

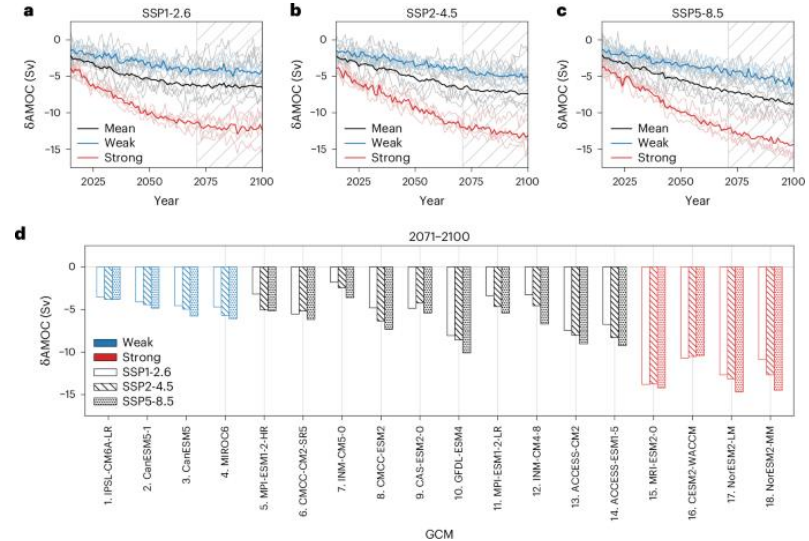
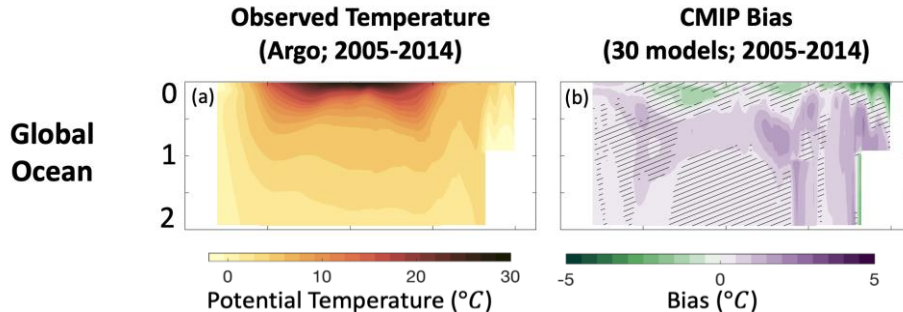


# LEAP-HCS

Leveraging differentiable Programming and online learning for Hybrid Climate Simulators

# LEAP-HCS Context & motivation

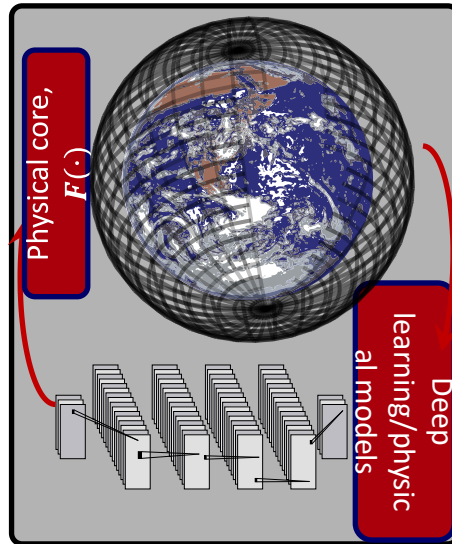
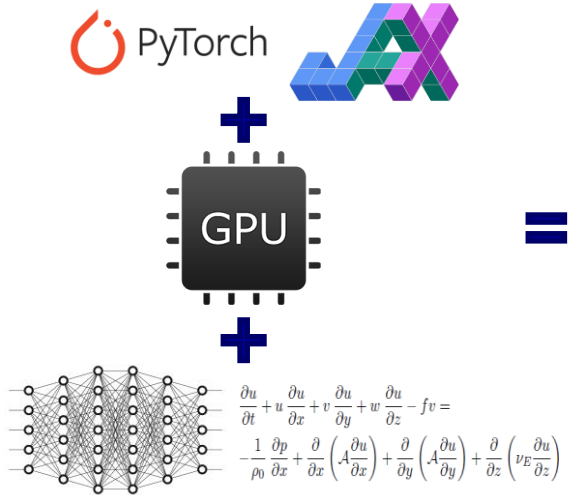
- Earth System Models are cornerstones of climate science
- Their skill depends on numerous uncertain parameters
- Calibration remains mostly manual and time-consuming



From Bonan et al., 2025

# LEAP-HCS project objectives

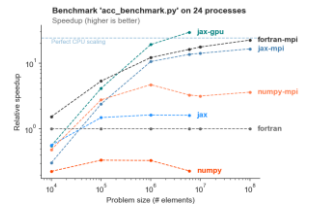
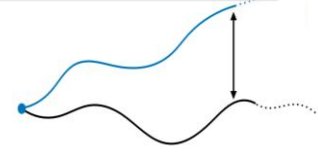
Overall objective: Study new computing paradigms, tools, and calibration methods for designing ESMs that are closely aligned with observations, faster, and augmented with AI-based models and computing infrastructure.



Fit historical data

accelerated simulations

Automated tuning



# LEAP-HCS project objectives

Overall objective: Study new computing paradigms, tools, and calibration methods for designing ESMs that are closely aligned with observations, faster, and augmented with AI-based models and computing infrastructure.

O1: Development of an AI-native ocean modeling benchmark



- AI native
- Supports Automatic differentiation
- Gradient based optimization

O2: Development of automated tuning methods for climate models



- Development of gradient based optimization for climate models
- Lack of Automatic differentiation


O3: Application on the ocean component of the IPSL climate model



- Subgrid scale parameterization tuning
- Spinup acceleration

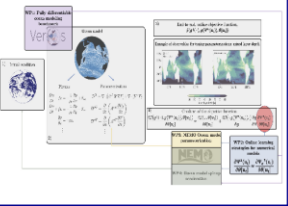
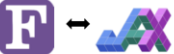
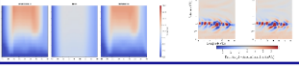
# LEAP-HCS poster

Session posters n°1 Mardi 3 février à 17h30,  
Salle Marie Curie



## Leveraging differentiable programming And online learning for Hybrid Climate Simulators (LEAP-HCS)

Saïd Oualla, IMT Atlantique, INRIA, Odyssey Team

<p style="text-align: center;"><b>Context</b></p> <p>In LEAP-HCS, We aim to solve estimation and parameter calibration challenges by treating them as optimal control problems. Current climate models often lack the differentiable programming capabilities required for efficient sensitivity analysis. In this context, we aim to develop gradient-based optimization methods that take into account the lack of AD platforms. Our methods will be demonstrated on the ocean component of climate models and will target improvements in spin-up acceleration and sub-grid scale model tuning.</p> 	<p style="text-align: center;"><b>Objectives</b></p> <p><b>We aim to develop optimization methods for calibration of climate models.</b></p> <ul style="list-style-type: none"> <li>• Objective 1: Validation of online learning based on numerical models that use DP for state and parameter calibration</li> <li>• Objective 2: Development and validation of gradient based optimization methods that take into account the lack of DP</li> <li>• Objective 3: Development of automated calibration methods for ocean model parameters and for spinup acceleration.</li> </ul>	<p><b>WP2: GRADIENT BASED OPTIMIZATION METHODS FOR NUMERICAL MODELS</b></p> <p>In LEAP-HCS, we are interested in optimizing objective functions of the following form:</p> $\hat{\theta}(x) = \arg \min_{\theta} \int_{t_{min}}^{t_{max}} \mathbb{E}[\Psi(x, \theta, x_t)] dt$ <p>Gradient based optimization requires computing the sensitivity of the solution i.e.:</p> $\frac{\partial \hat{\theta}(x)}{\partial x} = \frac{\partial}{\partial x} \left[ \arg \min_{\theta} \int_{t_{min}}^{t_{max}} \mathbb{E}[\Psi(x, \theta, x_t)] dt \right]$ <p>In this WP, we aim to develop gradient approximation methods. We have shown in previous works [2], that carefully designed gradient approximation can be suitable for such problems.</p> <p><b>WP3/4: APPLICATION TO PARAMETER CALIBRATION AND SPINUP ACCELERATION OF THE NEMO OCEAN MODEL</b></p> <ul style="list-style-type: none"> <li>• <b>Coupling of ML/optimization libraries in python with NEMO, in collaboration with TRACCS PCS</b></li> </ul> 
<p style="text-align: center;"><b>Organization</b></p> <p><b>WP1: FULLY DIFFERENTIABLE OCEAN MODELING BENCHMARK WITH VEROS</b></p> <p><b>Plan:</b> In this work package, we focus on developing a fully differentiable ocean modeling benchmark. This benchmark will be used to assess optimization based on DP and to develop learning methods that account for the lack of DP</p> <p><b>Current developments:</b></p> <ul style="list-style-type: none"> <li>• Differentiable VEROS [1]</li> <li>• Demonstration of AD in VEROS</li> <li>• Development of a 1° global ocean configuration.</li> </ul> 		<ul style="list-style-type: none"> <li>• <b>Automatic tuning of NEMO-ORCA1 parameterizations</b></li> <li>• <b>Spinup acceleration</b></li> </ul>

[1] Meunier, E., Oualla, S., Frezat, H., Sommer, J. L., & Fabiet, R. (2025). Towards fully differentiable neural ocean model with Veros. *arXiv preprint arXiv:2511.17427*.

[2] Oualla, S., Chaperon, B., Collard, F., Gualtieri, L., & Fabiet, R. (2024). Online calibration of deep learning sub-models for hybrid numerical modeling systems. *Communications Physics*, 7(1), 402.

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