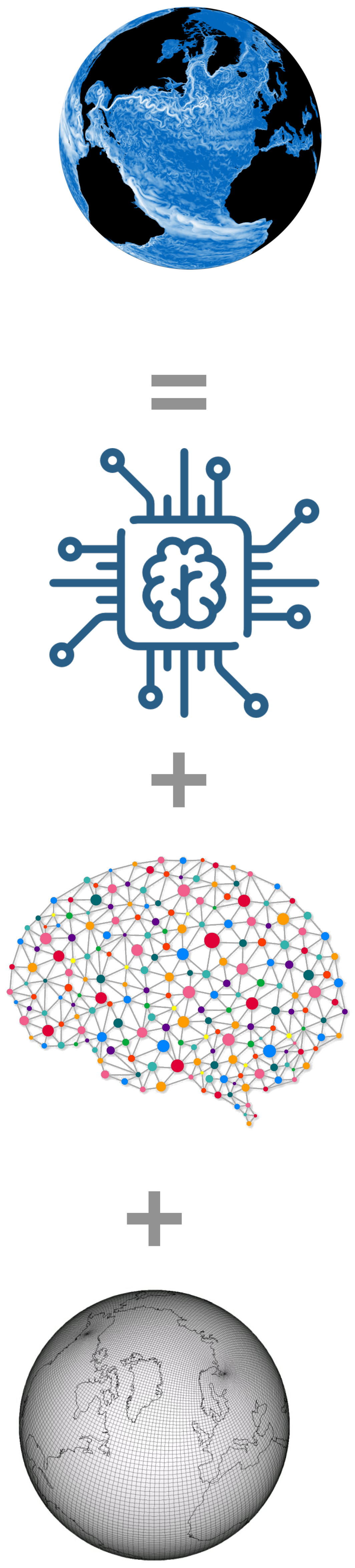
collab.
IGE, IMT-Atl, Datlas, CLS

supported by CNES, CMEMS





Summary



- 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
- Discussed some steps towards **AI-native hybrid** models
- Including the need for large **cross-disciplinary** efforts

A cross-disciplinary event later today

https://gap2024.sciencesconf.org

Starting today at 1:30PM