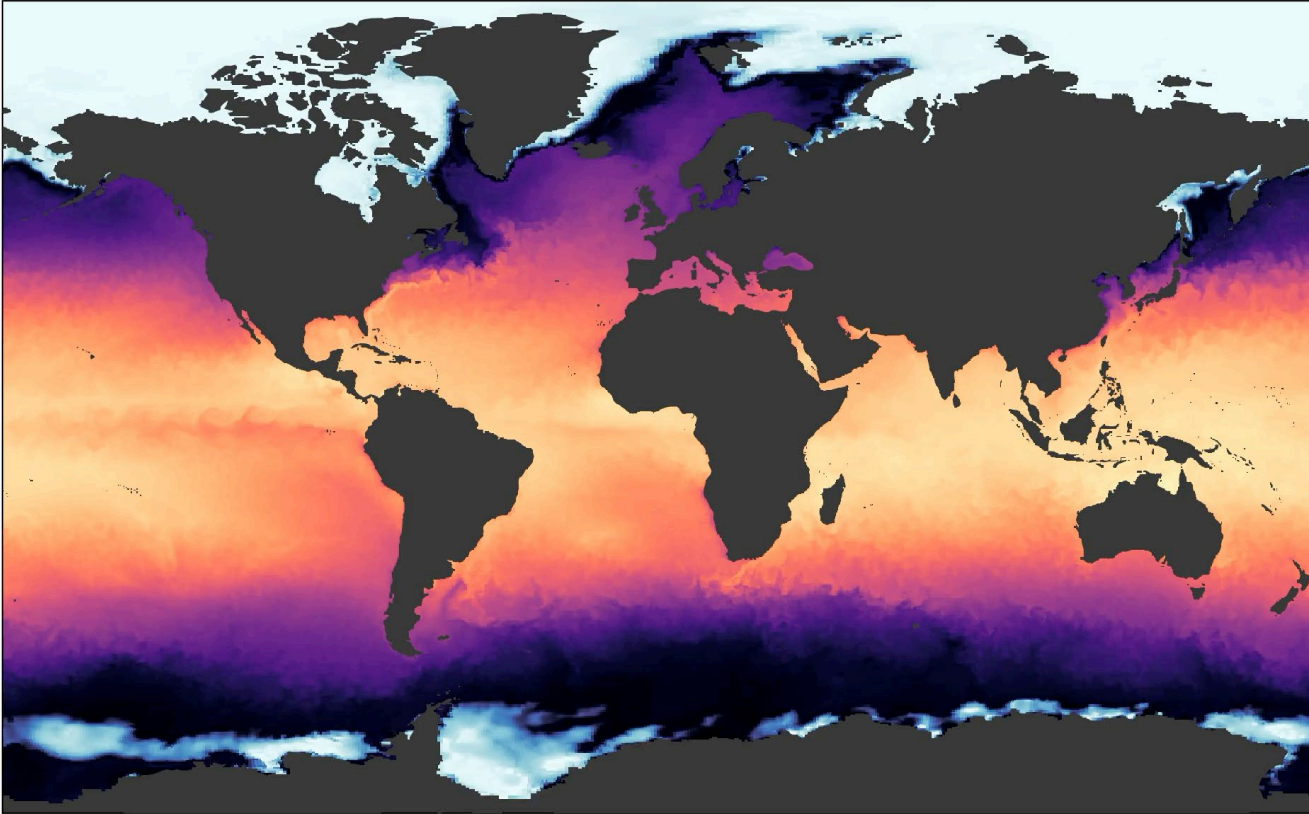


Workshop on surface process coupling and its interactions with the atmosphere
09.04.2025



Coupling approaches for data-driven Earth system model components

Lorenzo Zampieri
the AIFS and Ocean Teams

lorenzo.zampieri@ecmwf.int

Overview of the presentation

The basic functioning of Machine Learning (ML) models

Developing ML models beyond the atmosphere

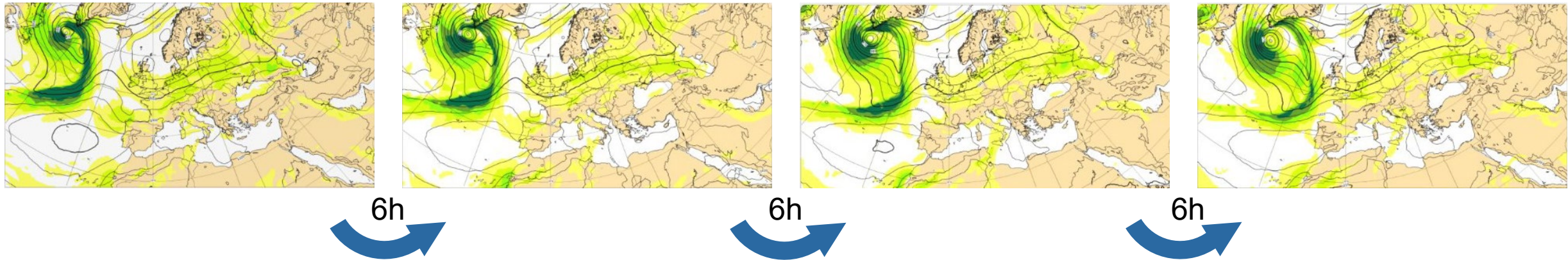
Coupling approaches for ML models

First results in the context of medium-range weather forecasts

Open questions and future research directions

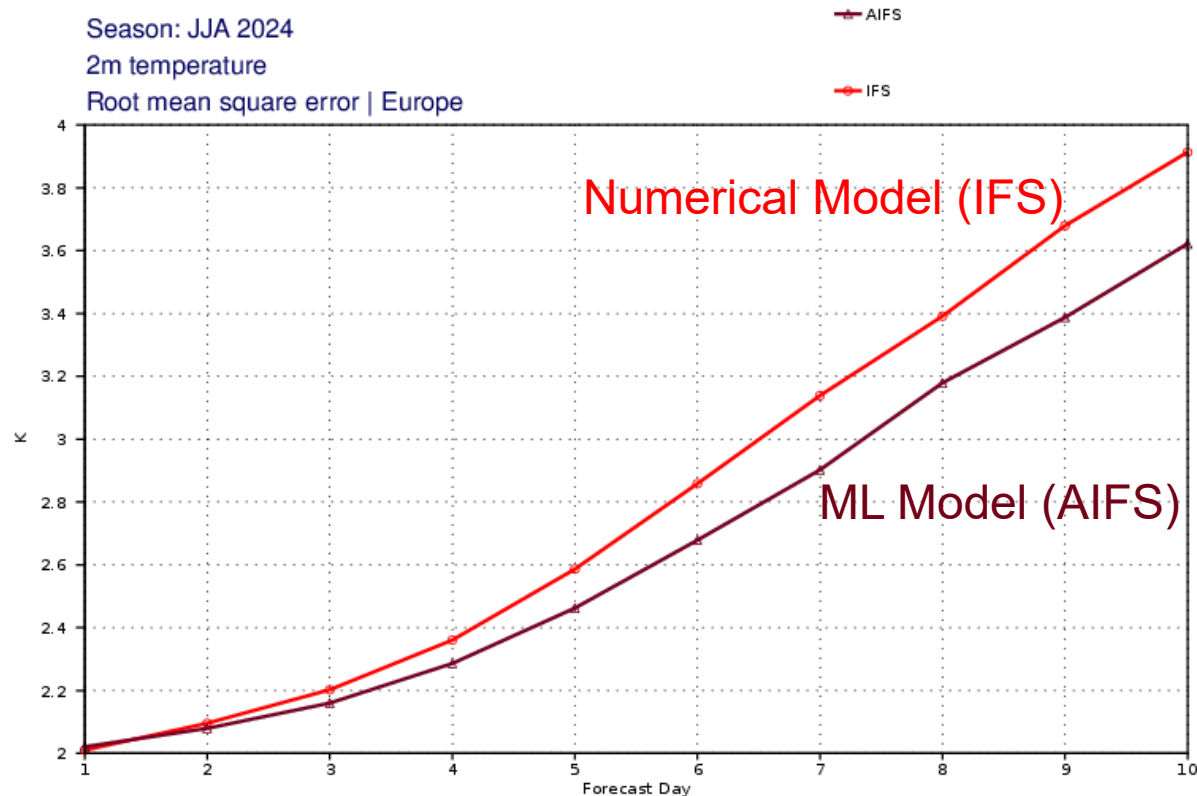
Basic functioning of machine learning models

TRAINING: ML models learn from several years of a high-quality dataset (e.g., ECMWF's ERA5 reanalysis), progressing from one analysis state to the next



For **FORECASTING**, we autoregressively step the trained model 6h into the future $x_n = f(x_{n-1})$

Basic features of machine learning models



Lower values indicate better skill

ML models provide a realistic representation of atmospheric dynamics and thermodynamics

ML models outperform traditional NWP systems across key metrics in both deterministic and probabilistic medium-range forecasts

Once trained, ML models are several orders of magnitude faster and energy-efficient

Expansion of AIFS to other Earth System Components



Funded by
the European Union

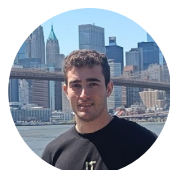
Destination Earth

DestinE funded the development of specialized ML emulators for the major Earth system components

- Ocean
- Ocean waves
- Sea ice
- Land
- Hydrology



Rilwan



Mario



Sara



Lorenzo



Rachel



Maria Luisa



Nina

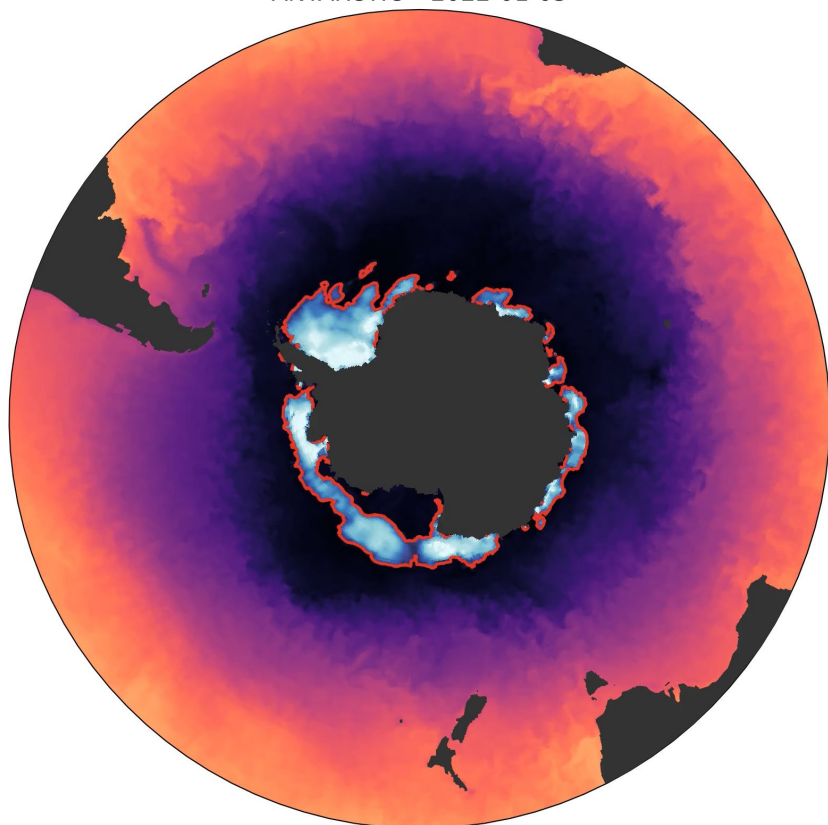


Ewan

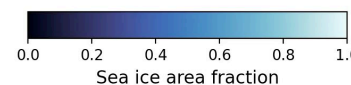
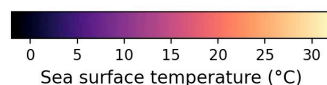
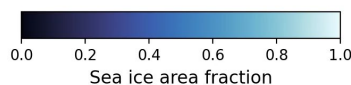
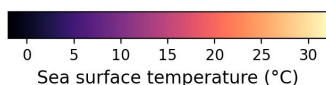
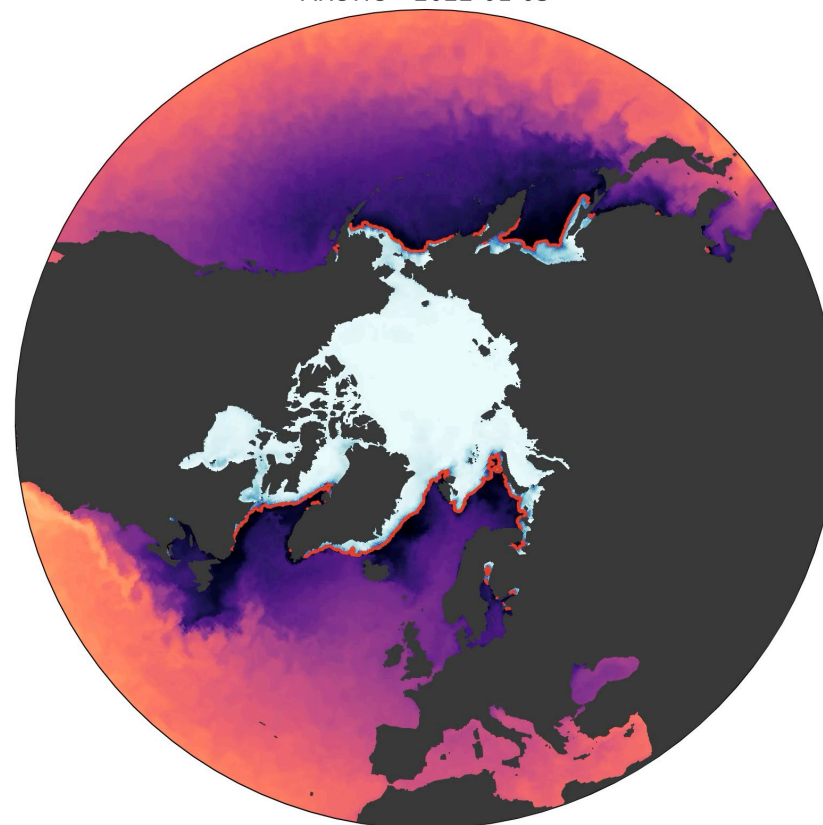
The goal is to obtain a comprehensive ML description of the Earth system for environmental predictions across timescales

An ML emulator of the sea ice and surface ocean

ANTARCTIC - 2022-01-03



ARCTIC - 2022-01-03



Standalone surface ocean
and sea ice model
(OMIP-like simulation)

Trained on ORAS6
(2005 – 2021)

24h timestep

1/4° resolution

Model Integration over 2022
forced by ERA5

An ML emulator of the sea ice and surface ocean

2D prognostic variables from ORAS6 (1h means)

sst	svn	snvol	siue
ssh	sve	sivol	sialb
sss	siconc	sivn	icesalt

2D dynamic atmospheric forcing (inst & 6h accumulations)

10u	10v	2t	2d
ssrd	strd	tp	msl

2D computed forcings

land-sea mask
cos(lat), cos(lon), etc.

Timestep is 24h: $t-24, t \rightarrow t+24$

Coupling numerical Earth System Models (ESMs)

Numerical models are coupled to obtain a **comprehensive** representation of the Earth's system

Coupling is key for closing the energy and mass budget

Coupling is required when **different numerical schemes** are applied to two or more model components

Coupling is needed to accommodate different **spatial discretisations** (both horizontal and vertical)

Coupling can be helpful when models run at different **timesteps**

Coupling is also driven by scientific specialization in the model development process

Coupling data-driven ESMs – some considerations

The same model architectures can handle successfully different Earth's system components

Longer timesteps are possible or even encouraged

Developing data-driven models requires less specialization

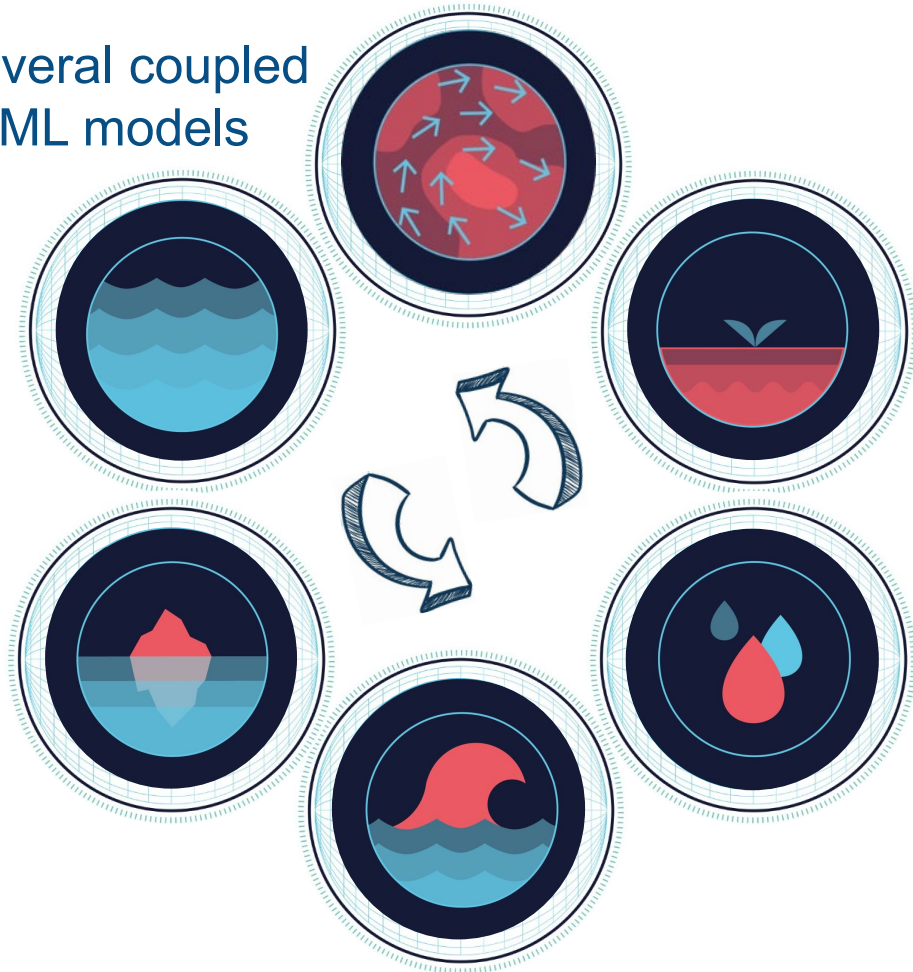
 Understanding training data is often easier than interpreting governing equations

Emphasis shifts **from the equations to the training data**

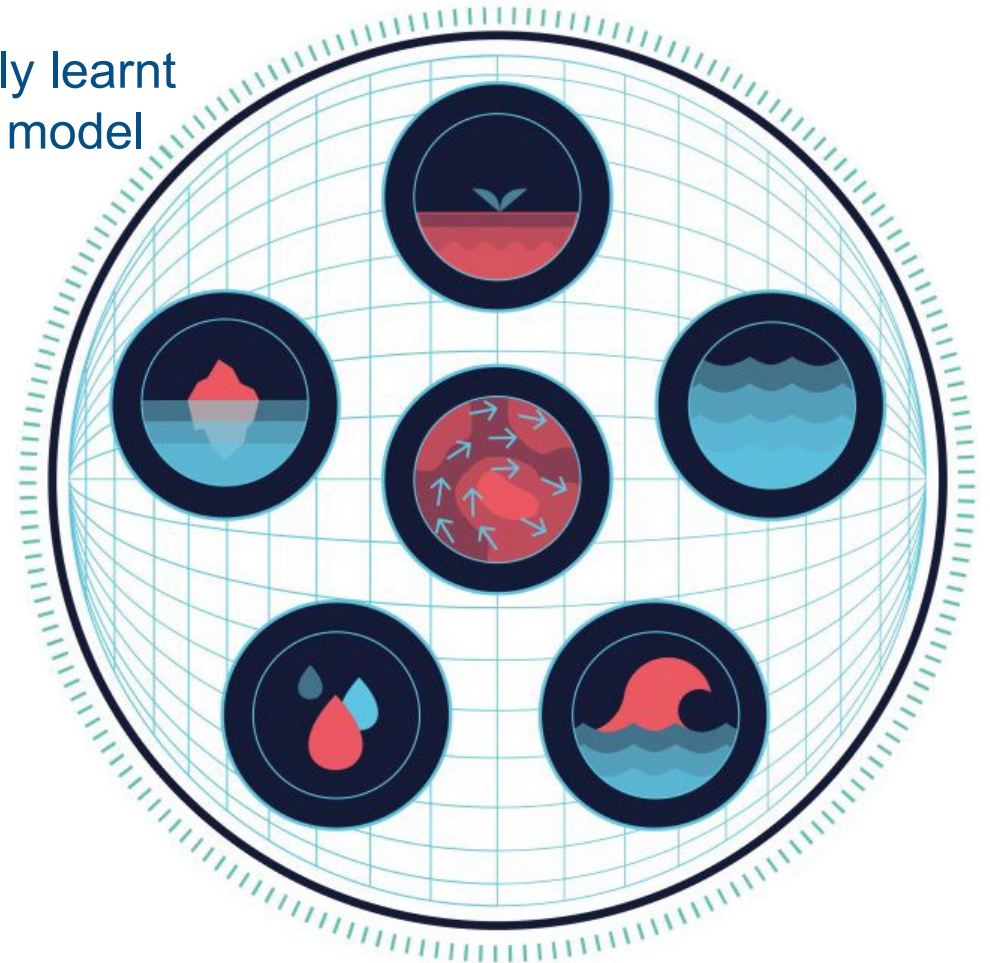
 Coupled processes influence training data

Coupling strategy for ML models

Several coupled
ML models



Jointly learnt
ML model



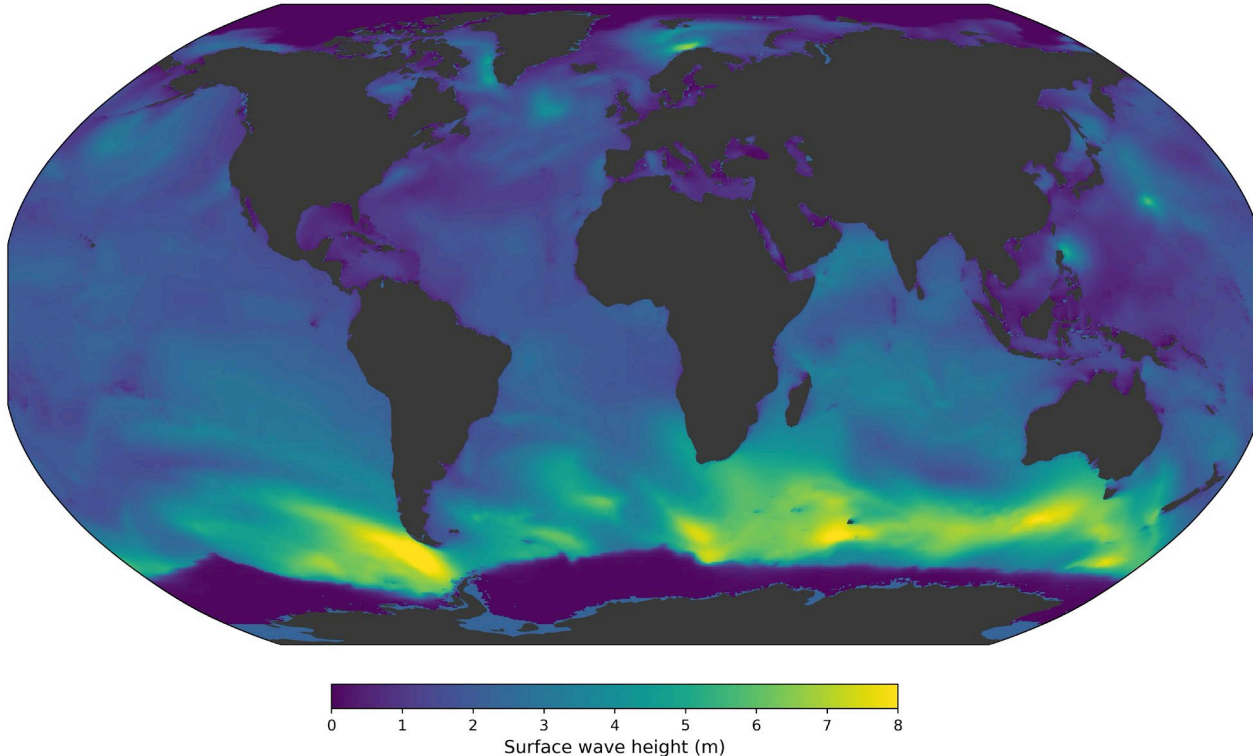
AIFS and waves – a joint model example

Add wave component to the AIFS Single → **joint model**

- Significant wave height 
- Mean wave direction 
- Mean wave period 
- Drag coefficient 

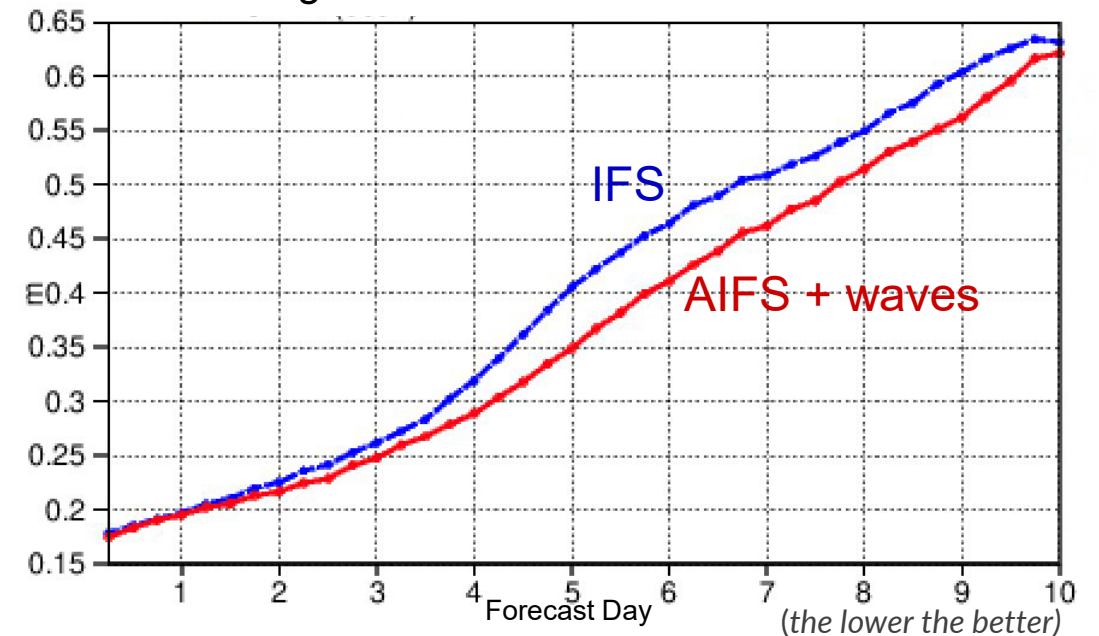
Significant Wave Height Forecast

Ocean Surface Waves - 2022-08-23T06:00



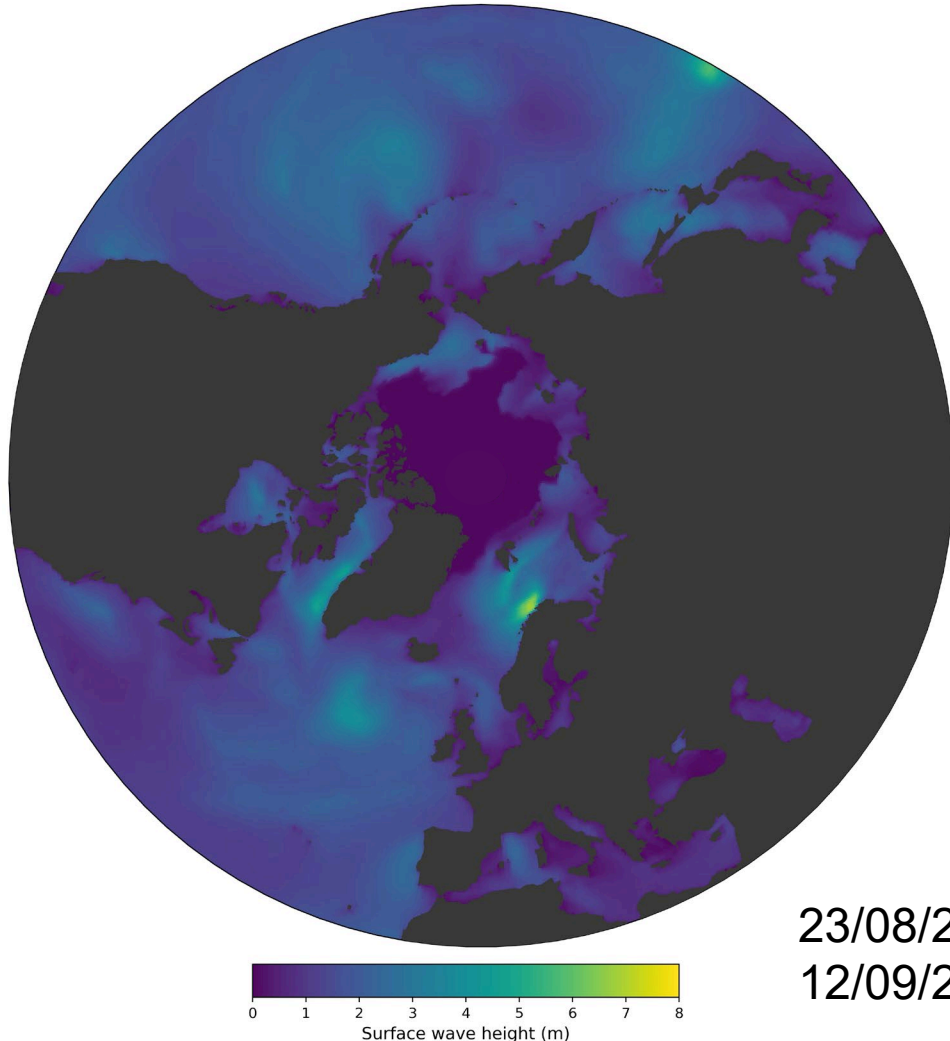
Northern Hemisphere Significant Wave Height

Standard deviation of forecast error
June – August 2023



Implicit representation of unresolved model components

Significant Wave Height Forecast



23/08/2023 to
12/09/2023

Variables Containing Sea Ice Information:

swh, 2t, 2d, 10u, 10v, radiation, etc.

Your model might not be coupled
in the traditional sense, but your
training data most certainly is!

Multi-model Coupling Strategy: **ATMOSPHERE** + **OCEAN**

Our Goal:

Building an ML modelling system that mimics the coupling strategy of traditional numerical models

Coupled fields from **atmosphere** to **ocean**:

10u
ssrd

10v
strd

2t
tp

2d
msl

Coupled fields from **ocean** to **atmosphere**:

sst
siconc



ORAS6 and ERA5 are compatible datasets



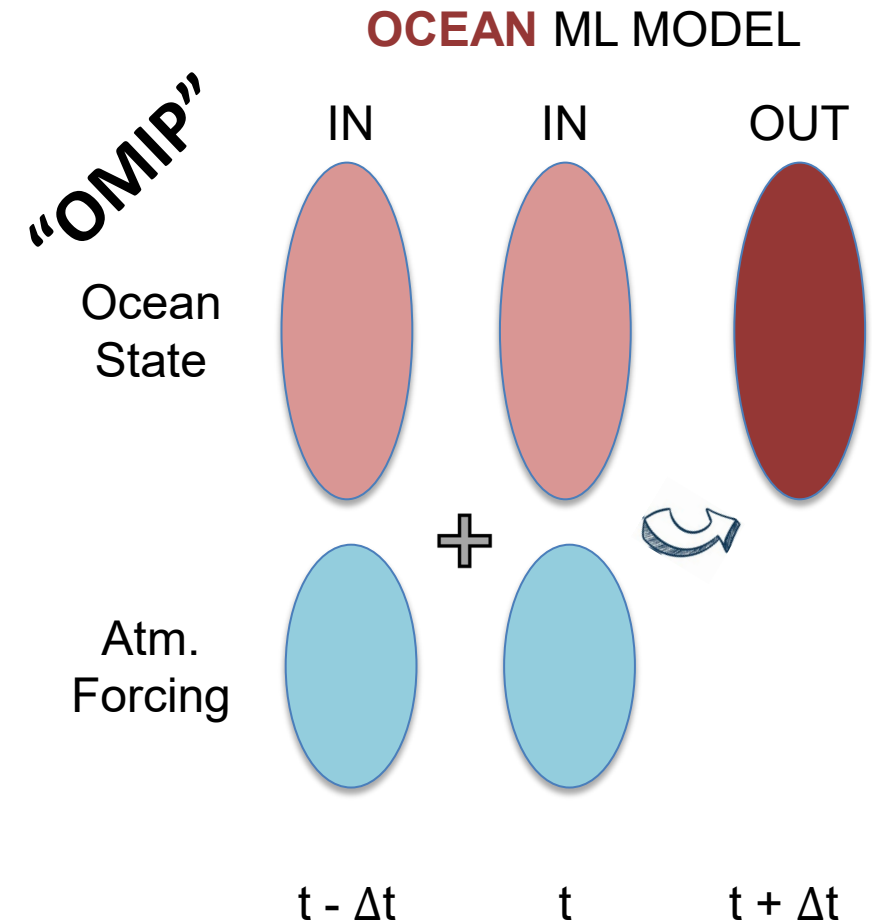
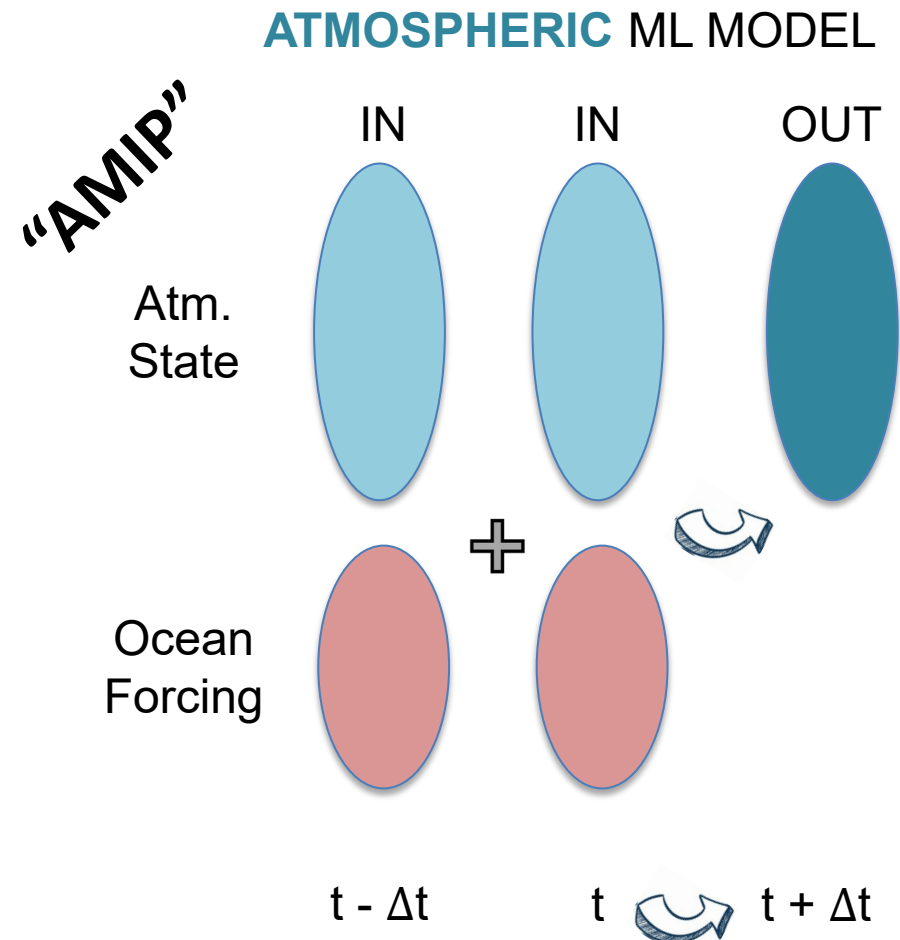
State variables and not fluxes are coupled



The bulk formulation is learned from data

Multi-model Coupling Strategy: **ATMOSPHERE** + **OCEAN**

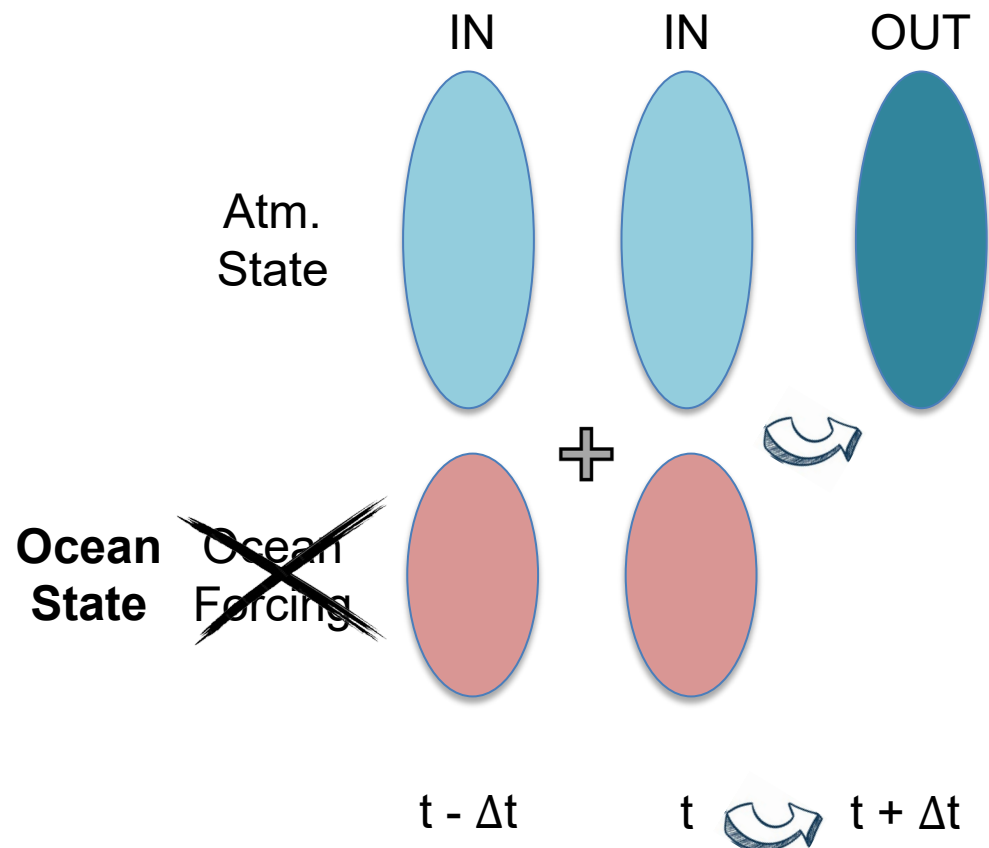
During training



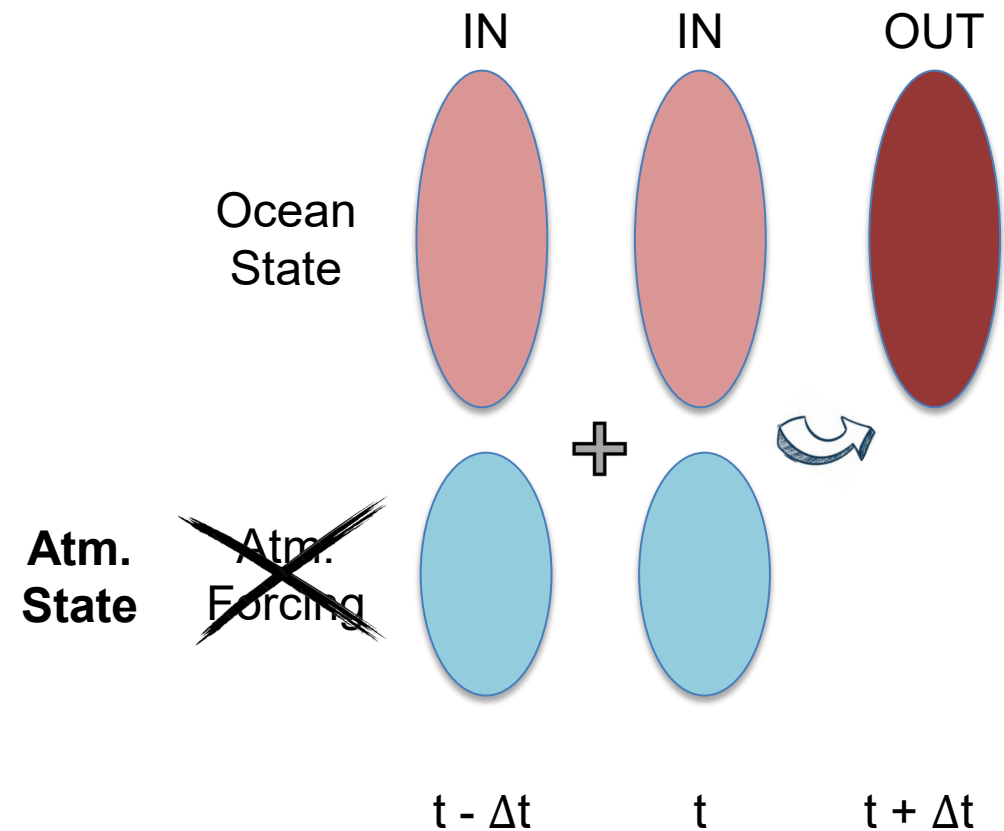
Multi-model Coupling Strategy: **ATMOSPHERE** + **OCEAN**

During inference

ATMOSPHERIC ML MODEL



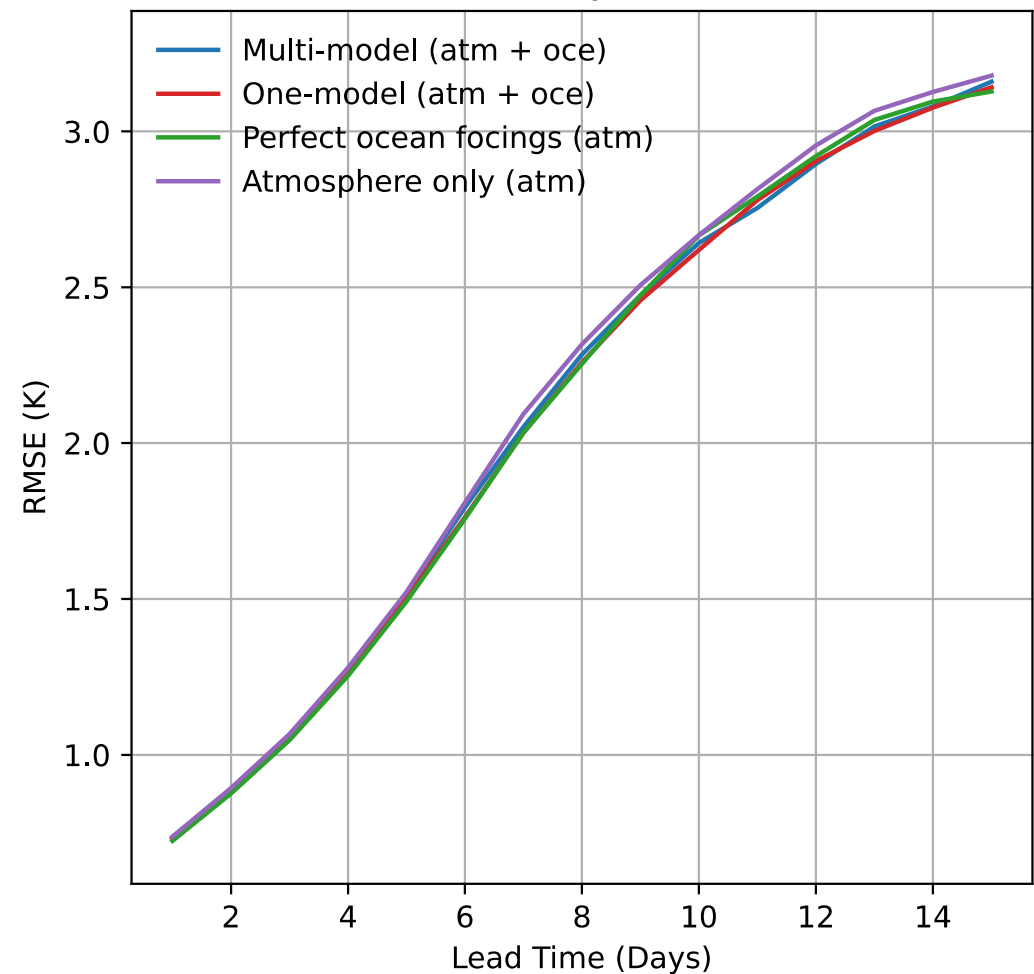
OCEAN ML MODEL



Multi-model vs joint model: Atmosphere + Surface Ocean

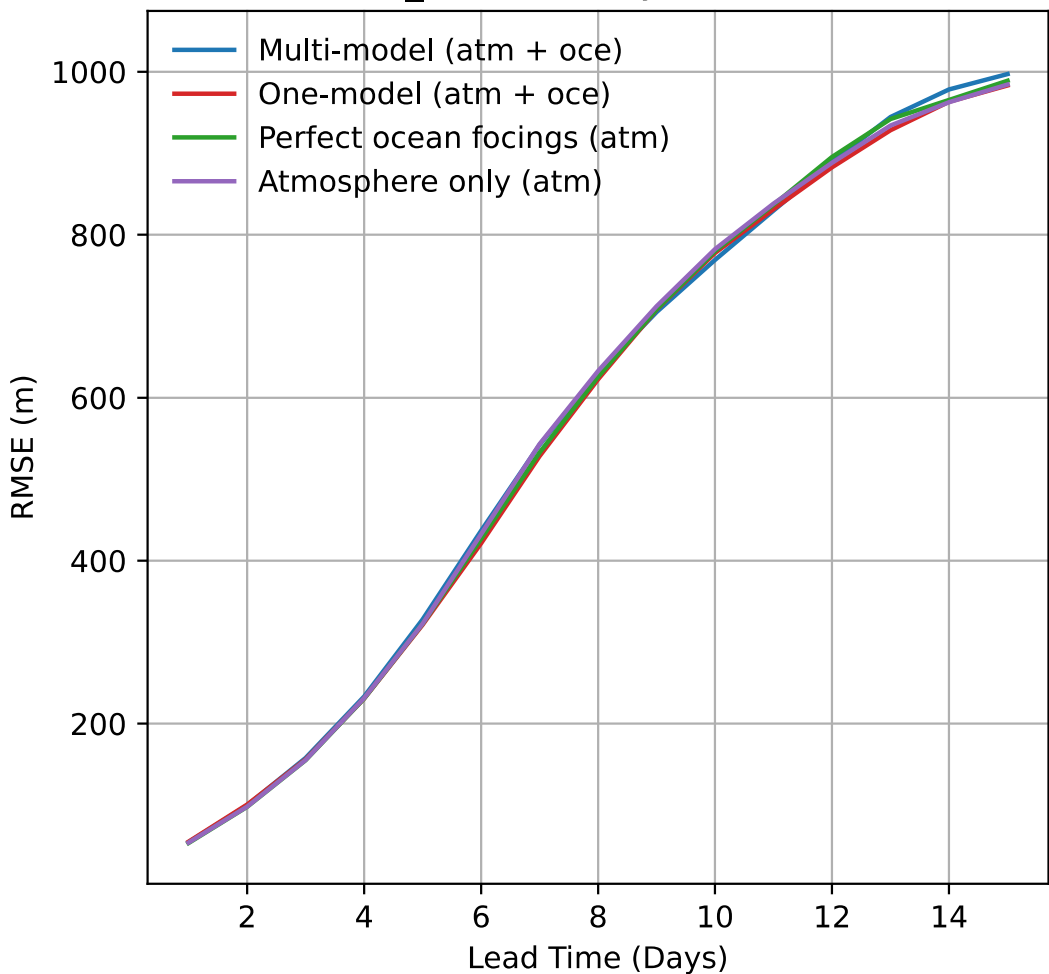
2m temperature

RMSE for 2t - Weekly forecasts in 2022



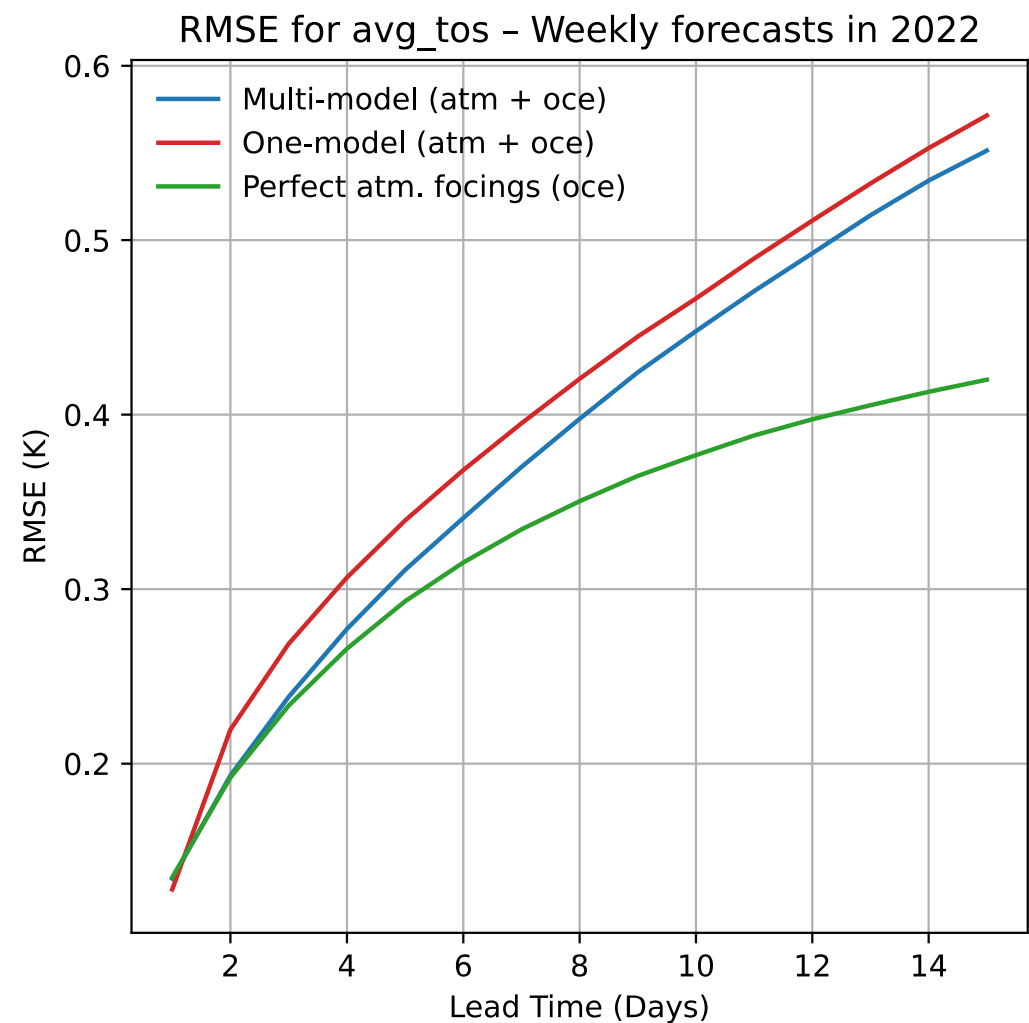
Z500

RMSE for z_500 - Weekly forecasts in 2022

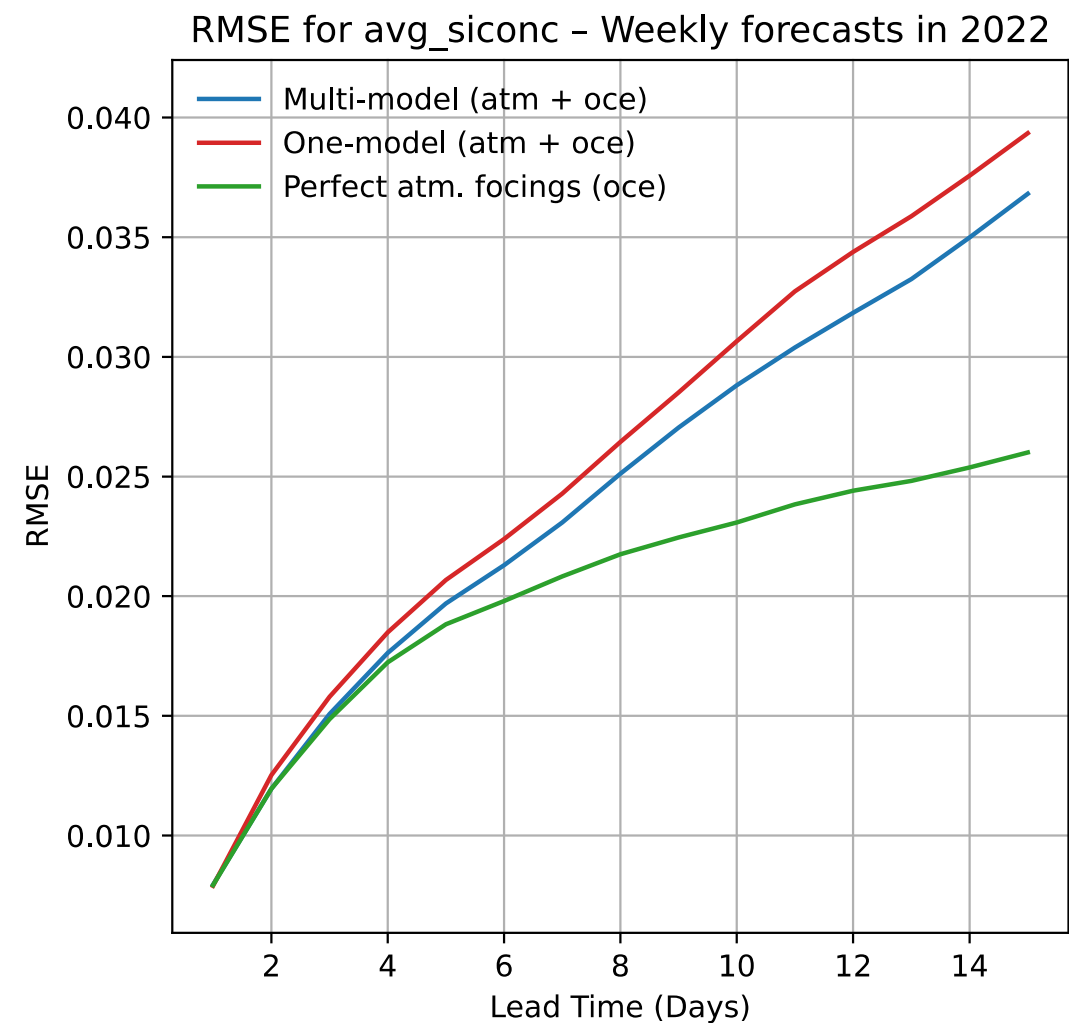


Multi-model vs joint model: Atmosphere + Surface Ocean

Surface Ocean Temperature



Sea Ice Concentration





Anemoi provides mature tools for training as well as coupling ML models beyond the atmosphere

What can already be done?

- Training forced models, run coupled simulations both with joint- and multi-model approaches

What cannot be done right now?

- Finetuning multi-model configurations
- Adding and removing variables
- Coupling ML and numerical models

A big thank you to the anemoi community

Conclusions and next steps

Coupling remains a key challenge in ML-based Earth system models — more work is needed to tackle model interactions effectively.

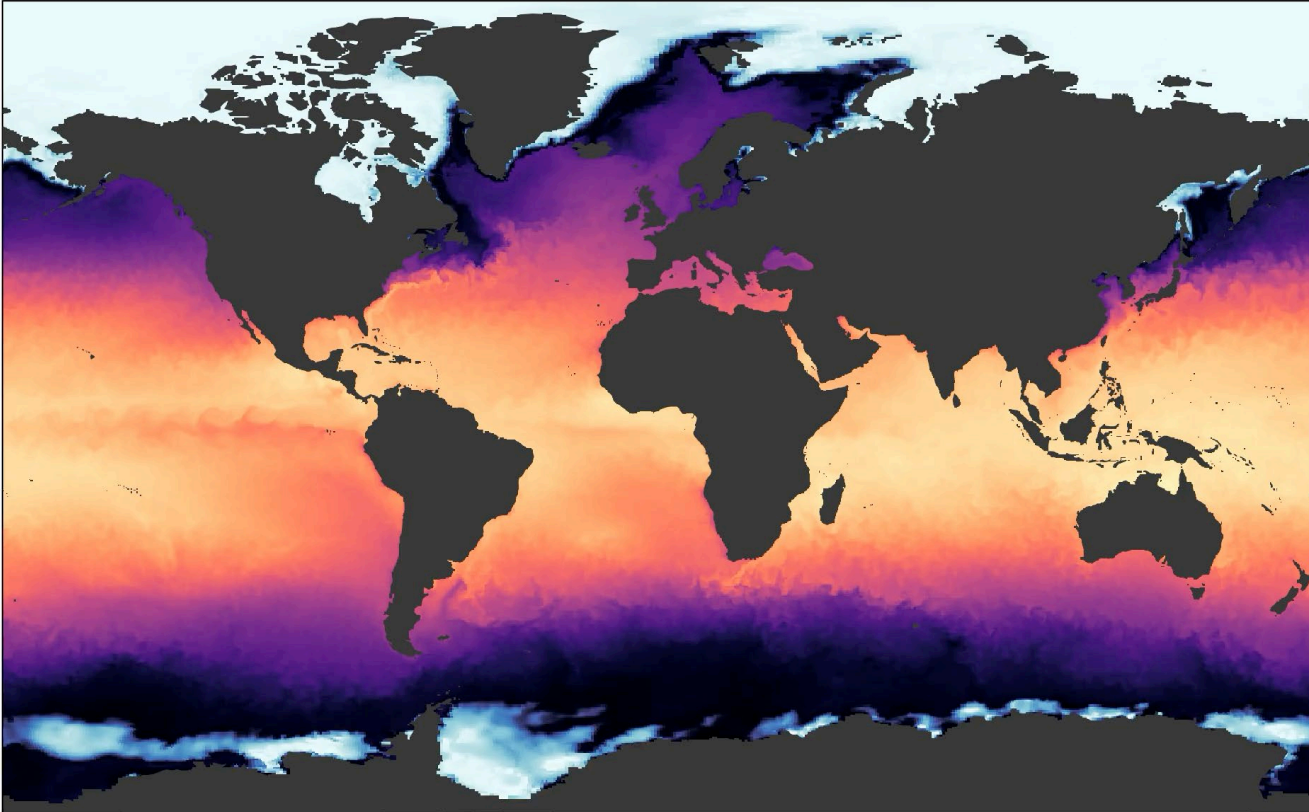
Multi-model and joint-model strategies are promising for building coupled ML Earth system models.

Model interactions are influenced not only by architecture but also by how coupling appears in the training data.

Best practices must be defined for prediction tasks across different timescales.

Significant progress has been made in developing tools to enable robust ML model coupling.

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Thank you!

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An ML emulator of the sea ice and surface ocean

