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Toward a new parameterization of ocean-atmosphere interactions based on a machine learning approach

Ocean-atmosphere coupling

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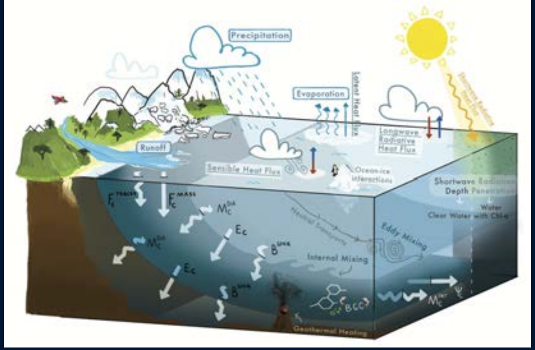
1. CONTEXT

Ocean-Atmosphere coupling

Context

Atmospheric and oceanic models

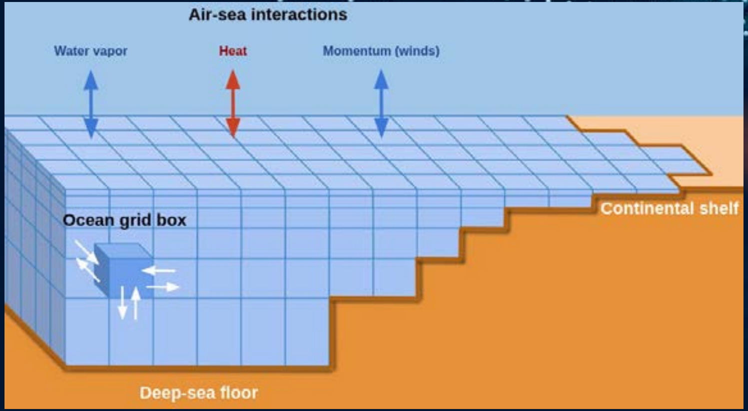


To model accurately some processes:

- High resolution
- Coupling

Ideas for using IA:

- Stochastically predicting processes
- Improve parameterization at interfaces



Two main ocean-atmosphere interactions:

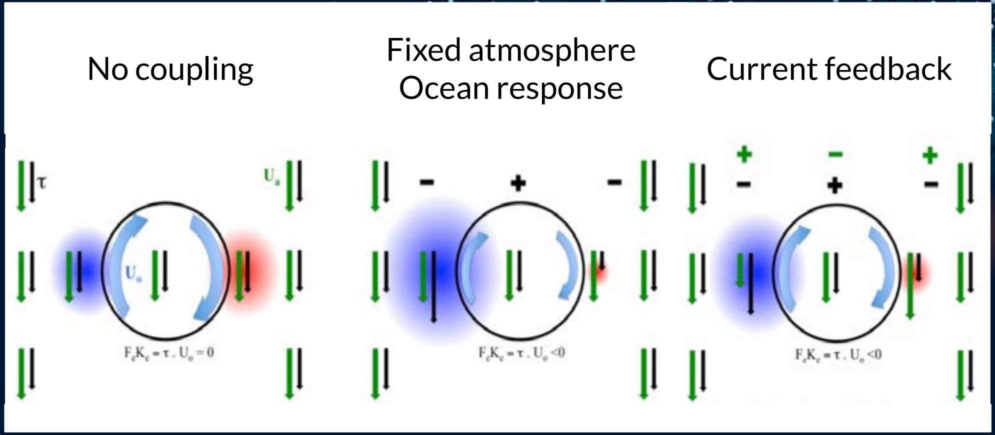
- Current feedback (CFB)
- Thermal feedback (TFB)

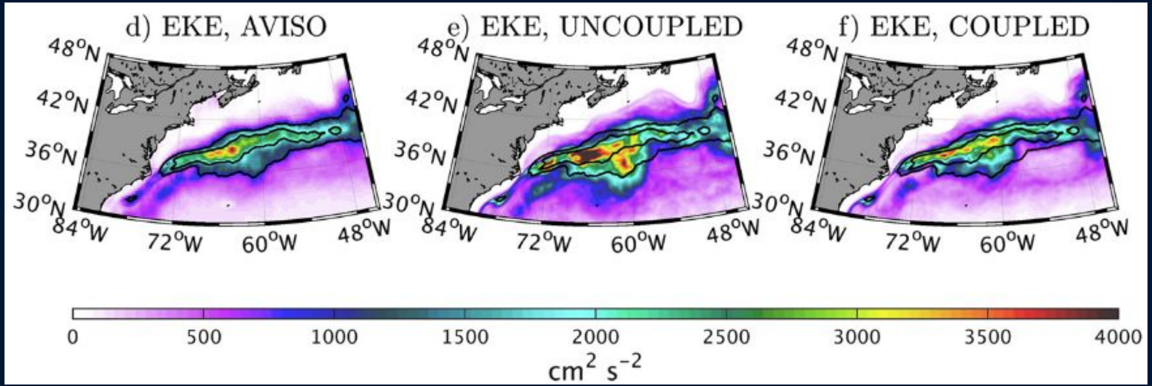
Context

Current feedback

Mechanic loop between surface current and overlying wind

Part of eddy kinetic energy (EKE) is transferred from ocean to atmosphere (to 30% at mesoscale)





Context

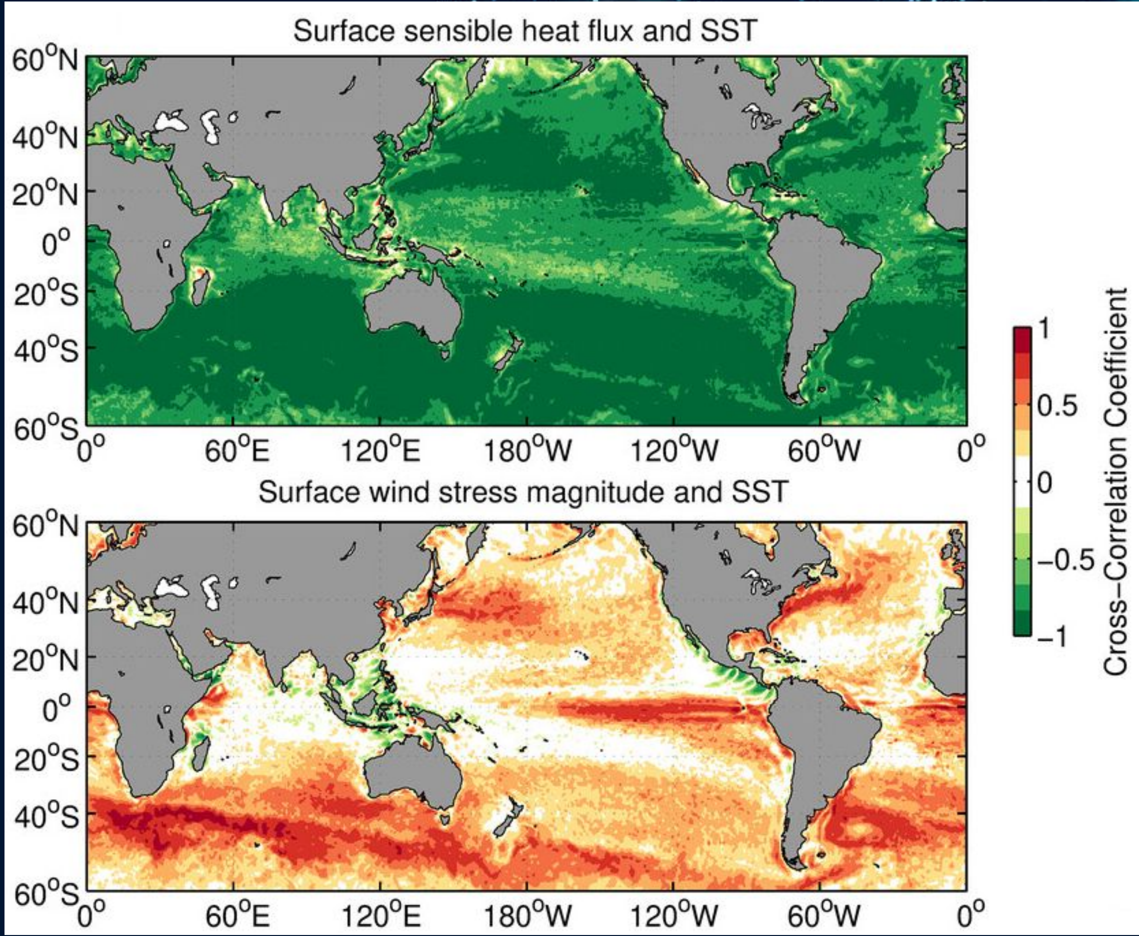
Thermal feedback

Thermal loop between SST and overlying wind, and heat flux

Two interactions:

Thermal

Kinetic



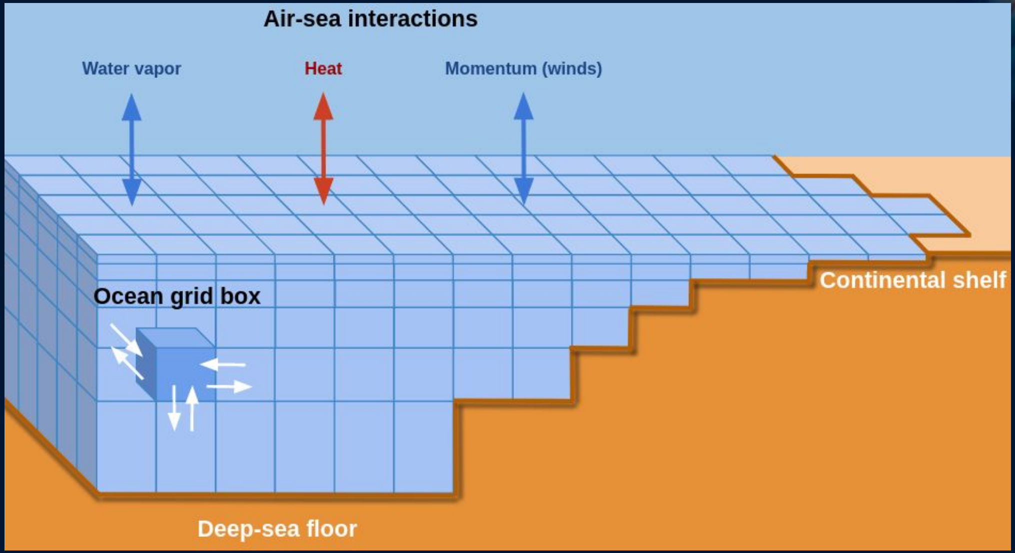
Context

To apply atmosphere fluxes to ocean models:

- Simulation coupled to an atmospheric model
- Forced model, no feedback loop
- Forced model, with a parameterization of the CFB

Alternative approach:

- Forced model with a neural network that reproduces the effects of atmosphere-ocean coupling



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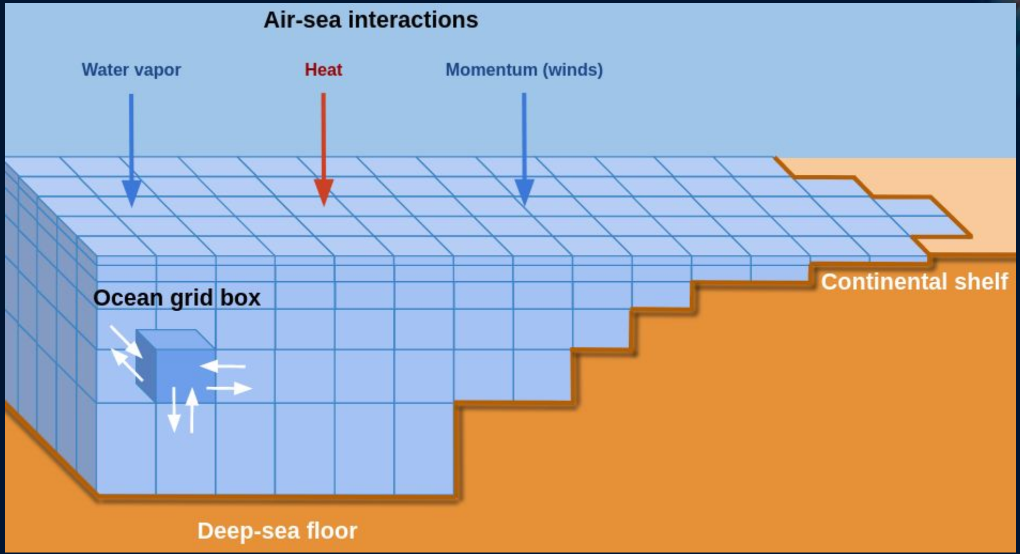

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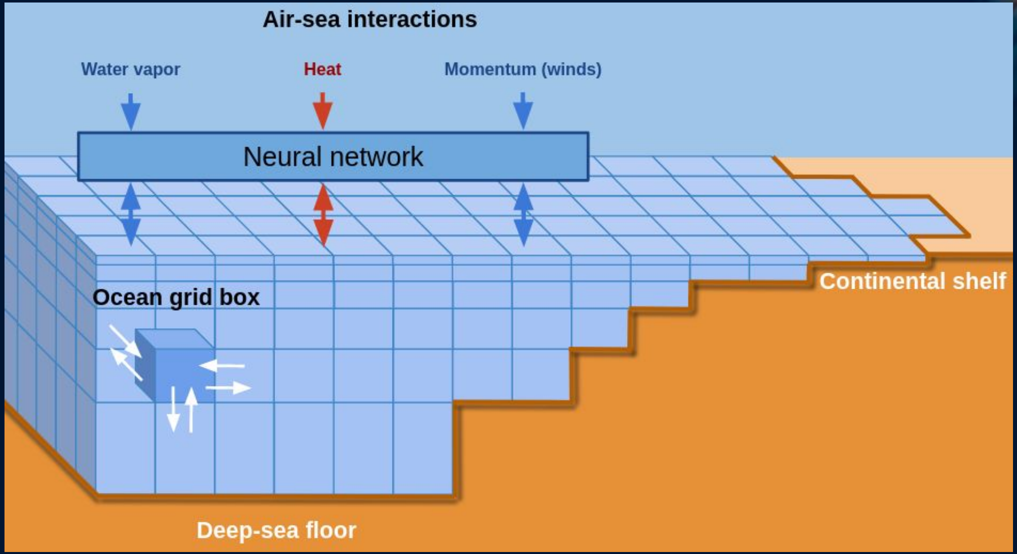


Context

Goal ⇒ Parametrize the mesoscale ocean-atmosphere coupling effects in forced model

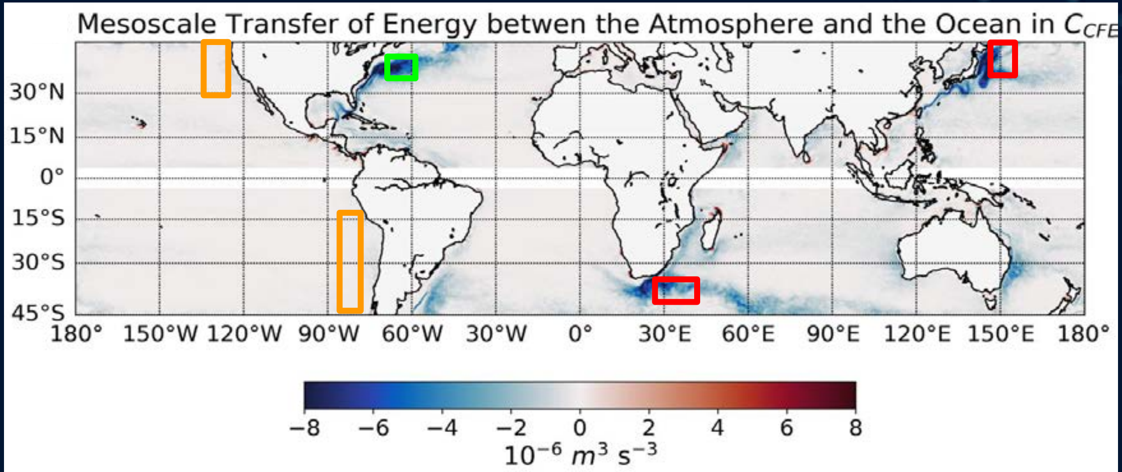
Target ⇒ Mesoscale surface stress (no consideration of heat flux)

Consideration ⇒ Large scale atmospheric data and all oceanic data

Methodology:

- Define the data for the NN research
- Find a NN that can reproduce the mesoscale surface stress
- Verify that the founded NN reproduces the coupling effects

Context



2 learning areas:

- Kuroshio
- Agulhas Current

1 validation area: Gulf Stream

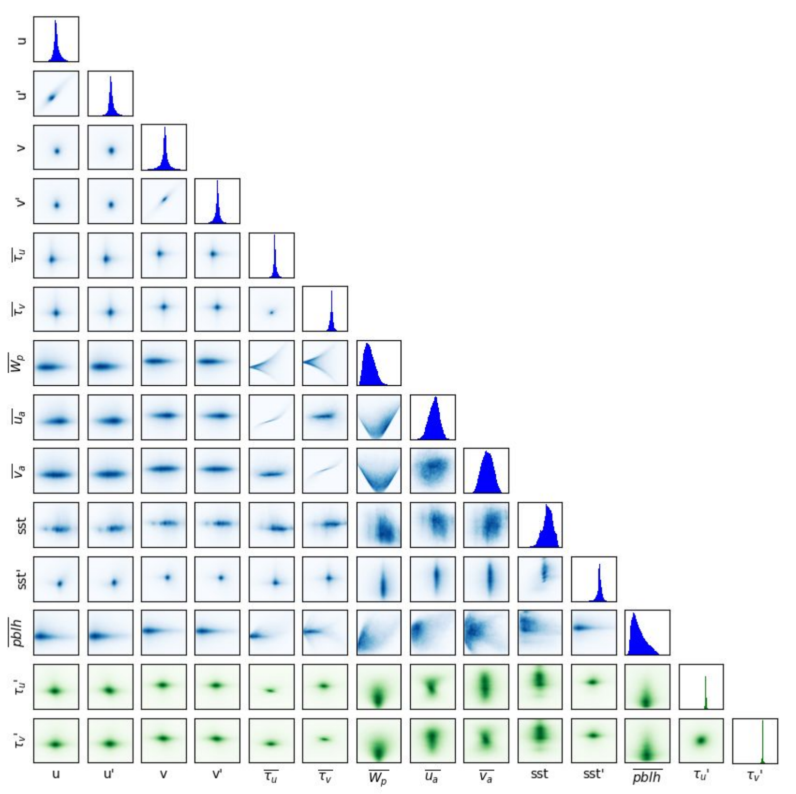
2 application areas:

- California coast
- Chile coast

Input: u, v, u', v', $\overline{\tau_u}$, $\overline{\tau_v}$, $\overline{Wp}$, $\overline{u_{10}}$, $\overline{v_{10}}$, sst, sst', $\overline{pblh}$

Output: τ_u', τ_v'

Context



Data :

- Coupled simulation (1/4° (~25 km), PULSATION project)
- Tropical realistic (45° N to 45°S)
- Daily output for 5 years
- Spatial filter: Gaussian filter (size: 4 → 1° (~100km))

Analysis :

- Correlation :
  - Surface currents and their anomalies
  - Magnitude of filtered wind and filtered wind
  - Filtered wind and filtered surface stress
  - Filtered pblh and magnitude of filtered wind
- No correlation: input and output
- Output: concentrated around zero

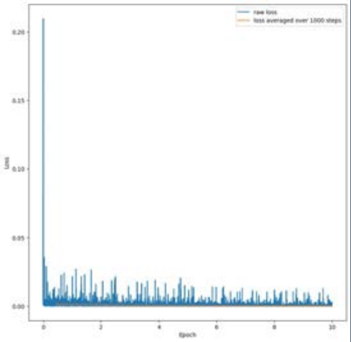
2.

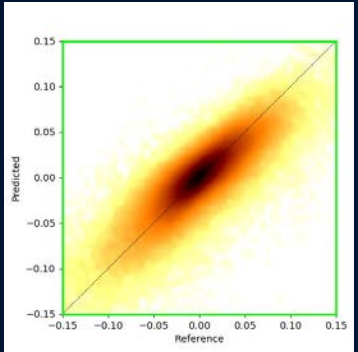
RESULTS

Practical application

Neural network for the

Ocean-atmosphere coupling





→ Rapid convergence

→ Snapshot ok, but can do better

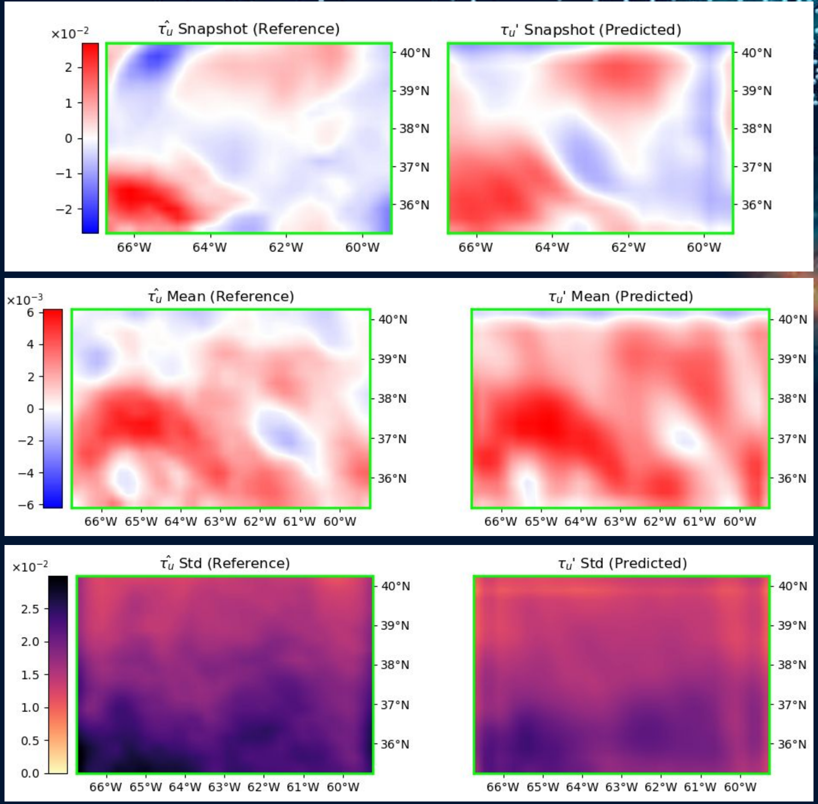
→ Average, correct pattern with bias

→ Similar variability

→ Distribution follows identity line well

⇒ Encouraging results

All figures shown are for the Gulf Stream



Neural network for the

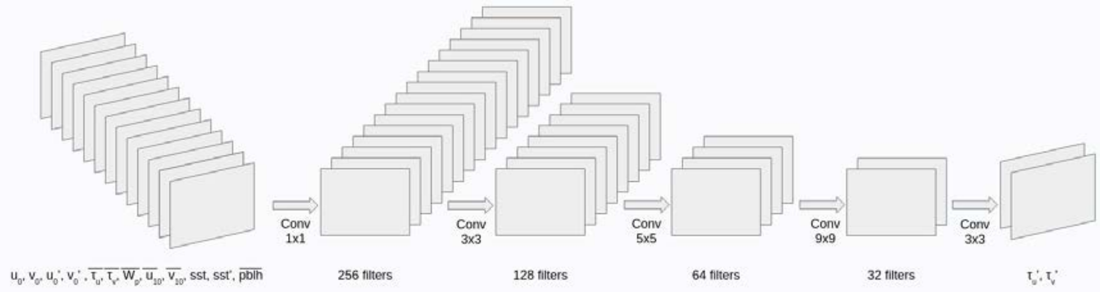
Ocean-atmosphere coupling

Many models tested (~ 150 models)

Best MSE on Gulf Stream

⇒ $1{,}619.10^{-4}$ with the following CNN :

- **256-1, 128-3, 64-5, 32-9**



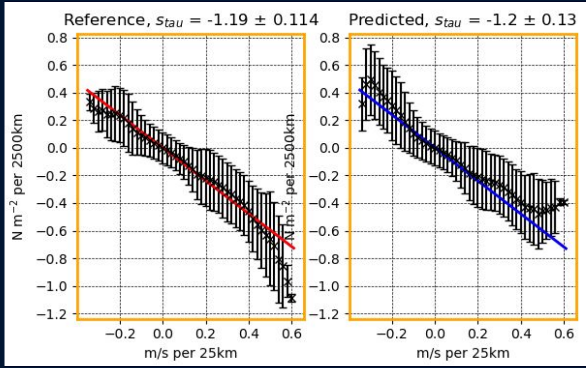
Using CNN instead of a classic NN greatly improves the results (if not overfitting)

No logic to find the right model :

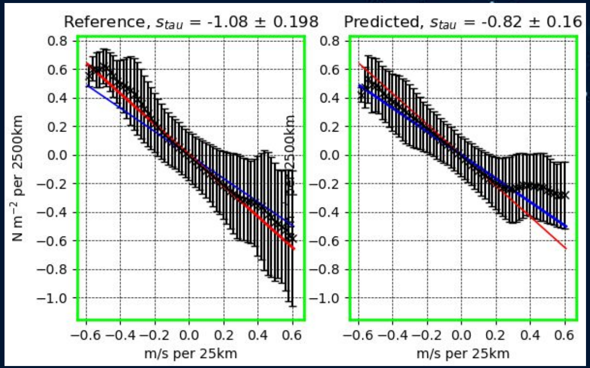
⇒ Improvement and selection requires the continuation of an empirical approach in the choice of hyperparameters

Neural network for the

Ocean-atmosphere coupling



California coast



Gulf Stream

S_T: Surface current curl and surface stress curl

Data : averaged over 29 days

Model : 2D : 256-1, 128-3, 64-5, 32-9

Results : Predicted slopes close to the coupled simulation

Neural network for the

Ocean-atmosphere coupling

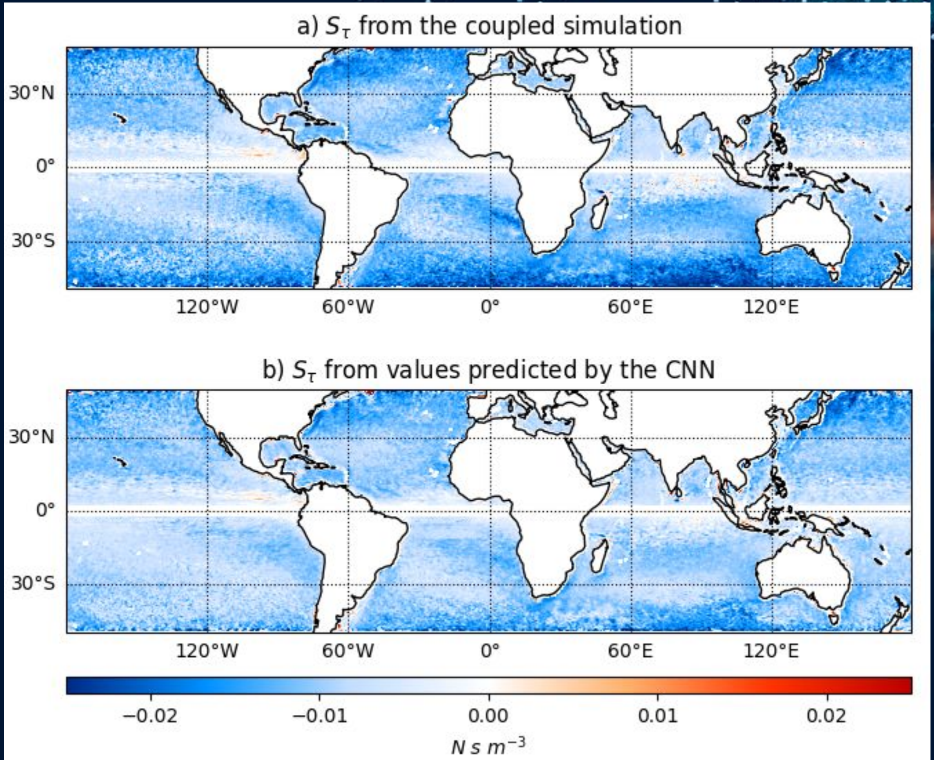
S_τ: Surface current curl and surface stress curl

Data : averaged over 29 days

Model: 2D: 256-1, 128-3, 64-5, 32-9

Results: Prediction close to the coupled simulation

Differences: Predicted underestimated for AAC and EBUS



Neural network for the

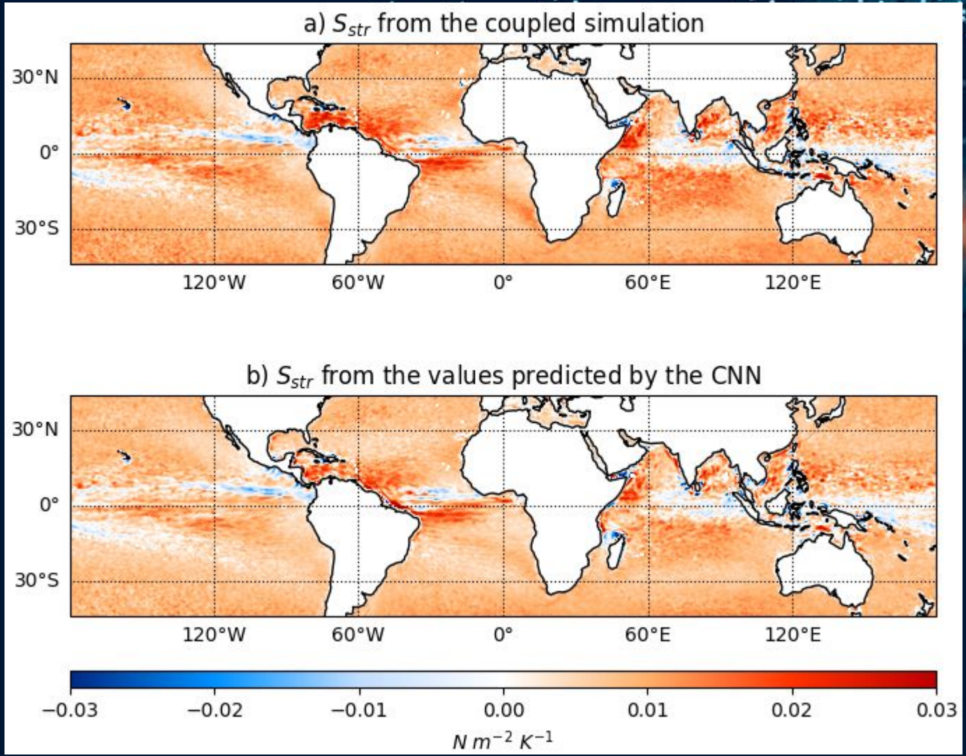
Ocean-atmosphere coupling

S_{str}: SST and surface stress magnitude

Data : averaged over 29 days

Model: 2D: 256-1, 128-3, 64-5, 32-9

Results: Prediction close to the coupled simulation



3. CONCLUSION

Continuations and perspectives

Conclusion

- **Using neural network for ocean-atmosphere coupling works well !!!**
- CFB and **TFB** parametrization
- But lack fidelity to EBUS and ACC ⇒ Add new learning areas

- Integration of turbulent heat flux to account for all ocean-atmosphere exchanges
- Possibilities for improvement (data augmentation, skip connections, PINNs, and temporal considerations, ...)
- Offline results only at the moment ⇒ Integration of a NN into an ocean simulation

Thank you for your attention !