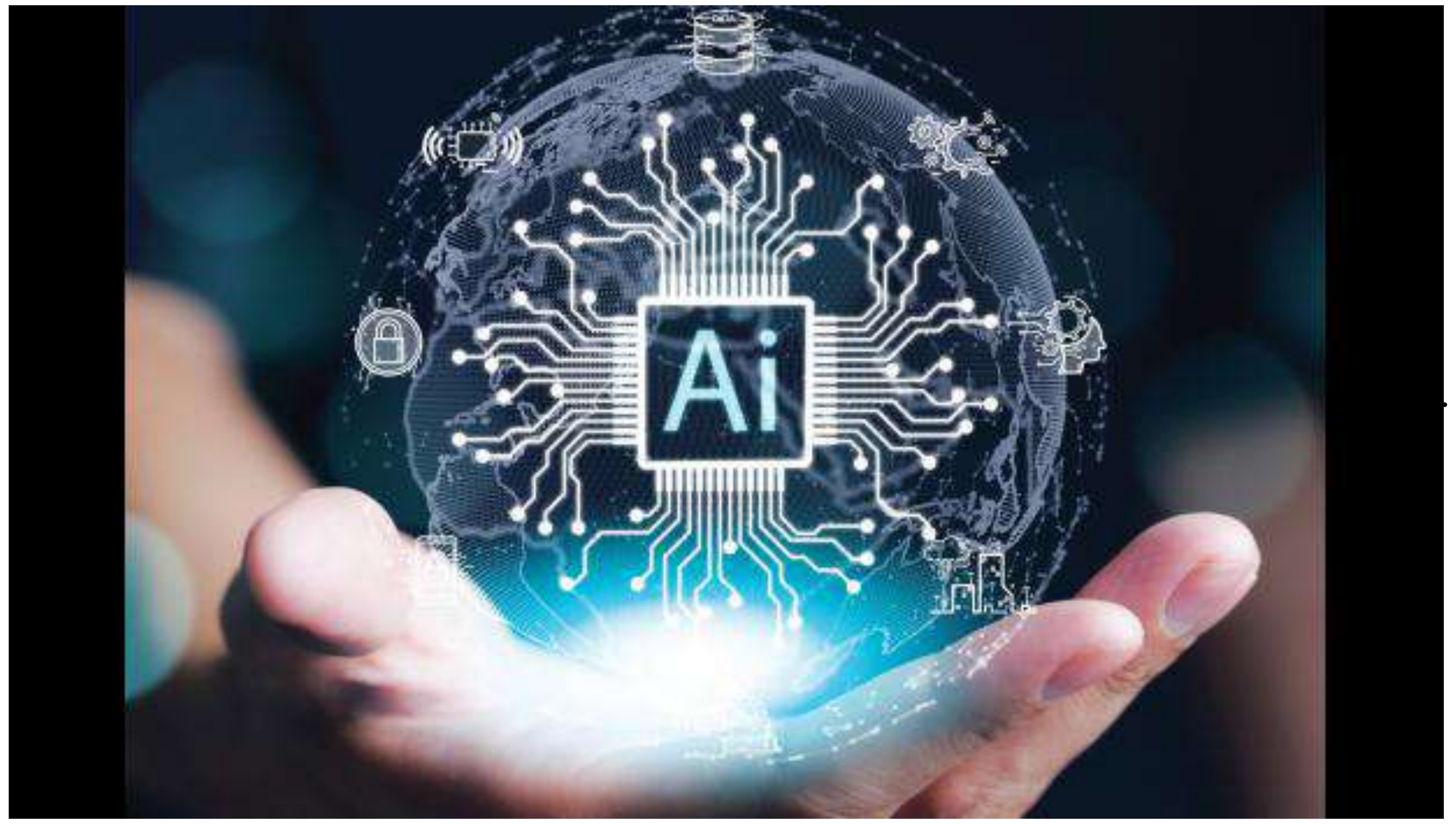
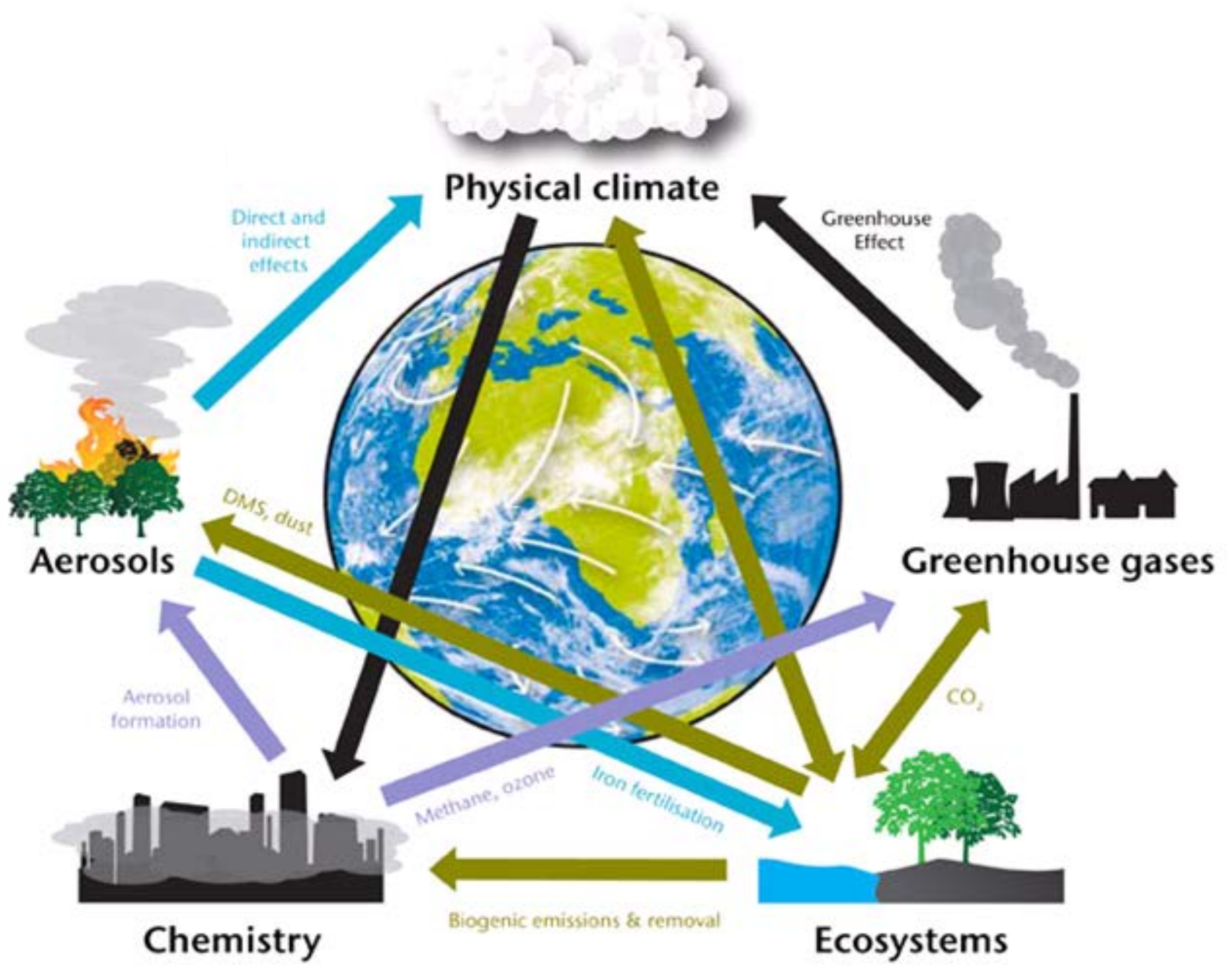
2.

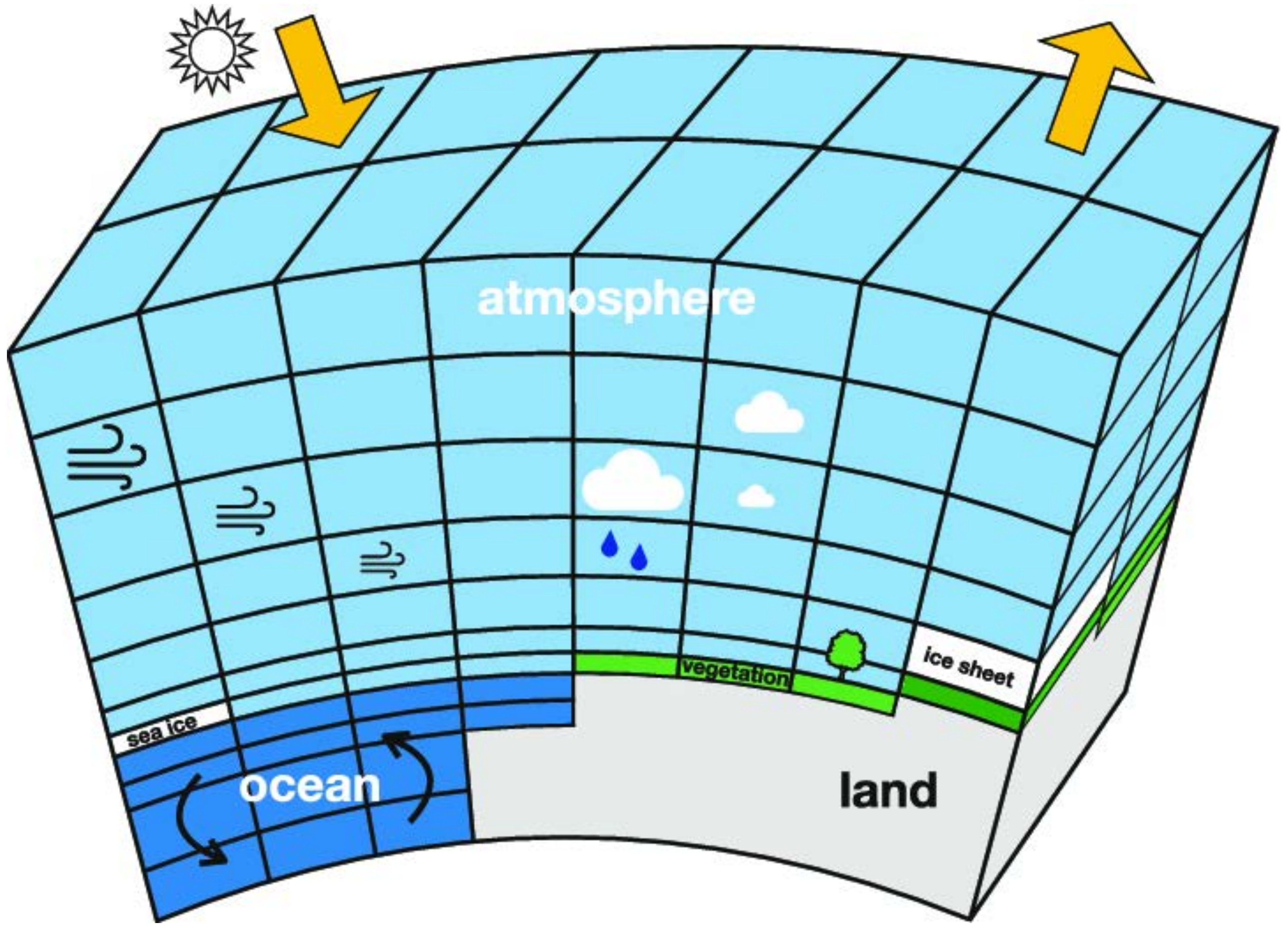
How AI (SciML) **is affecting our field ?**



How AI (SciML) **is affecting our field ?**

Tools are integrated into systems

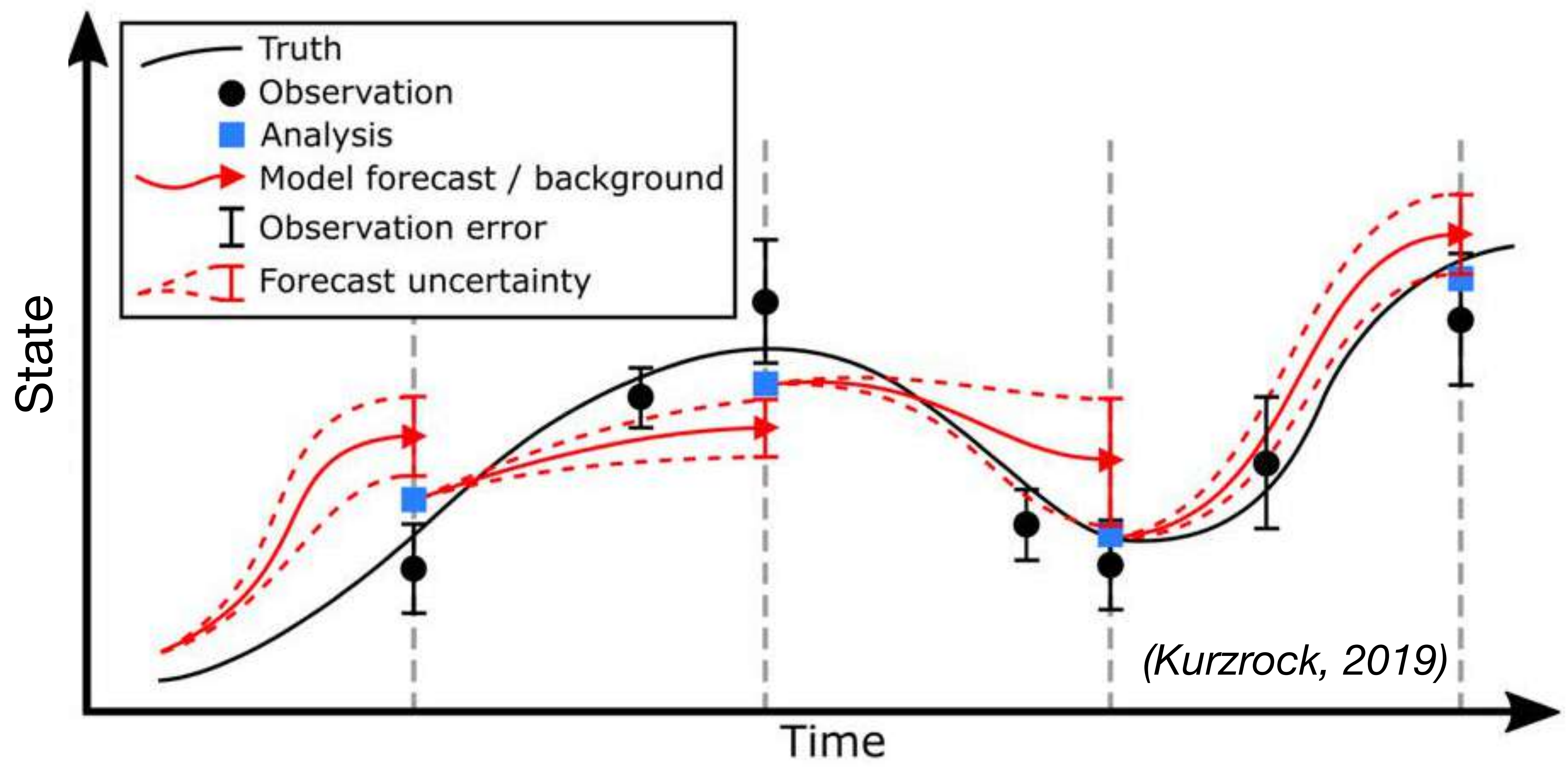




Earth System Models
(IPCC)

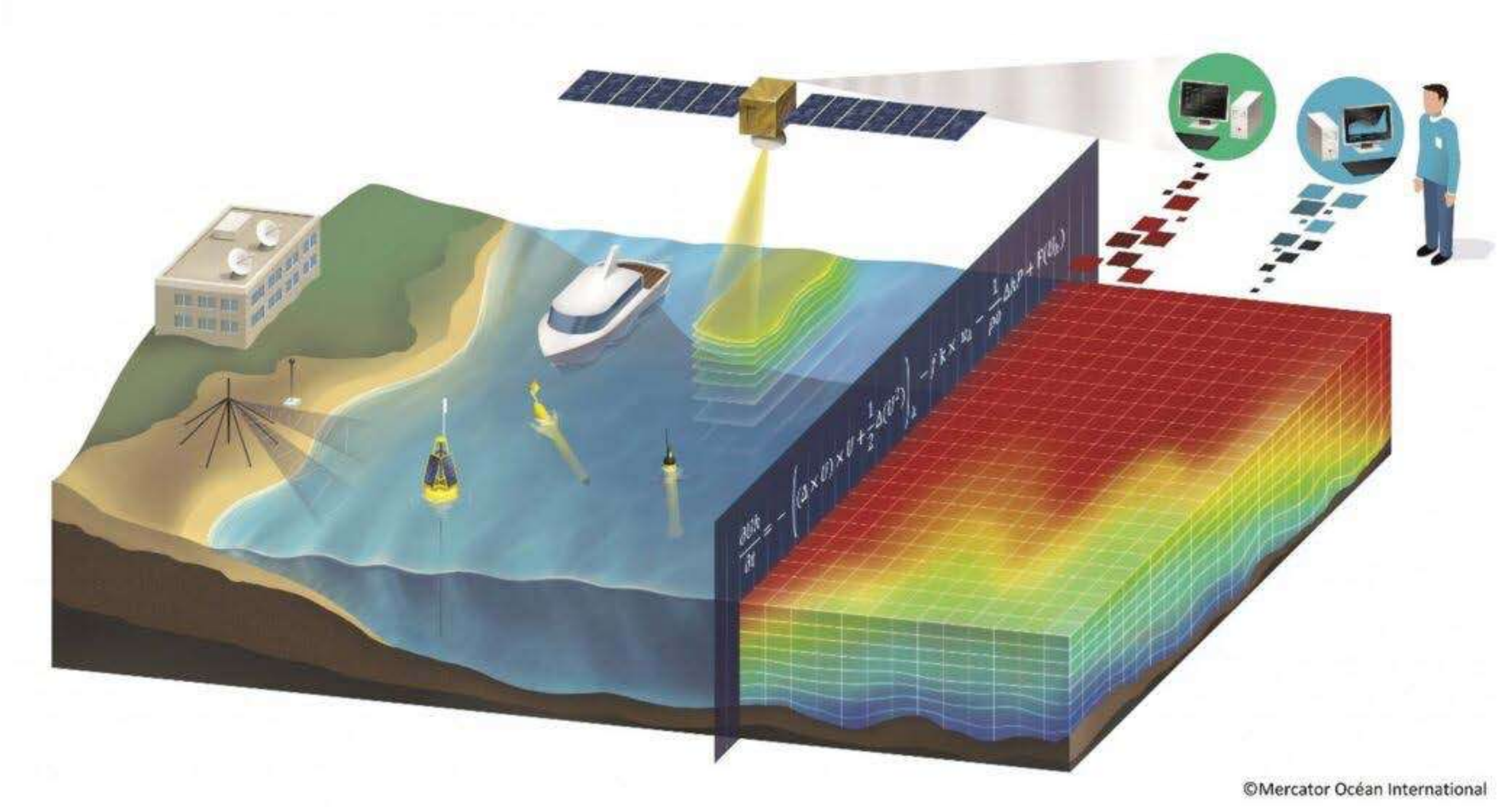
Combining models of each components of the climate system

Tools are integrated into systems



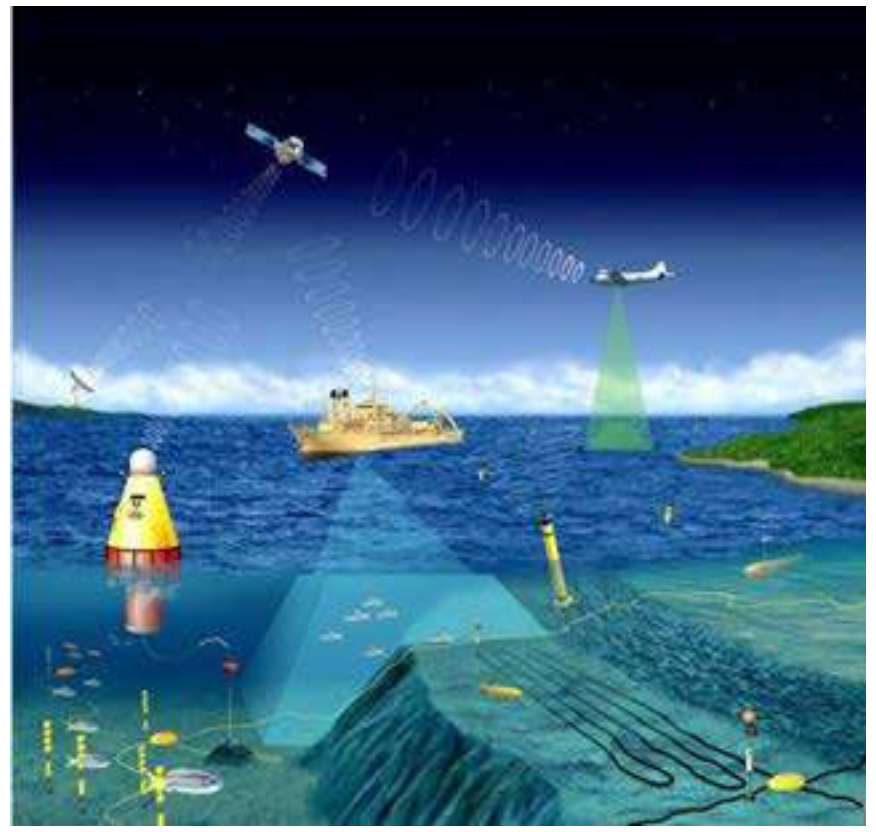
Combining models and observations to produce forecasts

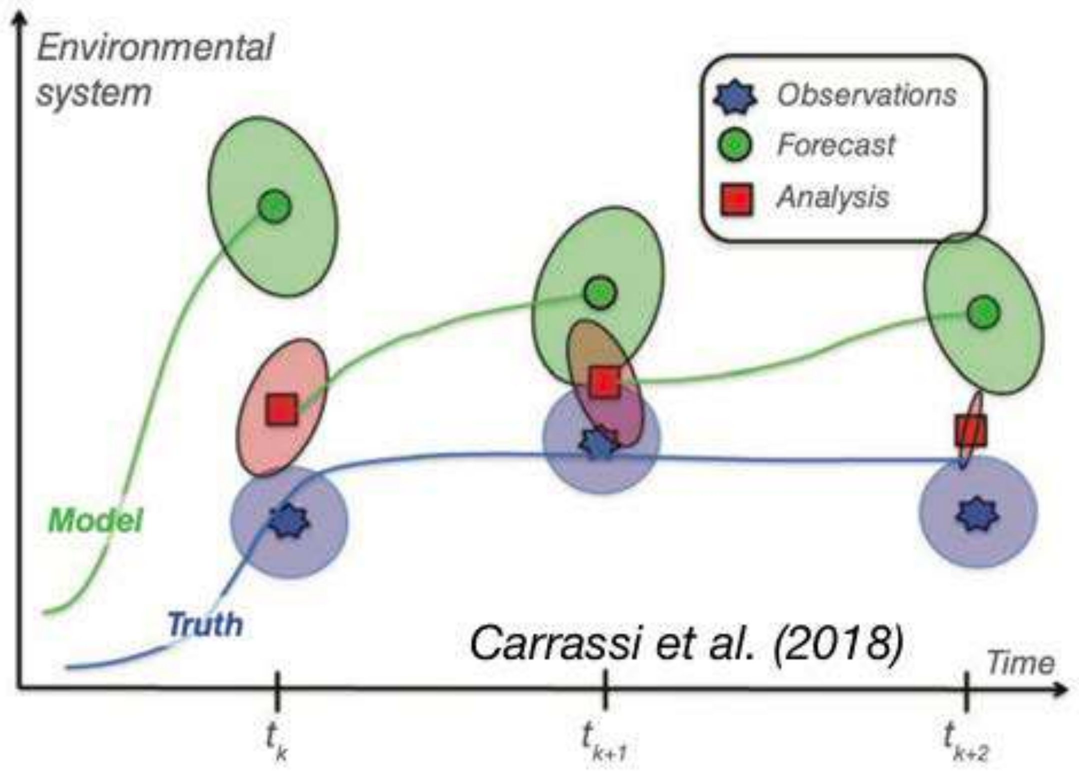
Copernicus Marine Service

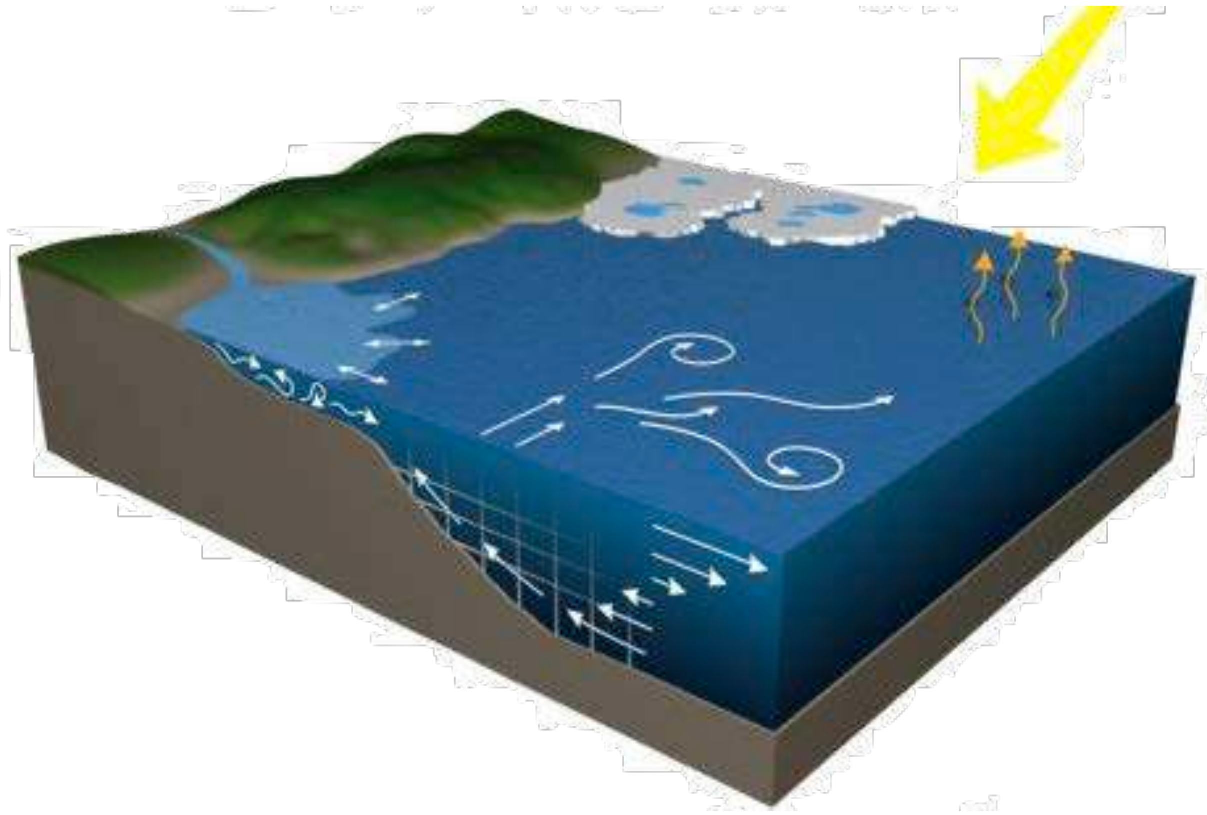


Operational prediction systems
(Copernicus)

How AI is affecting our systems







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

Upstream

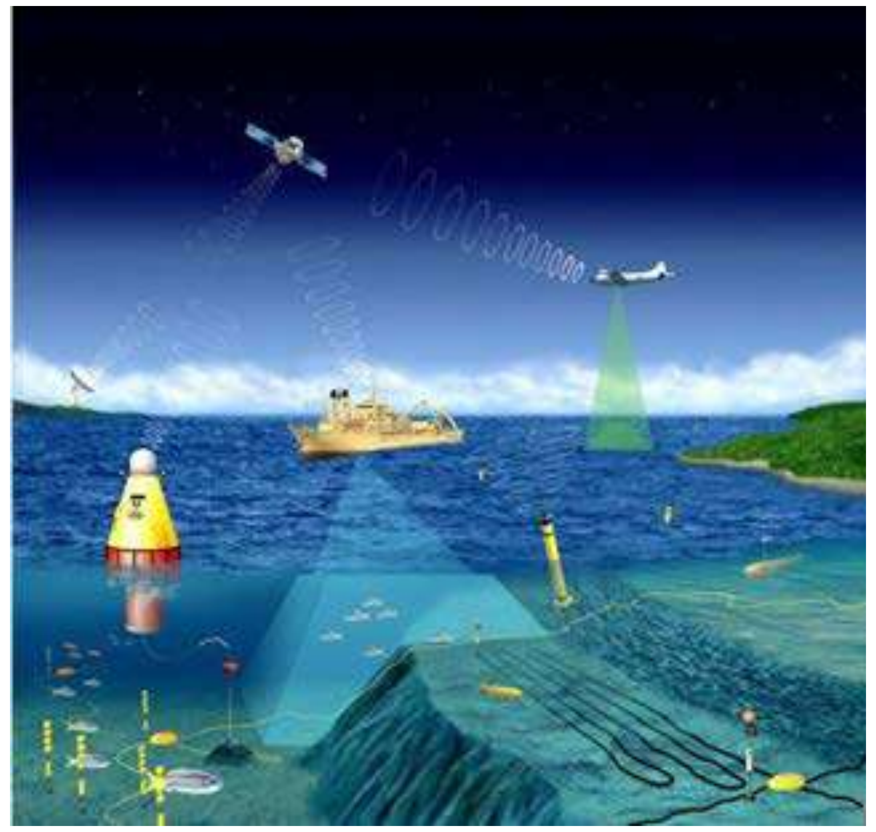
Downstream

denoising, inpainting
parameter retrieval
quality control

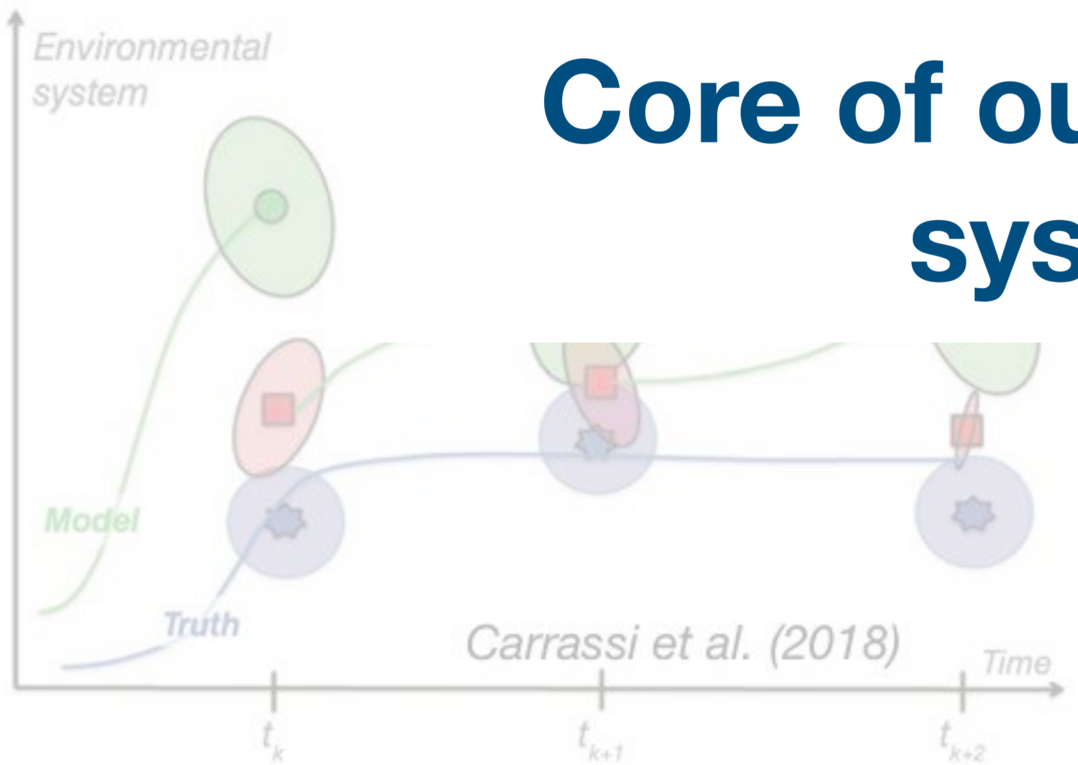
AI, machine learning & data-driven approaches

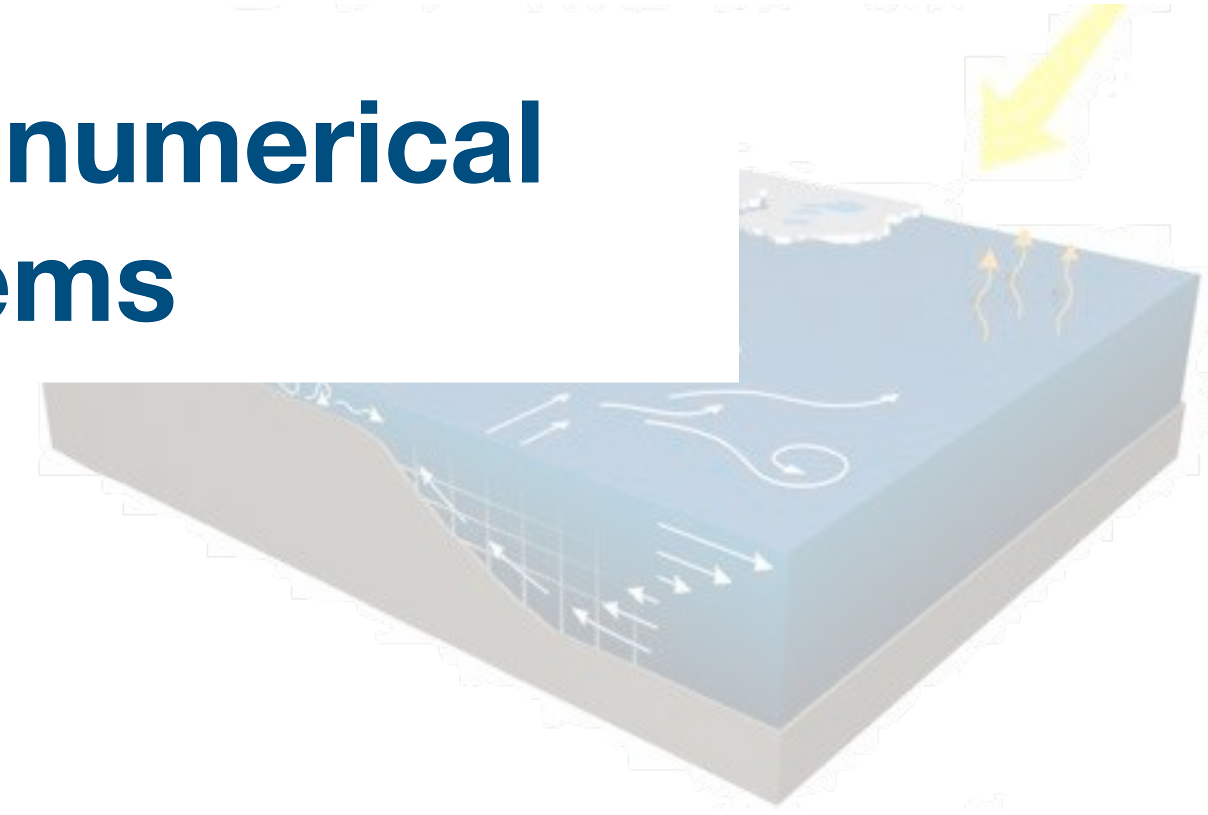
data fusion,
tailored services
data mining

How AI is affecting our 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

COMING UP

AI-based ocean forecasting

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

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- *Guihua Wang is with the Department of Atmospheric and Oceanic Sciences, Fudan University, Shanghai 200438, China.*
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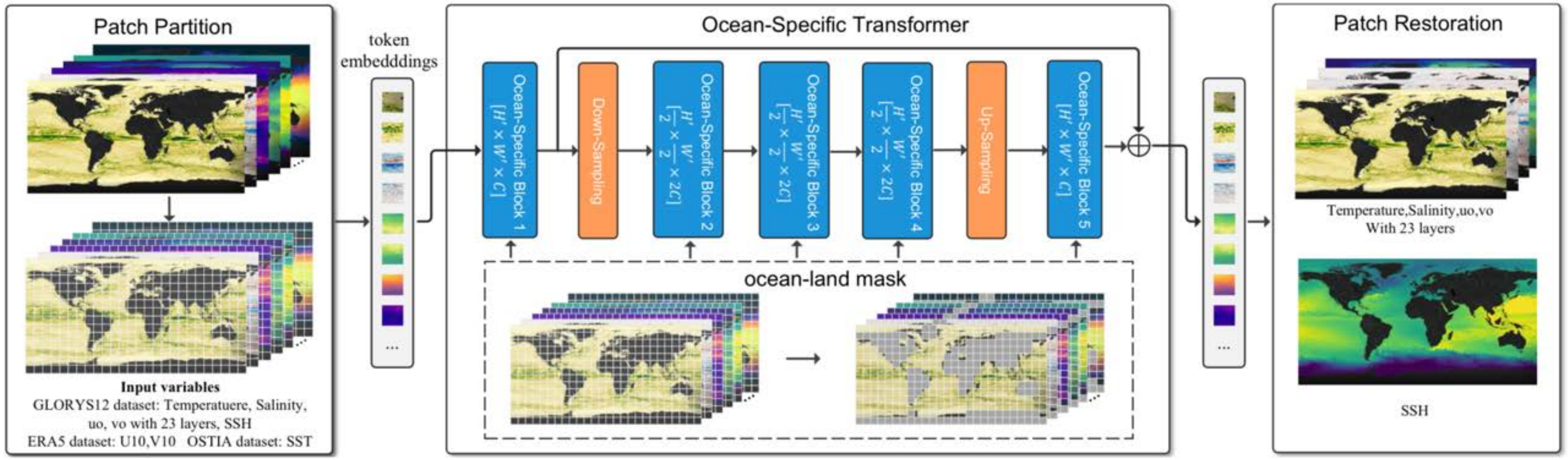
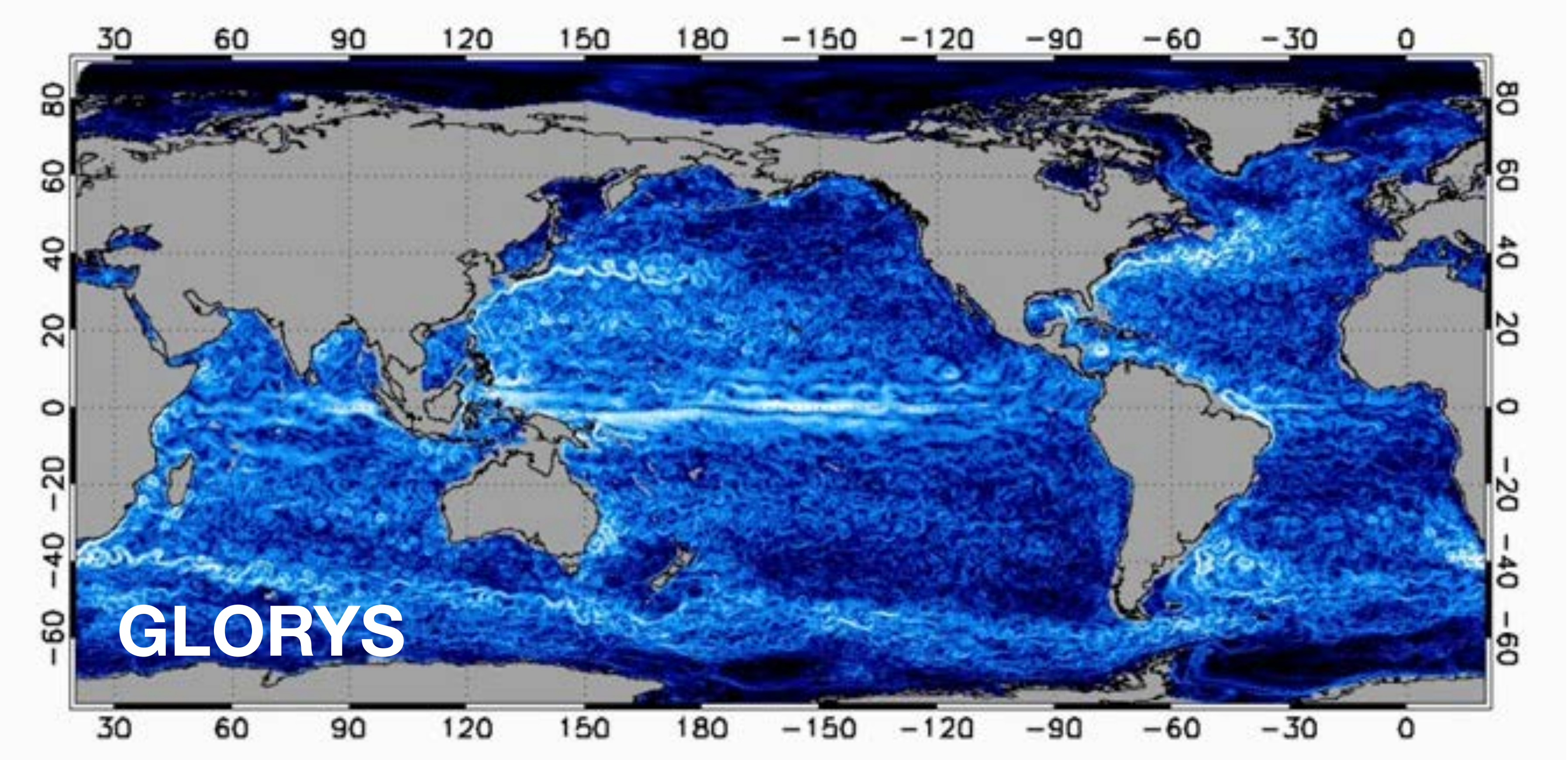
- *Guihua Wang, Huizan Wang, Senzhang Wang, and Weimin Zhang are the corresponding authors.*

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

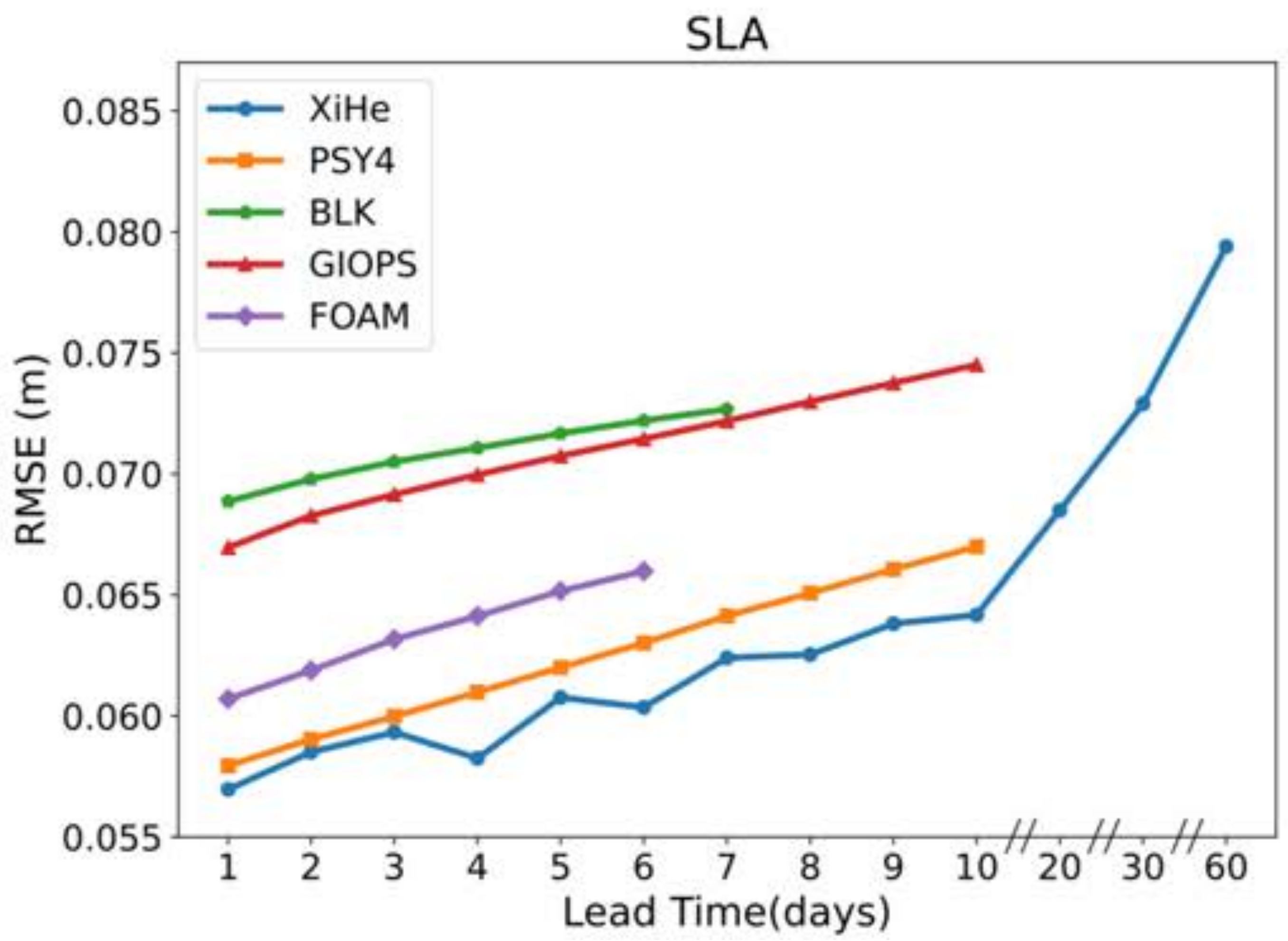
https://arxiv.org/abs/2402.02995

Wang et al. (2024)





Trained from ocean reanalyses



Short term forecast skill

AI-based ocean forecasting

COMING UP

MANUSCRIPT

XiHe: A Data-Driven Model for Global Ocean

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

arXiv:2412.05454v1 [physics.flu-dyn] 6 Dec 2024

GLONET: MERCATOR'S END-TO-END NEURAL FORECASTING SYSTEM

A PREPRINT

Anass El Aouni * Quentin Gaudel Charly Regnier Simon Van Gennip

Marie Drevillon Yann Drillet Jean-Michel Lellouche

Mercator Ocean International

December 10, 2024

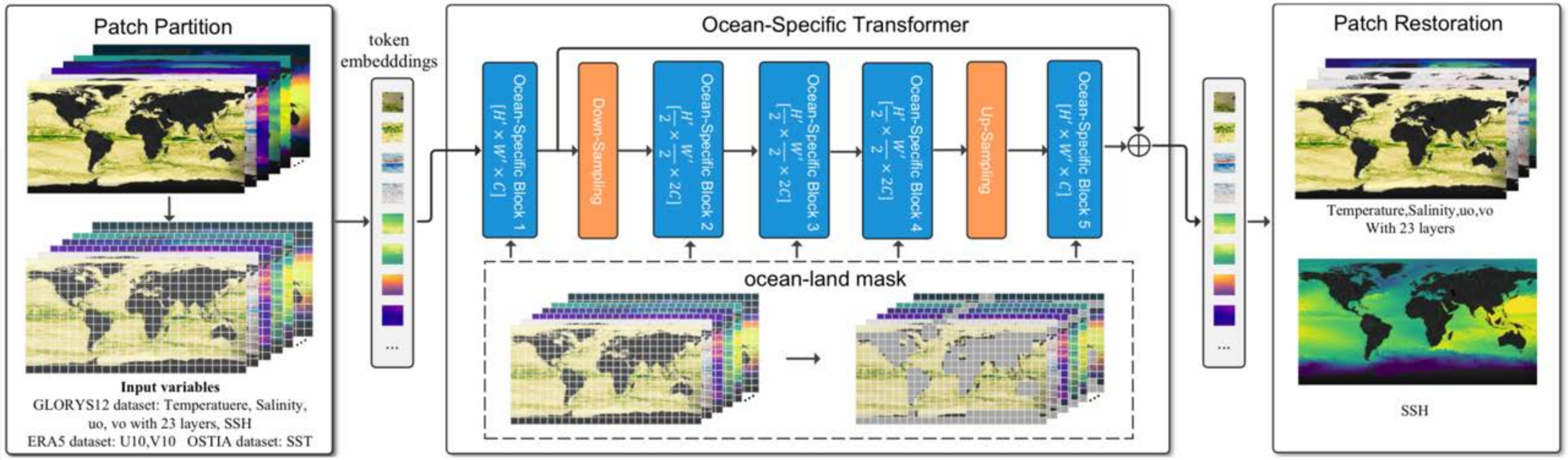
ABSTRACT

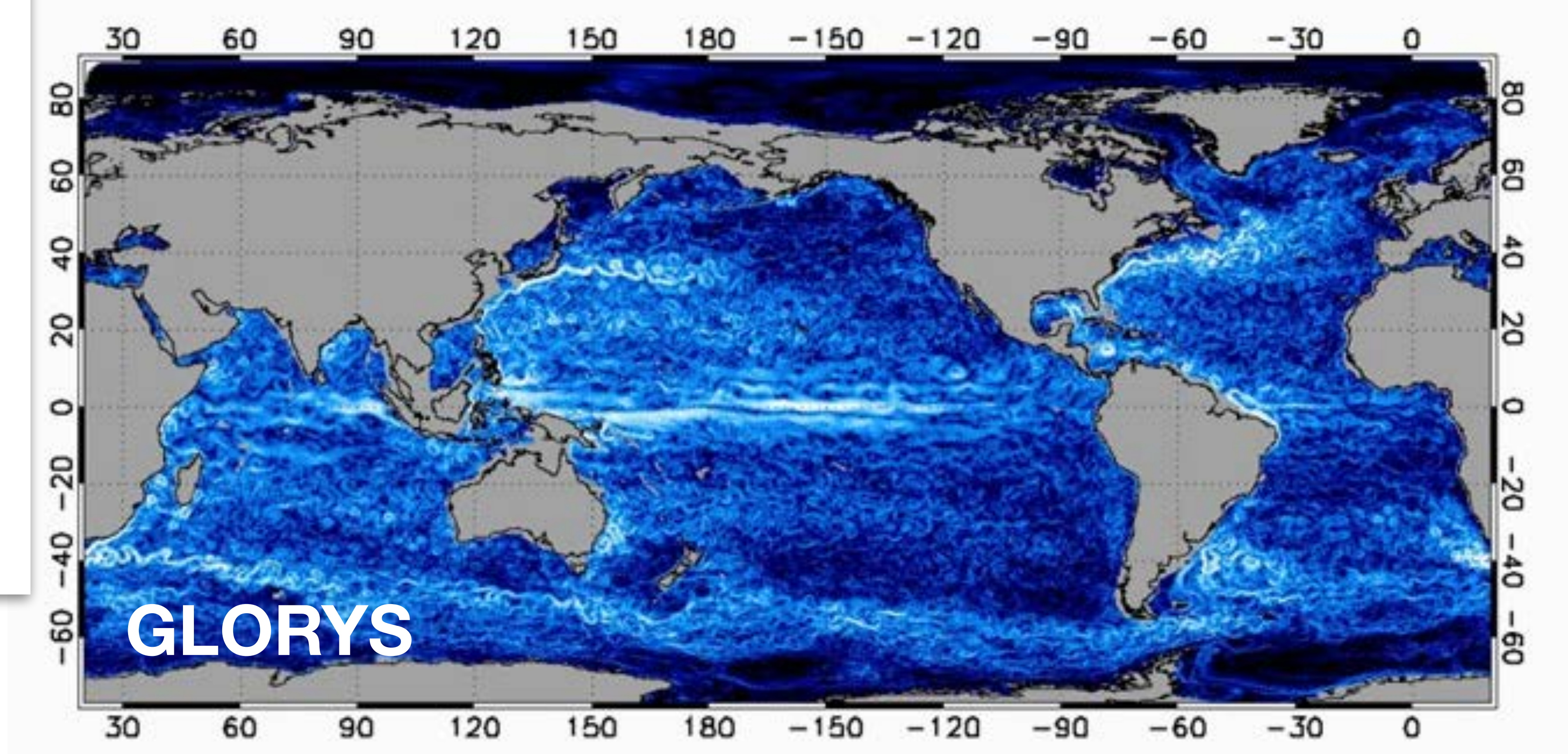
Accurate ocean forecasting is crucial in different areas ranging from science to decision making. Recent advancements in data-driven models have shown significant promise, particularly in weather forecasting community, but yet no data-driven approaches have matched the accuracy and the scalability of traditional global ocean forecasting systems that rely on physics-driven numerical models and can be very computationally expensive, depending on their spatial resolution or complexity. Here, we introduce GLONET, a global ocean neural network-based forecasting system, developed by Mercator Ocean International. GLONET is trained on the global Mercator Ocean physical reanalysis GLORYS12 to integrate physics-based principles through neural operators and networks, which dynamically capture local-global interactions within a unified, scalable framework, ensuring high small-scale accuracy and efficient dynamics. GLONET's performance is assessed and benchmarked against two other forecasting systems: the global Mercator Ocean analysis and forecasting 1/12° high-resolution physical system GLO12 and a recent neural-based system also trained from GLORYS12. A series of comprehensive validation metrics is proposed, specifically tailored for neural network-based ocean forecasting systems, which extend beyond traditional point-wise error assessments that can introduce bias towards neural networks optimized primarily to minimize such metrics. The preliminary evaluation of GLONET shows promising results, for temperature, sea surface height, salinity and ocean currents. GLONET's experimental daily forecast are accessible through the European Digital Twin Ocean platform EDITO.

*Corresponding author: aelaouni@mercator-ocean.fr

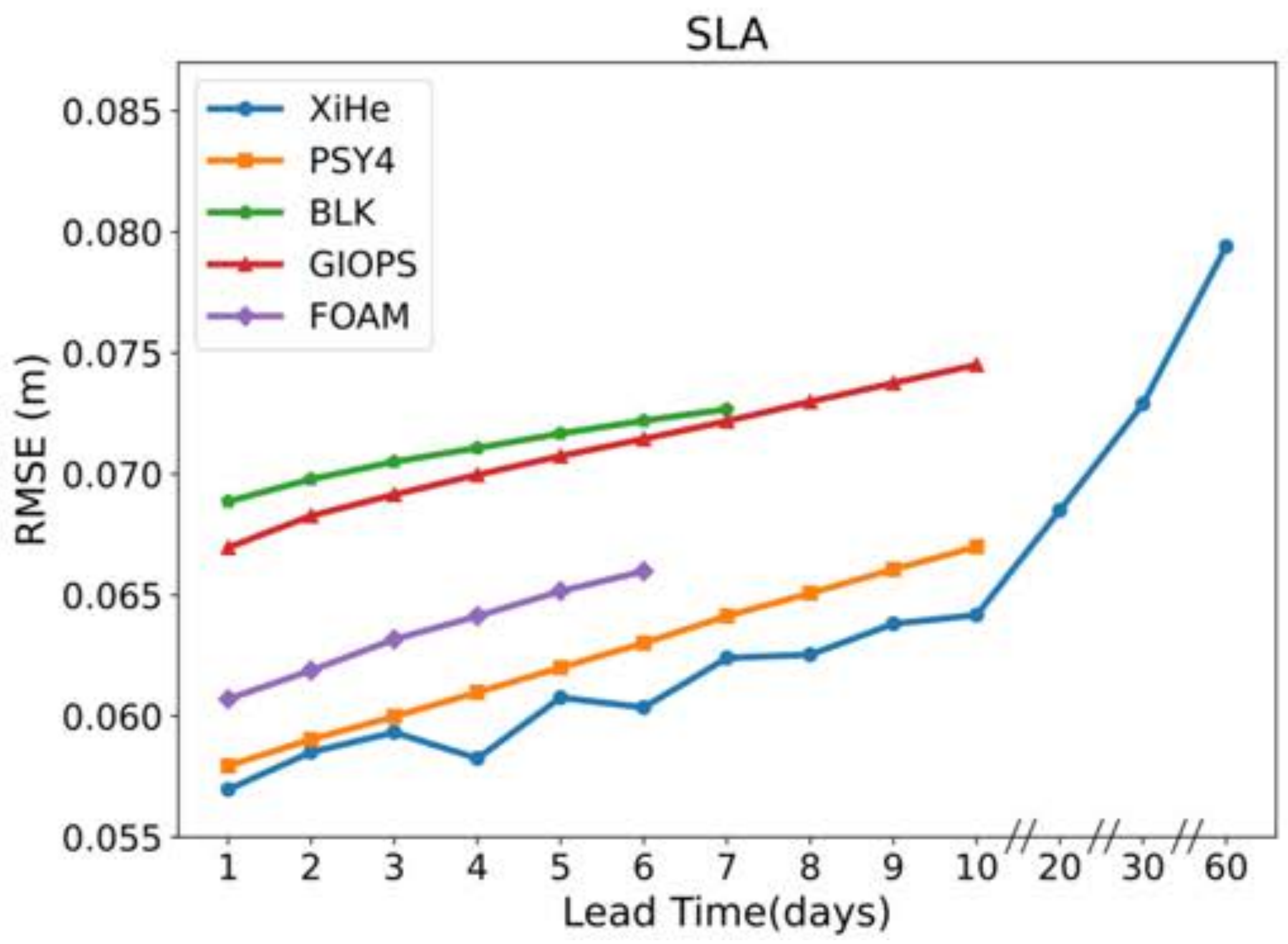
https://arxiv.org/abs/2412.05454

El Aouni et al. (2024)





Trained from ocean reanalyses



Short term forecast skill

COMING UP

AI-native hybrid models

Article

Neural general circulation models for weather and climate

https://doi.org/10.1038/s41586-024-07744-y
Received: 13 November 2023
Accepted: 15 June 2024
Published online: 22 July 2024
Open access
Check for updates

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General circulation models (GCMs) are the foundation of weather and climate prediction[1,2]. GCMs are physics-based simulators that combine a numerical solver for large-scale dynamics with tuned representations for small-scale processes such as cloud formation. Recently, machine-learning models trained on reanalysis data have achieved comparable or better skill than GCMs for deterministic weather forecasting[3,4]. However, these models have not demonstrated improved ensemble forecasts, or shown sufficient stability for long-term weather and climate simulations. Here we present a GCM that combines a differentiable solver for atmospheric dynamics with machine-learning components and show that it can generate forecasts of deterministic weather, ensemble weather and climate on par with the best machine-learning and physics-based methods. NeuralGCM is competitive with machine-learning models for one- to ten-day forecasts, and with the European Centre for Medium-Range Weather Forecasts ensemble prediction for one- to fifteen-day forecasts. With prescribed sea surface temperature, NeuralGCM can accurately track climate metrics for multiple decades, and climate forecasts with 140-kilometre resolution show emergent phenomena such as realistic frequency and trajectories of tropical cyclones. For both weather and climate, our approach offers orders of magnitude computational savings over conventional GCMs, although our model does not extrapolate to substantially different future climates. Our results show that end-to-end deep learning is compatible with tasks performed by conventional GCMs and can enhance the large-scale physical simulations that are essential for understanding and predicting the Earth system.

Solving the equations for Earth's atmosphere with general circulation models (GCMs) is the basis of weather and climate prediction[1,2]. Over the past 70 years, GCMs have been steadily improved with better numerical methods and more detailed physical models, while exploiting faster computers to run at higher resolution. Inside GCMs, the unresolved physical processes such as clouds, radiation and precipitation are represented by semi-empirical parameterizations. Tuning GCMs to match historical data remains a manual process[5], and GCMs retain many persistent errors and biases[6–8]. The difficulty of reducing uncertainty in long-term climate projections[9] and estimating distributions of extreme weather events[10] presents major challenges for climate mitigation and adaptation[11].

Recent advances in machine learning have presented an alternative for weather forecasting[3,4,12,13]. These models rely solely on machine-learning techniques, using roughly 40 years of historical data from the European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis v5 (ERA5)[14] for model training and forecast initialization. Machine-learning methods have been remarkably successful, demonstrating state-of-the-art deterministic forecasts for 1- to 10-day weather prediction at a fraction of the computational cost of traditional models[3,4]. Machine-learning atmospheric models also require considerably less code, for example GraphCast[3] has 5,417 lines versus 376,578 lines for the National Oceanic and Atmospheric Administration's FV3 atmospheric model[15] (see Supplementary Information section A for details).

Nevertheless, machine-learning approaches have noteworthy limitations compared with GCMs. Existing machine-learning models have focused on deterministic prediction, and surpass deterministic numerical weather prediction in terms of the aggregate metrics for which they are trained[3,4]. However, they do not produce calibrated uncertainty estimates[4], which is essential for useful weather forecasts[1]. Deterministic machine-learning models using a mean-squared-error loss are rewarded for averaging over uncertainty, producing unrealistically blurry predictions when optimized for multi-day forecasts[3,13]. Unlike physical models, machine-learning models misrepresent derived (diagnostic) variables such as geostrophic wind[16]. Furthermore,

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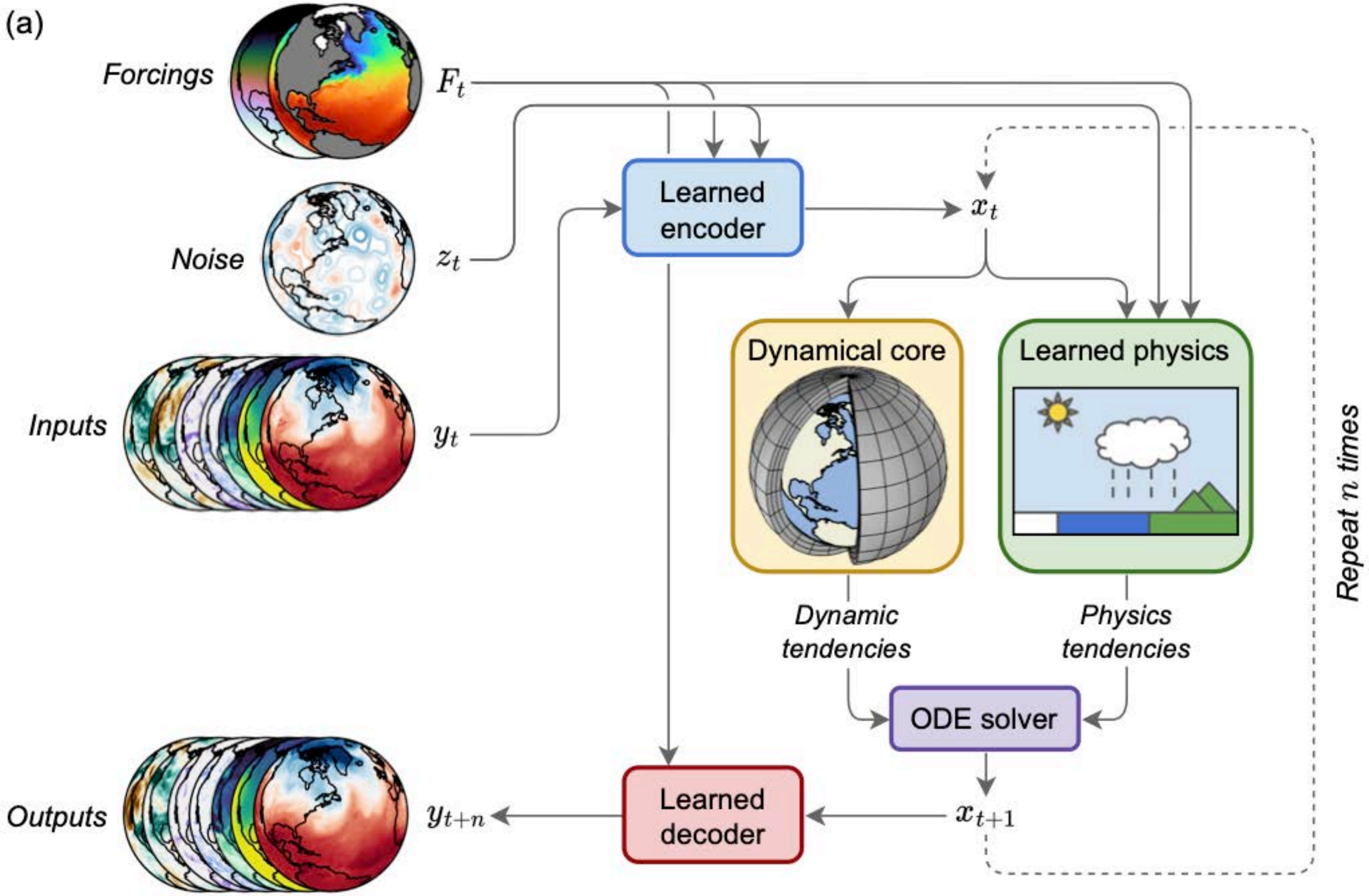
https://doi.org/10.1038/s41586-024-07744-y

Kochkov et al. (2024)



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

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

3.

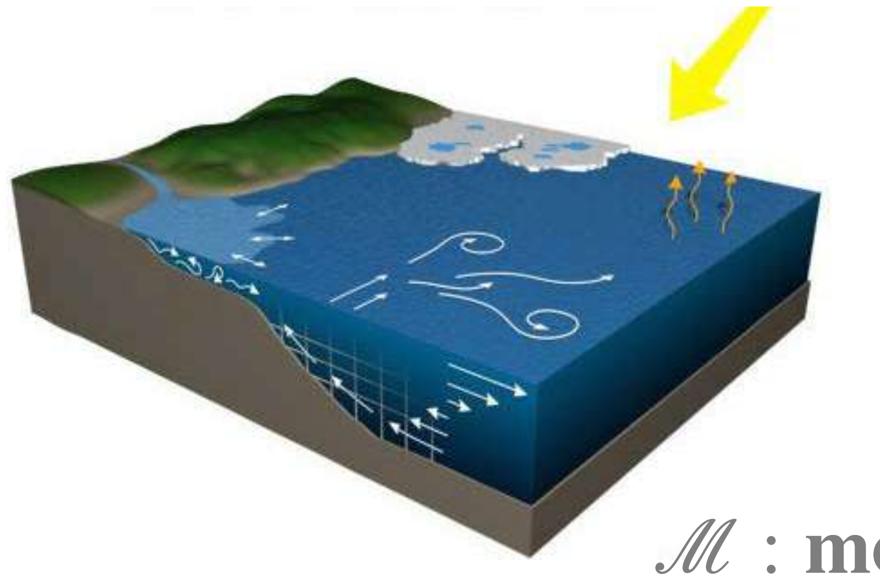
Hybrid models combining physics and ML

Hybrid models combining physics and ML

Augmenting ocean models with ML components

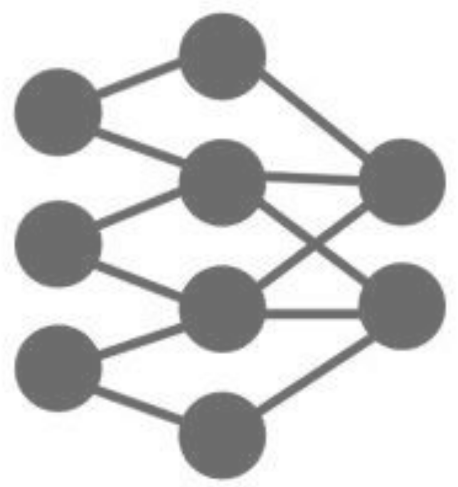
Input

step n



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

+



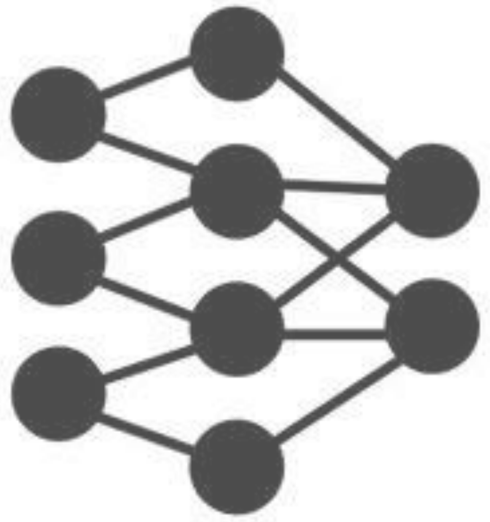
θ : **parameters**

step n+1

Output

The model is augmented with a **trainable** component

with



θ : **parameters**

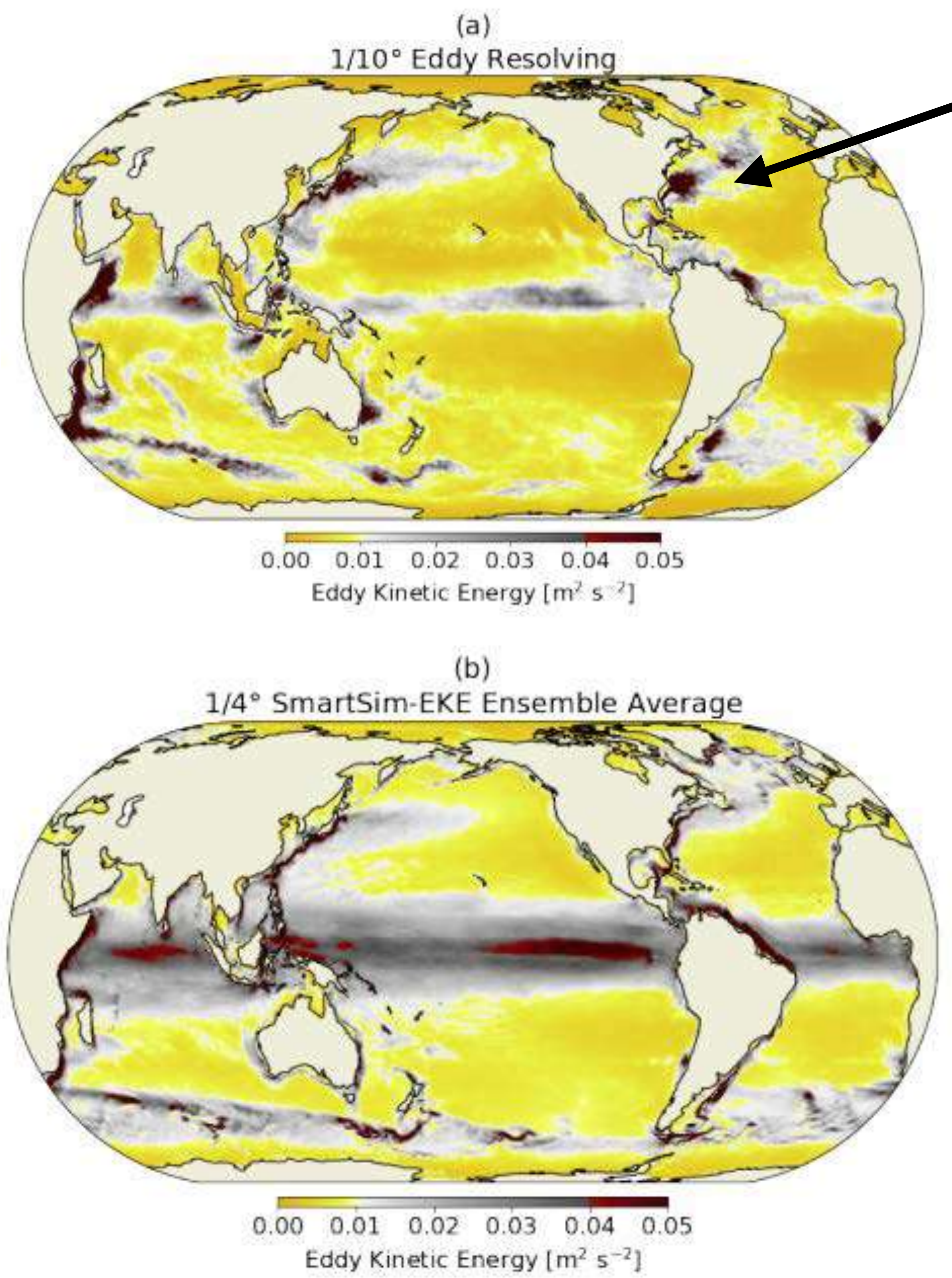
trained to minimise :

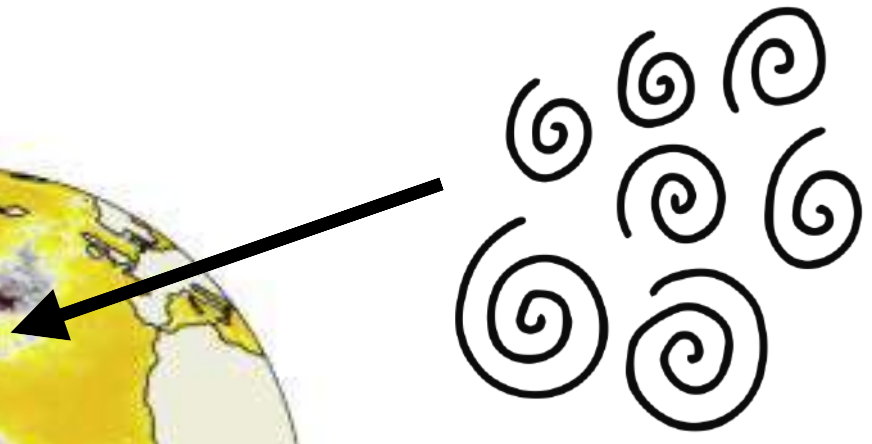
$$\mathscr{L}(\theta) = \textbf{training objective}$$

- improving physical **consistency**
- correcting model **errors** (vs obs.)
- **accelerating** execution (x10-100)

NB : does not have to be deterministic

ML for ocean models subgrid physics (1/2)



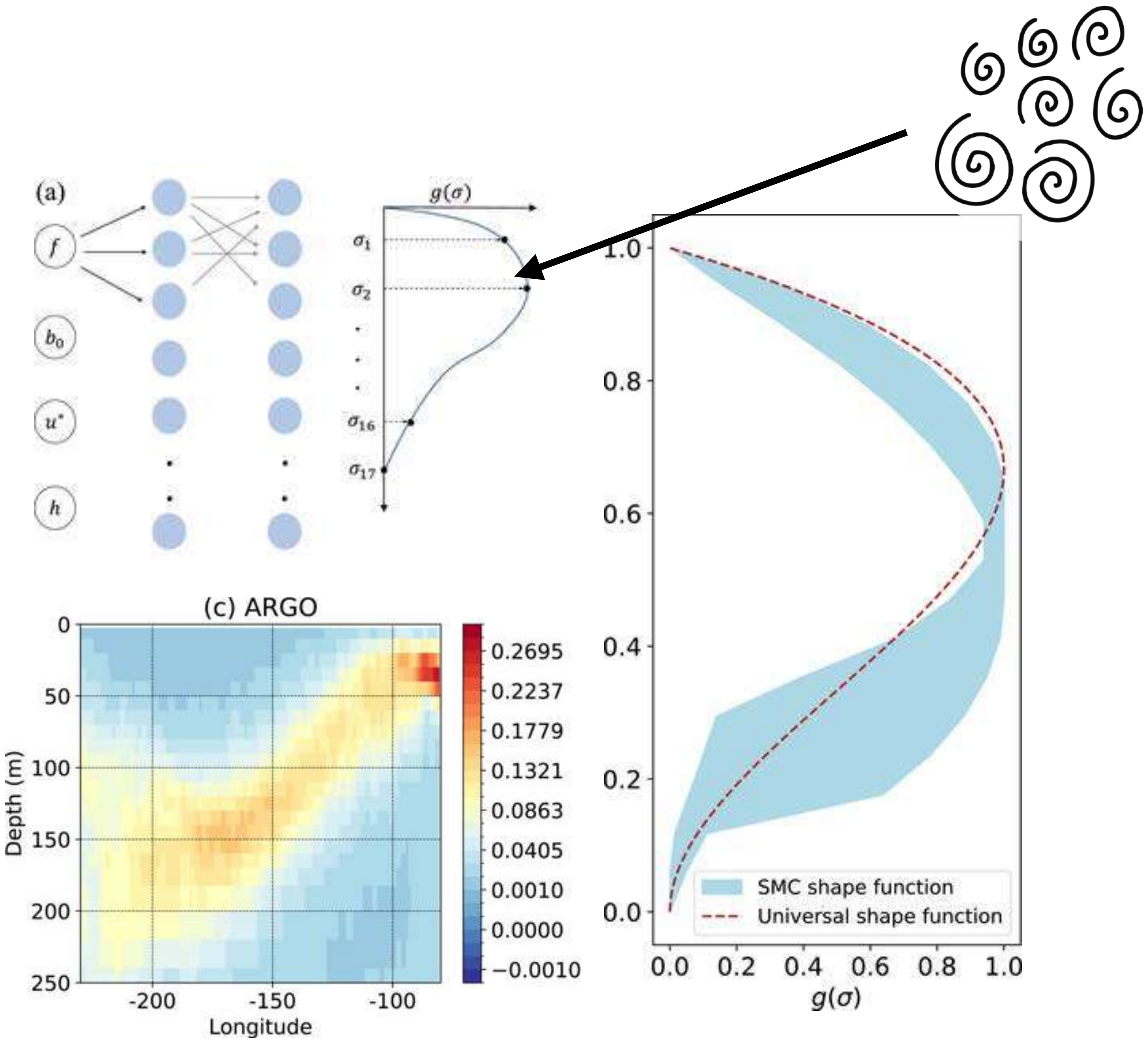


oceanic macro-scale turbulence

- 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)

Partee et al. 2022
https://doi.org/10.1016/j.jocs.2022.101707

ML for ocean models subgrid physics (1/2)



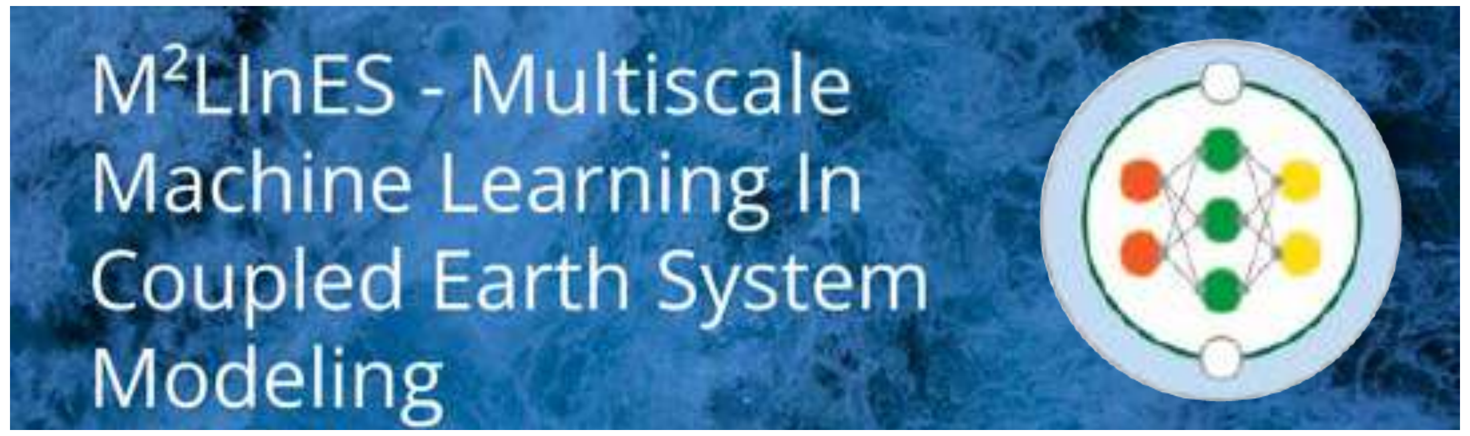
oceanic micro-scale turbulence

- 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)

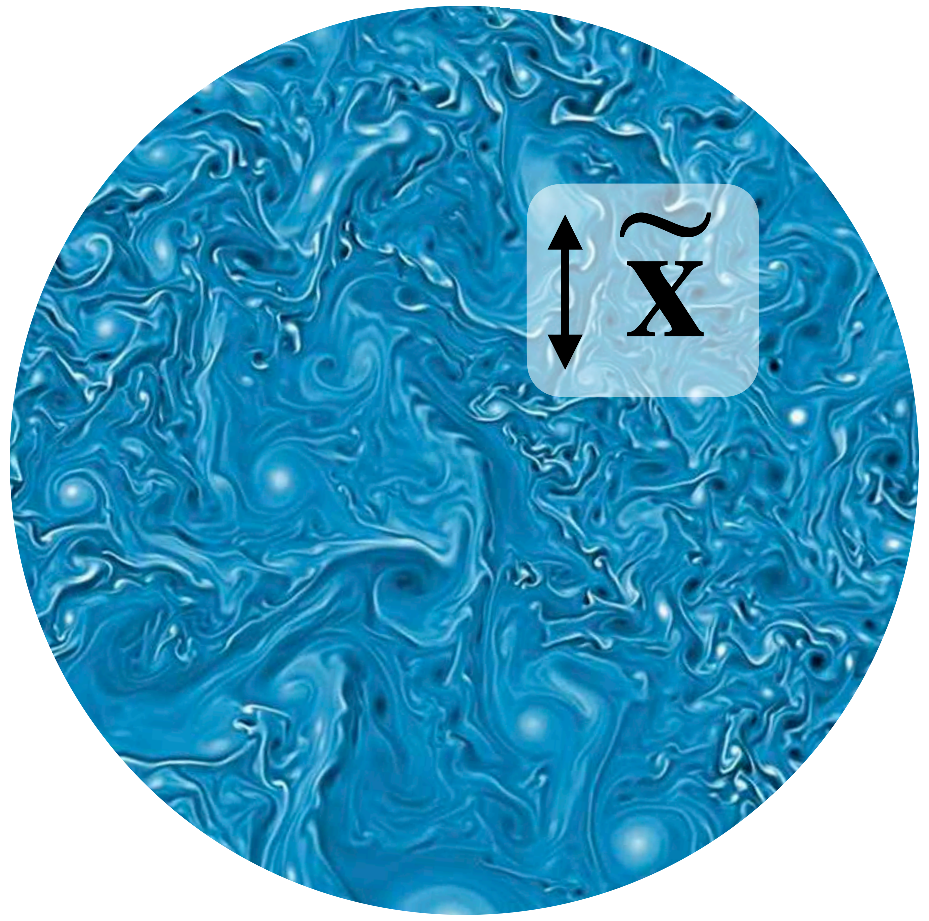
Sane et al. 2023
https://doi.org/10.1029/2023MS003890

See for instance :
M2LInES consortium

https://m2lines.github.io



ML for ocean models subgrid physics (2/2)



Dynamical system

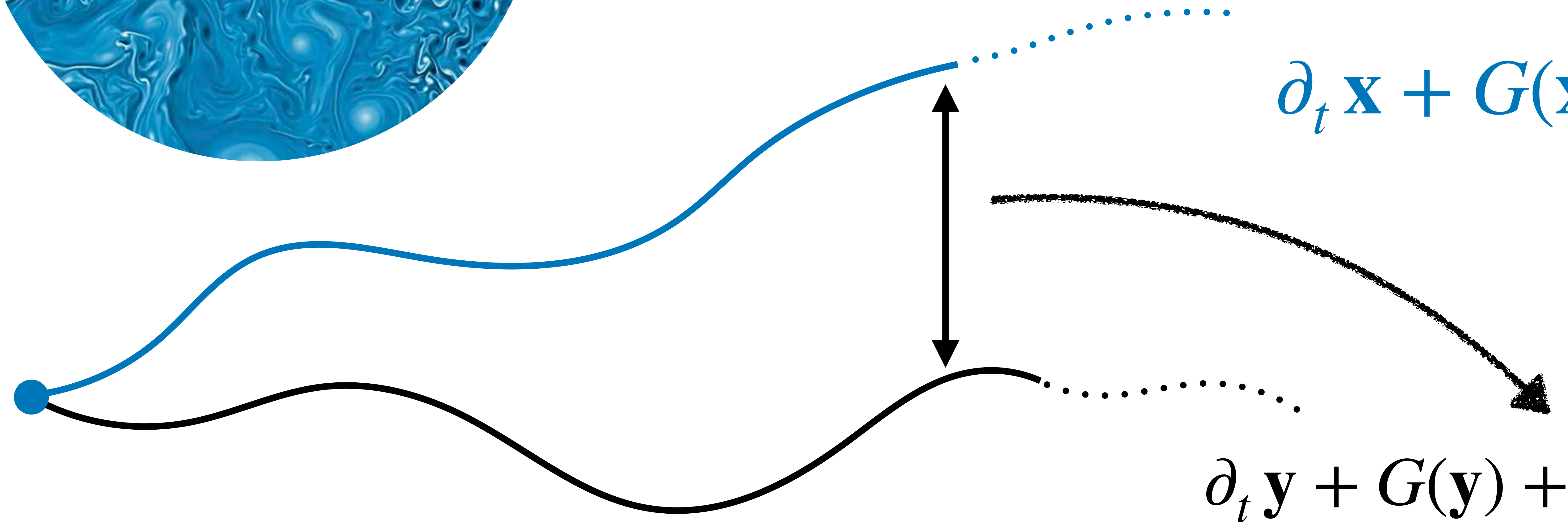
$$\partial_t \mathbf{x} + \mathscr{L}\,\mathbf{x} + \mathscr{N}(\mathbf{x}) = 0$$

Resolved equations

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

Subgrid closure

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

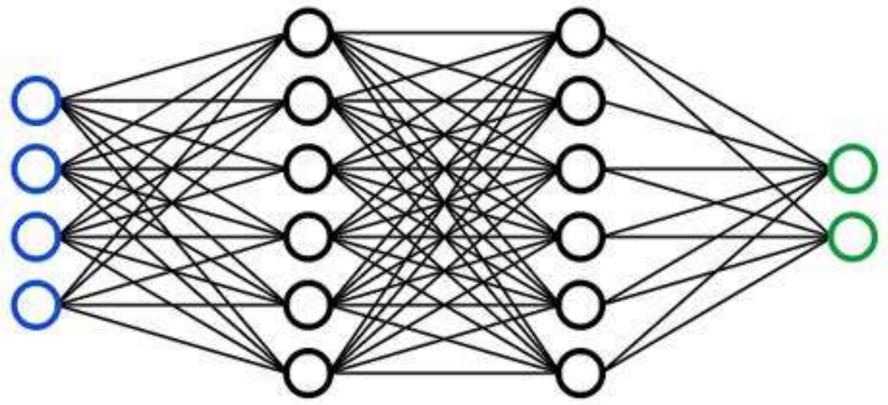


$$\partial_t \mathbf{x} + G(\mathbf{x}) = 0$$

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

Learning the mapping

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



θ : **parameters**

Performance, stability

Generalisation, interpretability

Frezat et al. (2022)

End-to-end training

online vs offline training
w/ same architecture
barotropic QG

Yan et al. (2024)

Online strategies

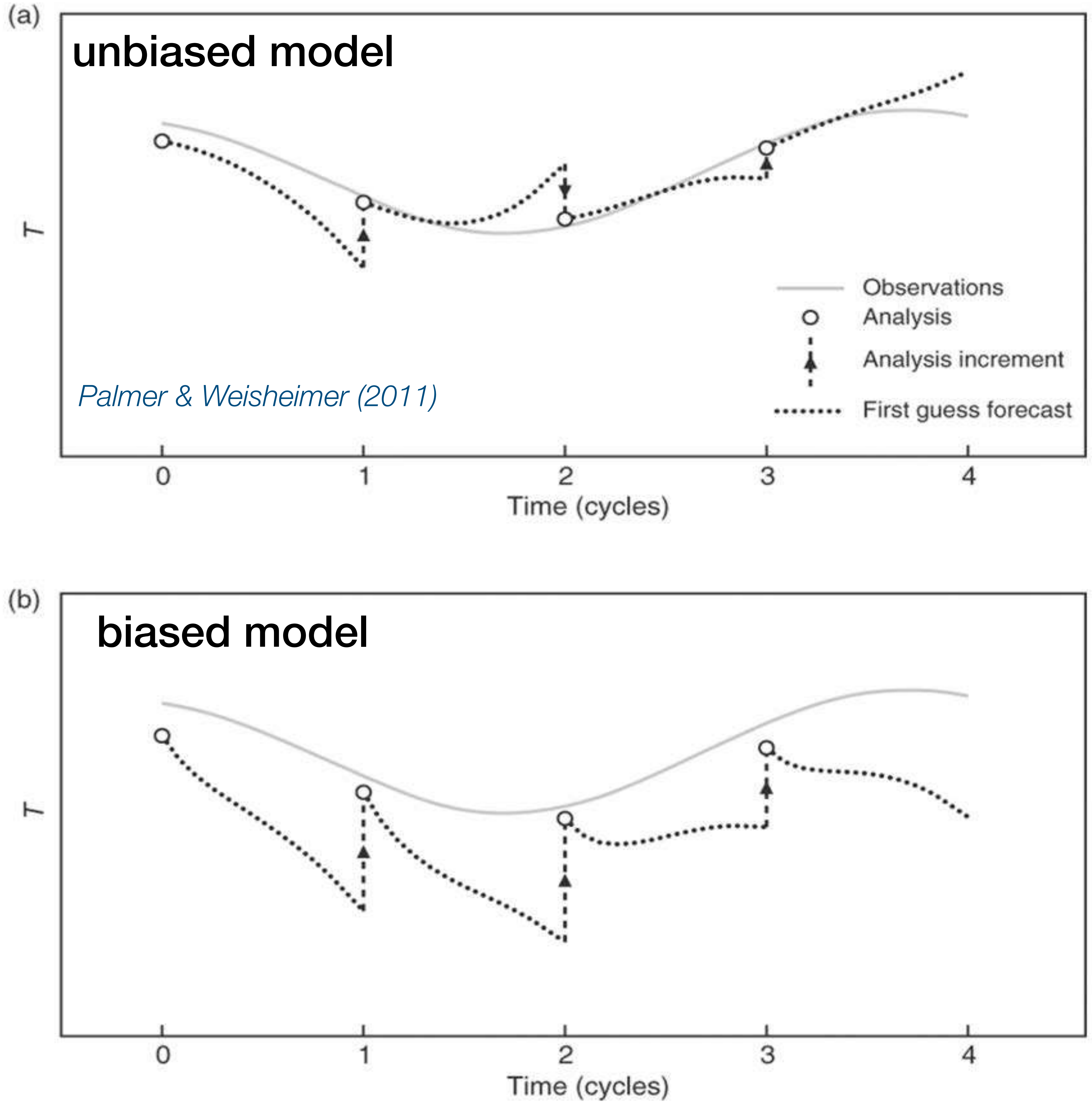
baroclinic turbulence
compared to baseline
w/ more metrics

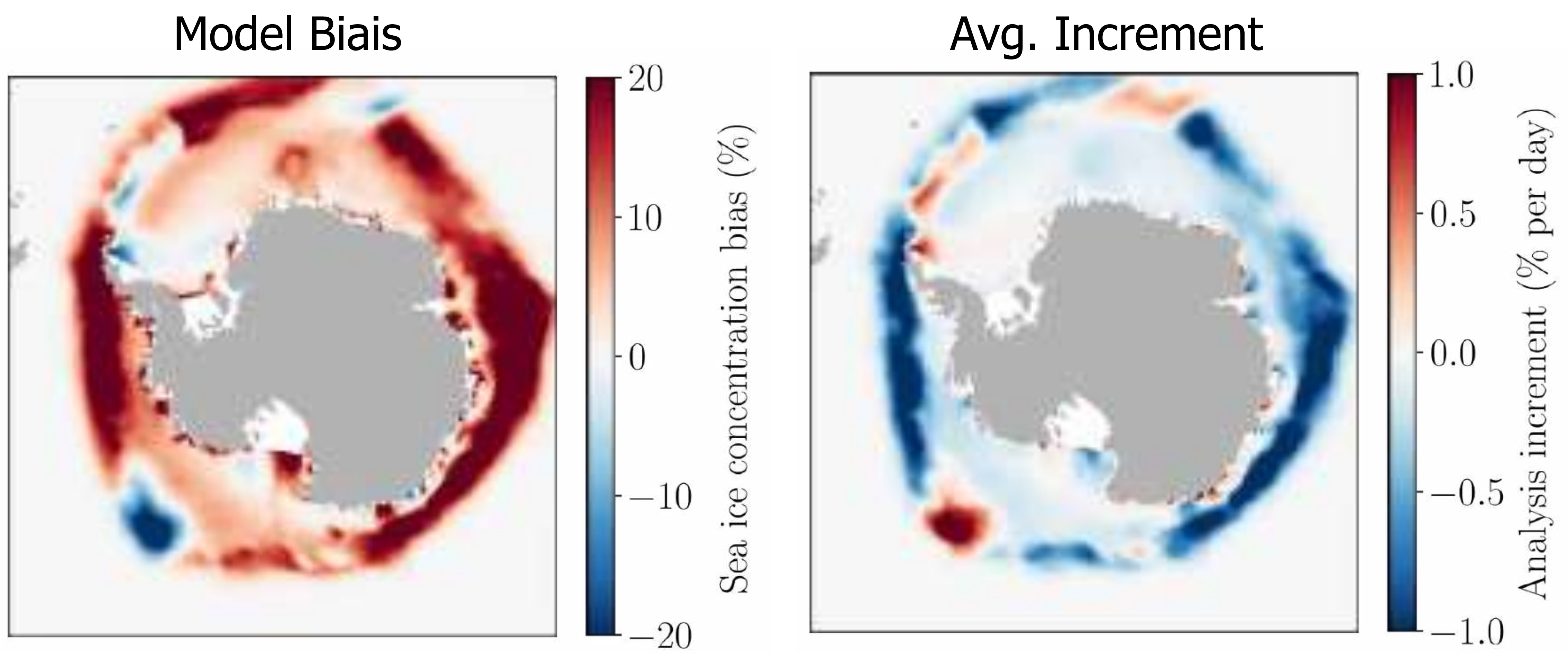
Frezat et al. (2024)

Gradient-free training

training model emulator
for approx. gradient
wrt NN parameters

Learning model error from observations (1/2)

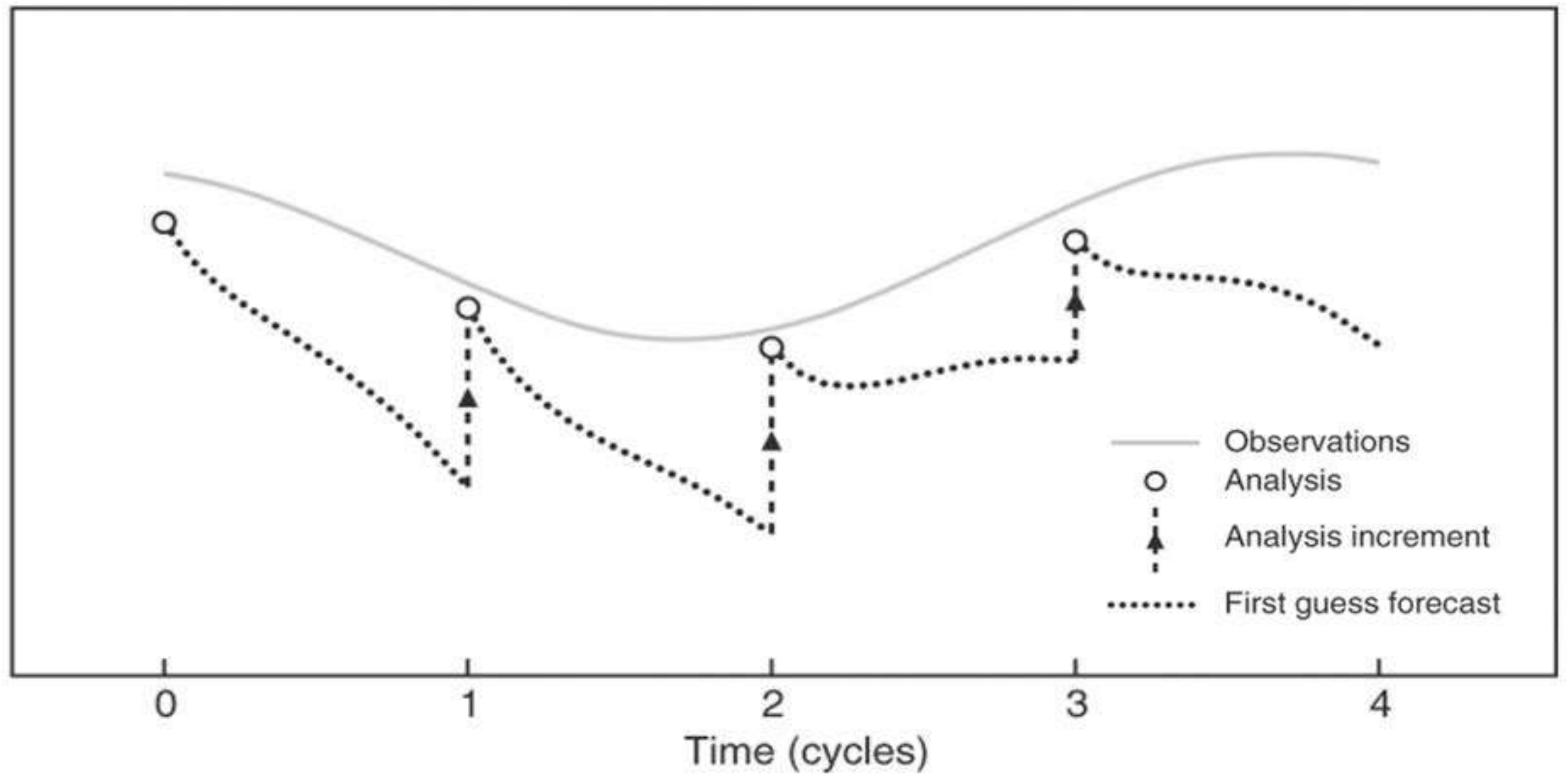




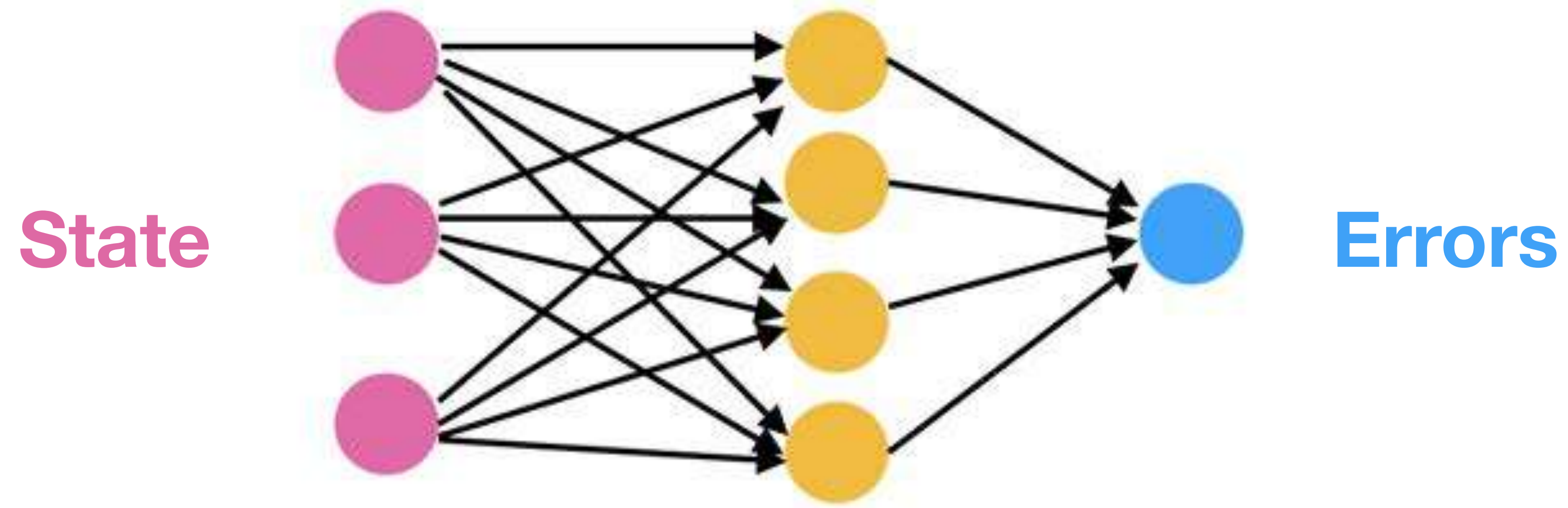
Gregory et al. (2023)

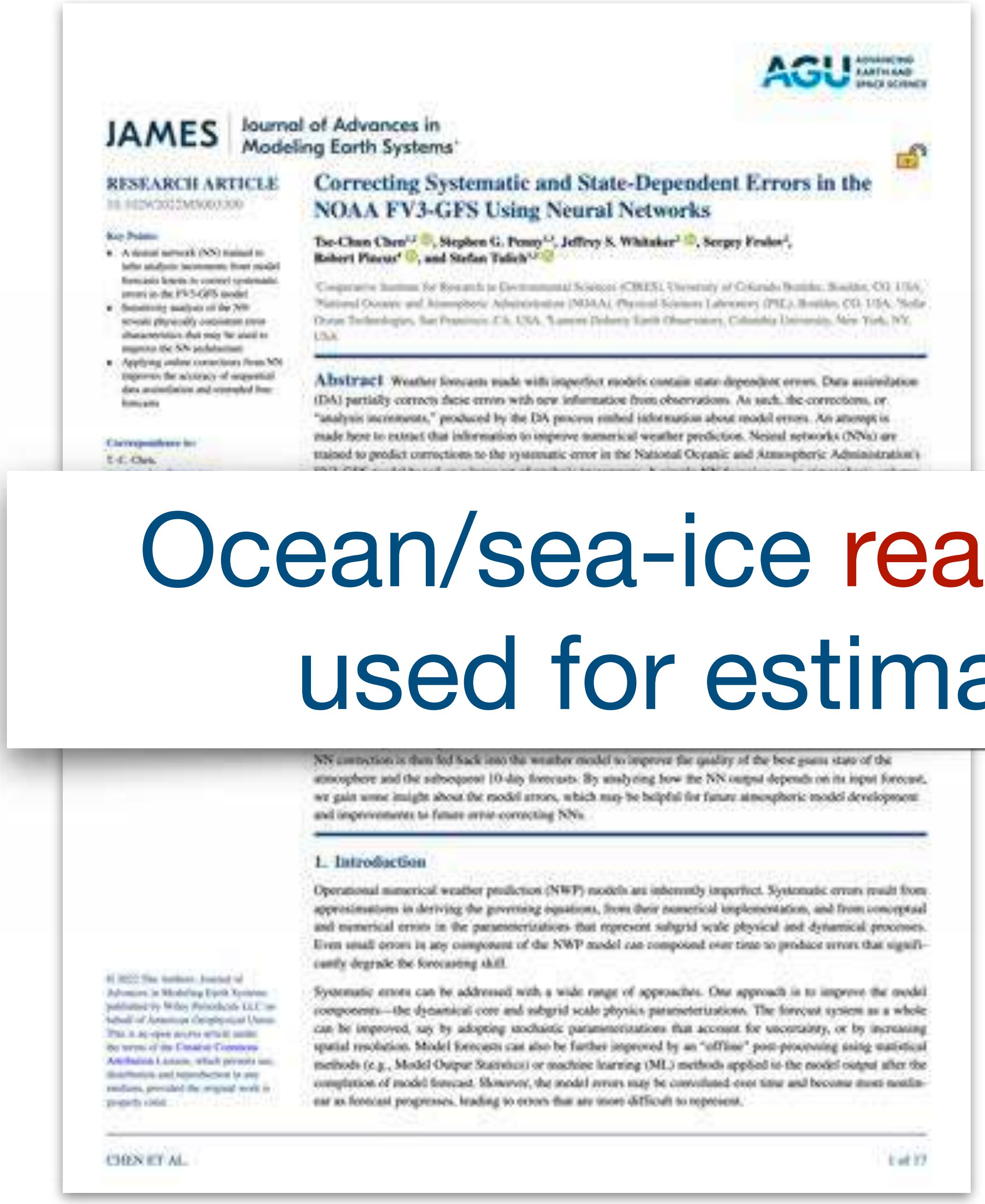
- w/ unbiased observations, analysis increments compensate for model biais
- estimating state-dependent bias corrections (Leith, 1978; Saha, 1992; DelSole and Hou, 1999)
- state-dependent biais corrections provide a representation of model errors

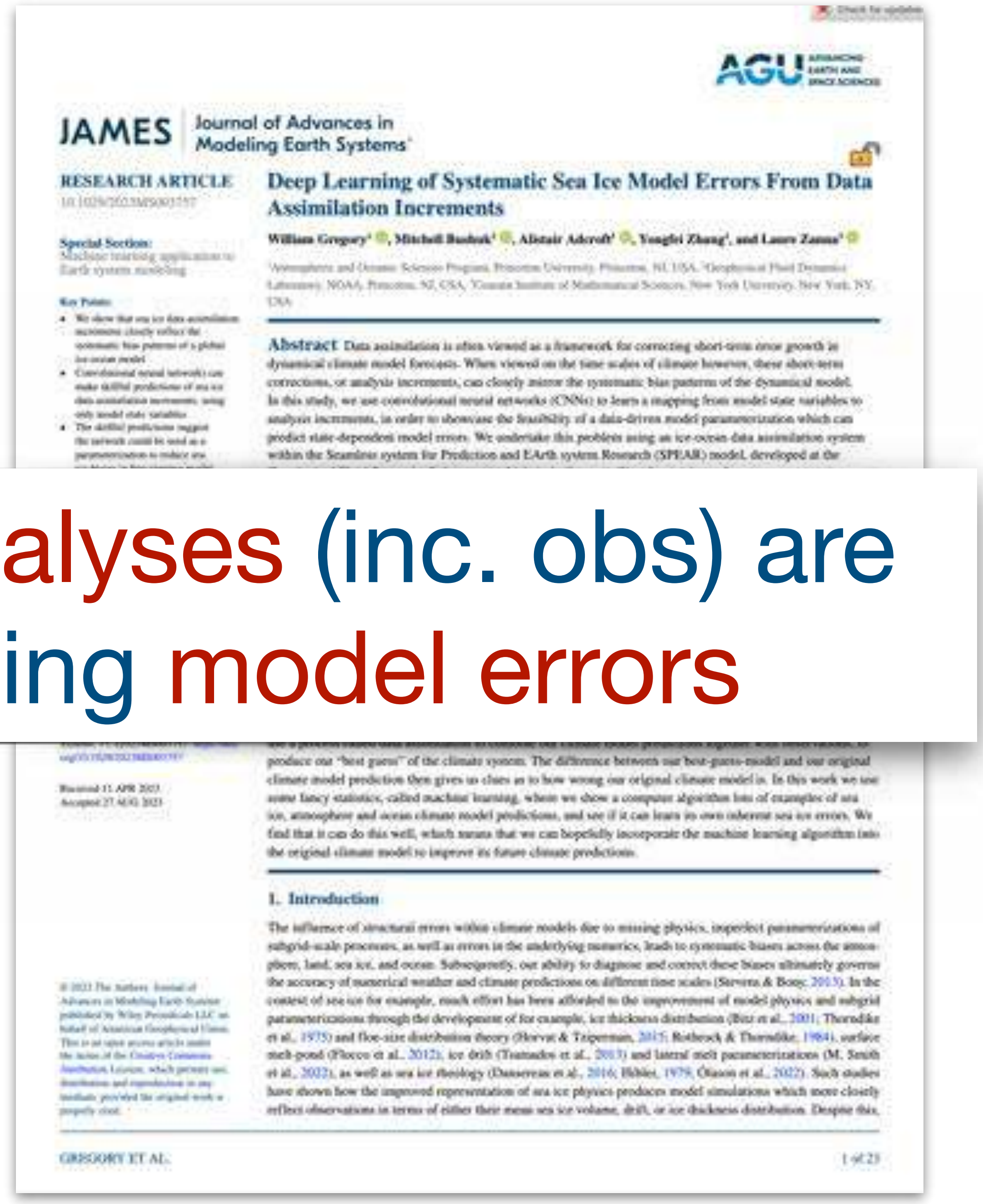
Learning model error from observations (2/2)



Offline







Ocean/sea-ice reanalyses (inc. obs) are used for estimating model errors

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

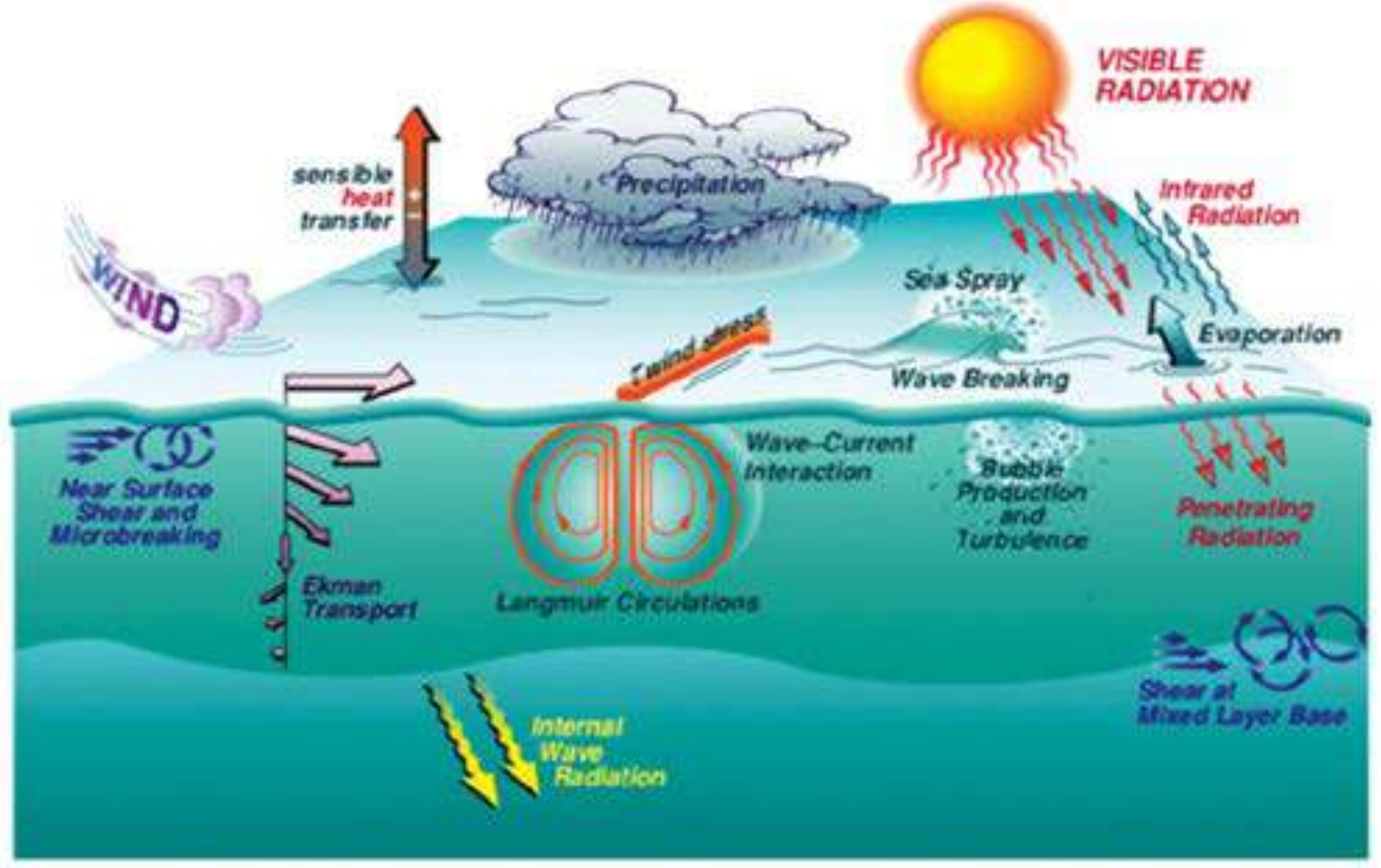
https://doi.org/10.1029/2023MS003757

- 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

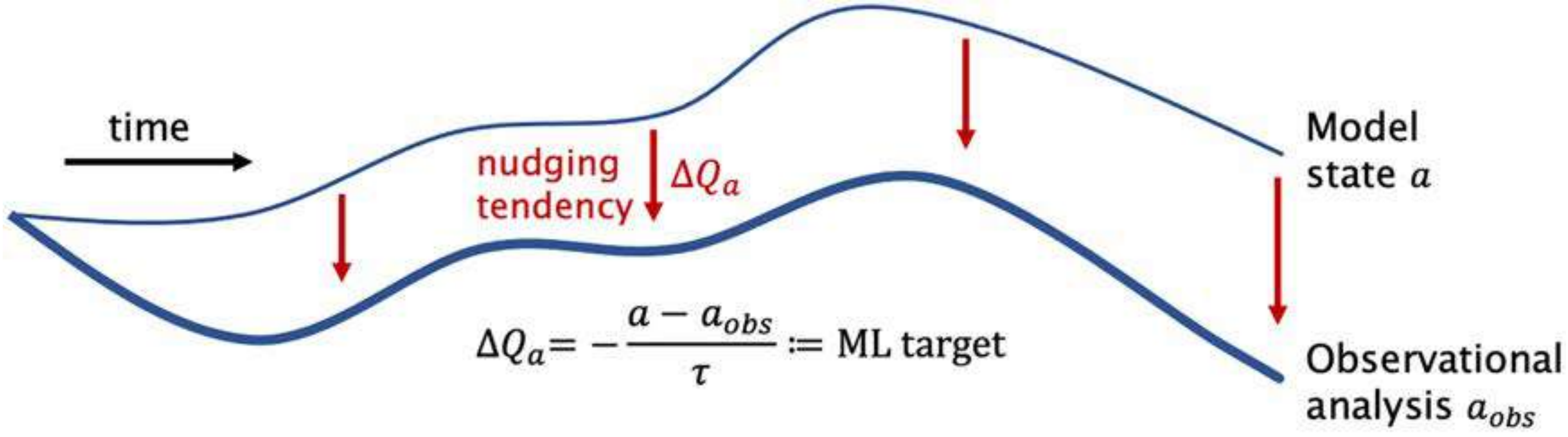
Bonavita and Laloyaux, 2020; Watt-Meyer et al., 2021; Chen et al., 2022; Gregory et al. 202
Chapman and Berner 2023

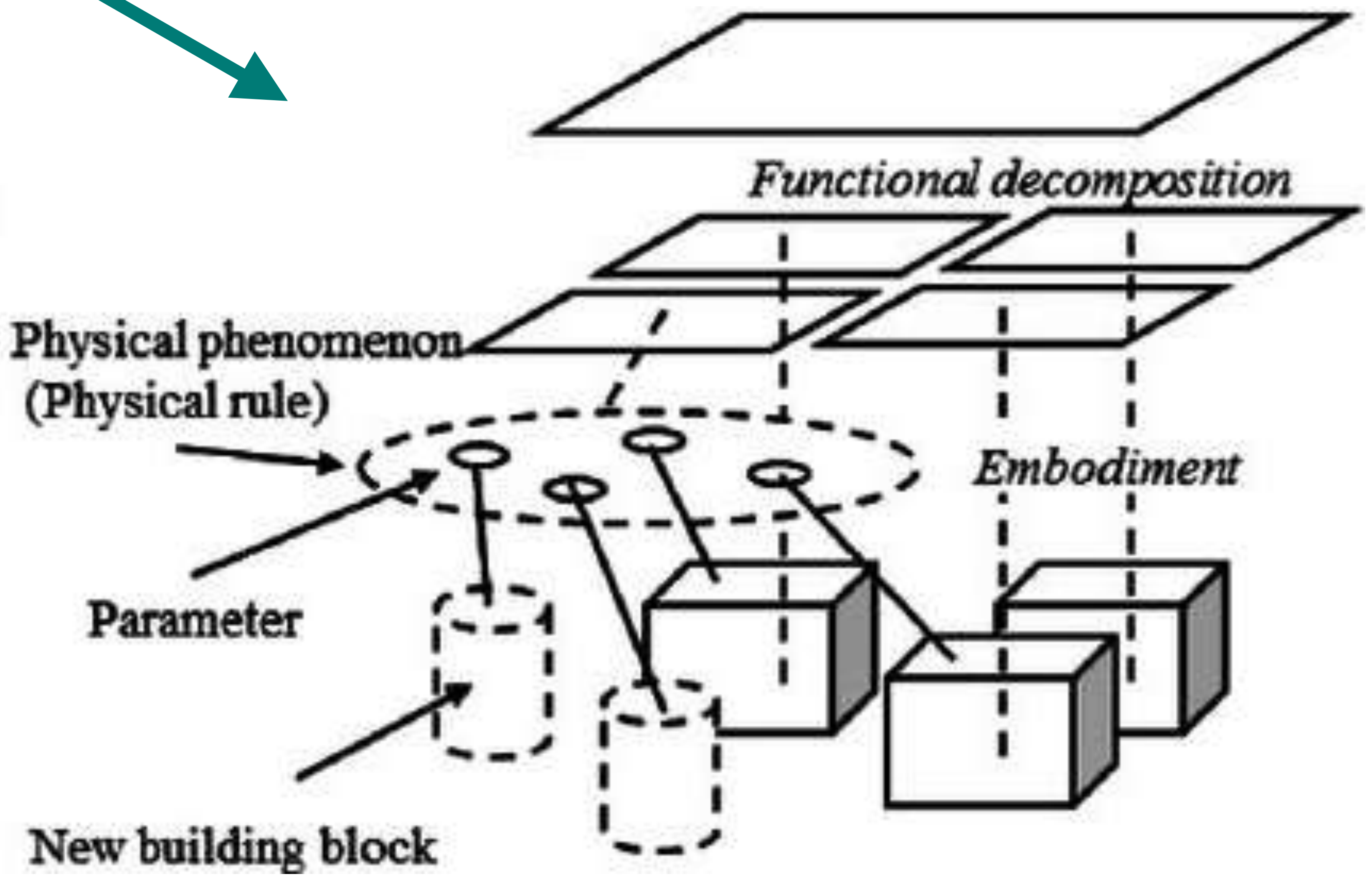
Bridging bias correction and parameterizatons

Parameterising unresolved physics



Learning correction from observations





In combination with uncertainty quantification and parameter calibration

Tools for better understanding the missing physics in our models