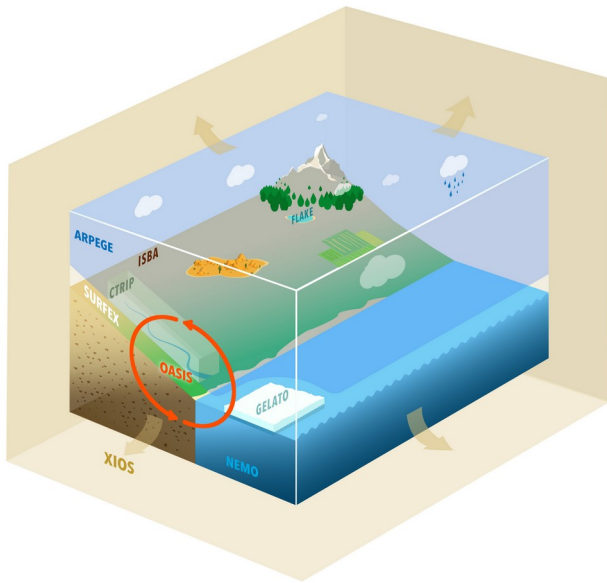
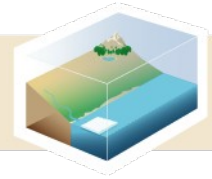


Couplages dans le système climatique



Aurore Voldoire, aurore.voldoire@meteo.fr
CNRM, Météo-France/CNRS, Toulouse

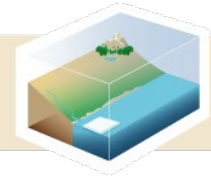




1. The CNRM-CM climate model : a complex system
2. Understanding the emergent properties of a climate model
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4. Conclusion

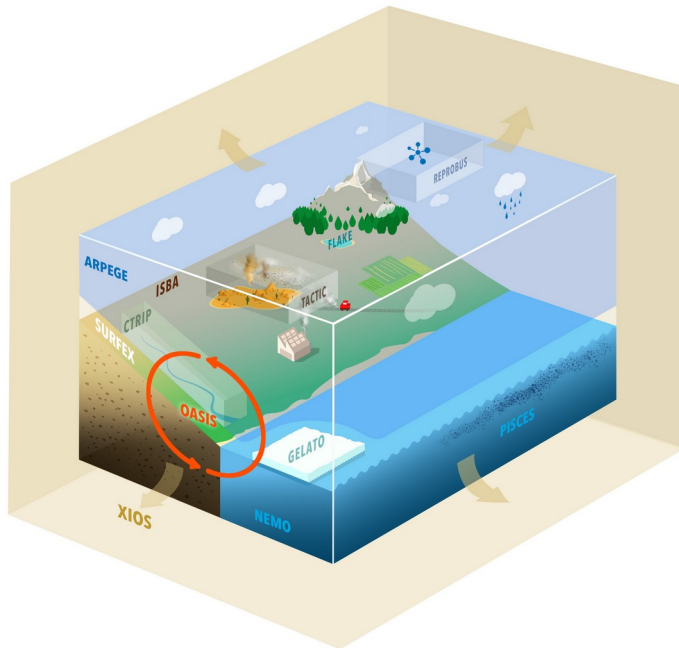
1 The CNRM-CM climate model

CNRM
CM

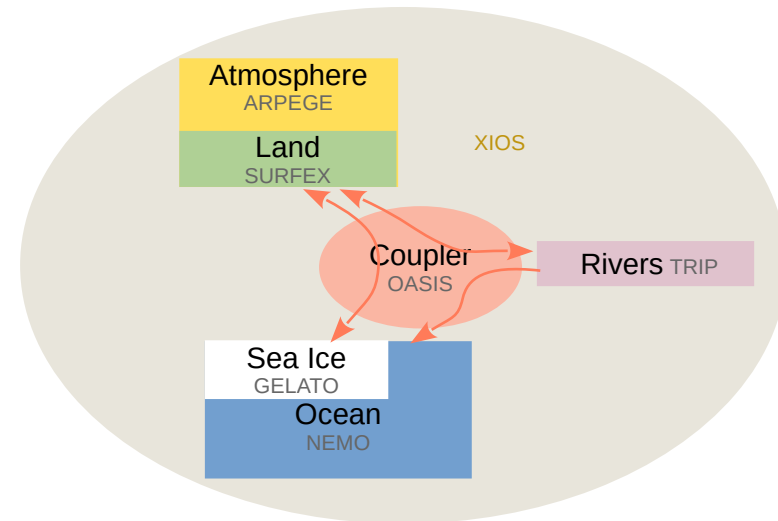


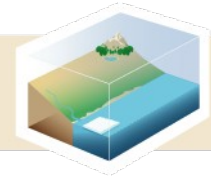
Integrating components developed in different labs (consistency not warranted)

- gain expertise on each component
- adapt components to climate time-scales
- develop consistent interfaces
- towards an homogeneous level of complexity in all components



CNRM-CM





Why developing a global climate model at CNRM-Cerfacs?

- Understand the climate system = numerical lab
- Make seasonal forecasts
- Make future projections
 - ▶ An input to climate impact studies
 - ▶ A tool to assess our impact on possible futures

Developing group common objectives :

- Time-scale from months to century
- A common tool for diverse scientific interest
 - ▶ Physical core : CNRM-CM
 - ▶ Earth System : CNRM-ESM

International context

- CMIP : Coupled model Intercomparison Project

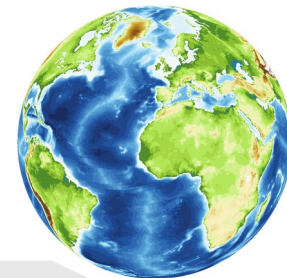
CMIP Phases

CMIP2



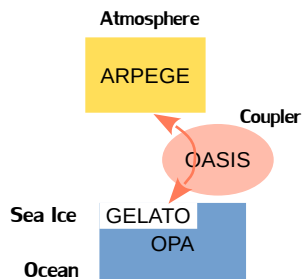
2002

280 km / 2°
ATM OCE



CNRM-CM development history

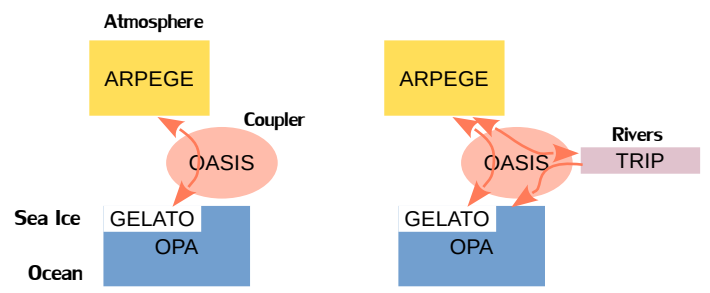
CNRM-CM2
Royer et al., 2002



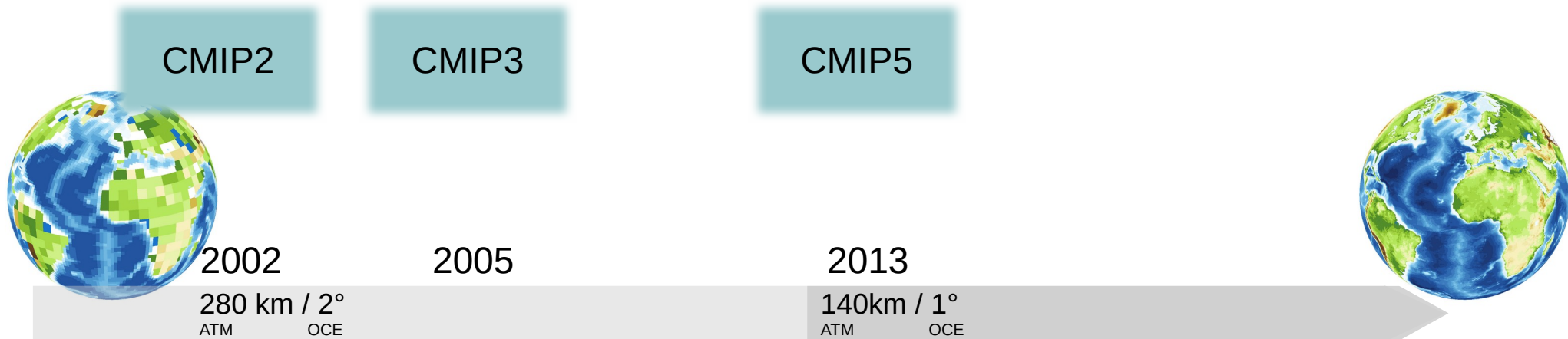
CMIP Phases



CNRM-CM development history



CMIP Phases

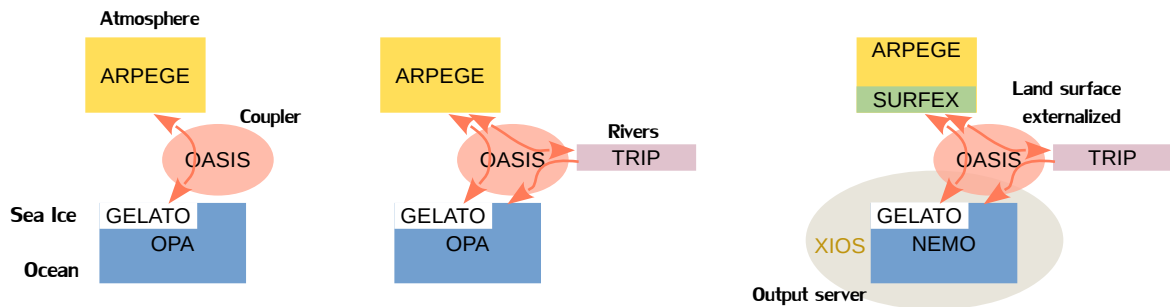


CNRM-CM development history

CNRM-CM2
Royer et al., 2002

CNRM-CM3
Salas y Mélia et al., 2005

CNRM-CM5.1
Voltaire et al., 2013

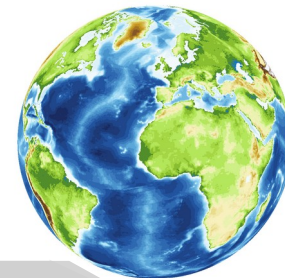


CMIP Phases

CMIP2

CMIP3

CMIP5



2002

2005

2013

2016

280 km / 2°
ATM OCE

140km / 1°
ATM OCE

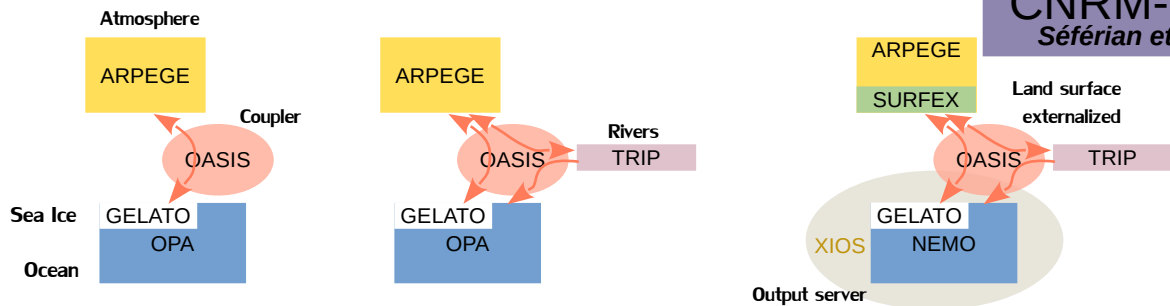
CNRM-CM2
Royer et al., 2002

CNRM-CM3
Salas y Mélia et al., 2005

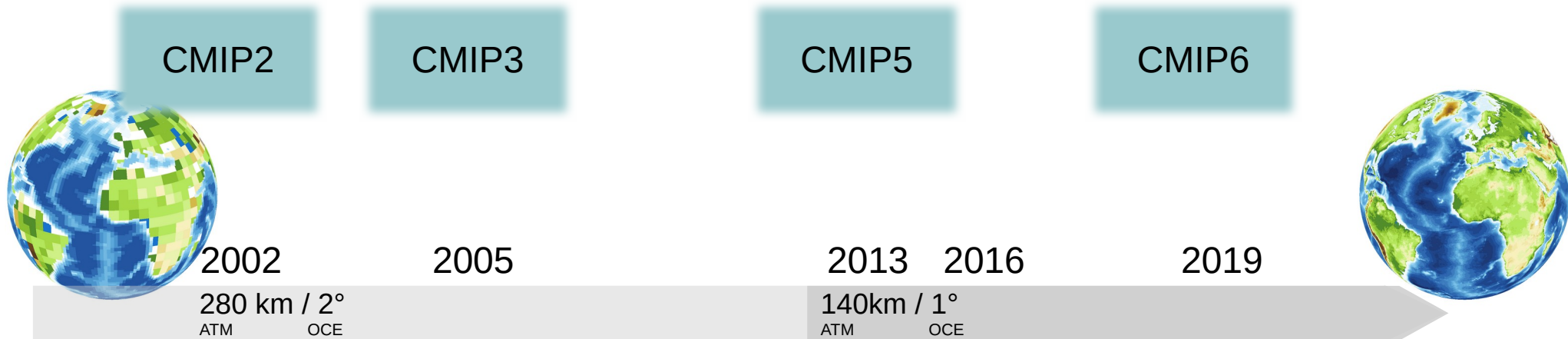
CNRM-CM5.1
Voltaire et al., 2013

CNRM-ESM1
Séférian et al., 2016

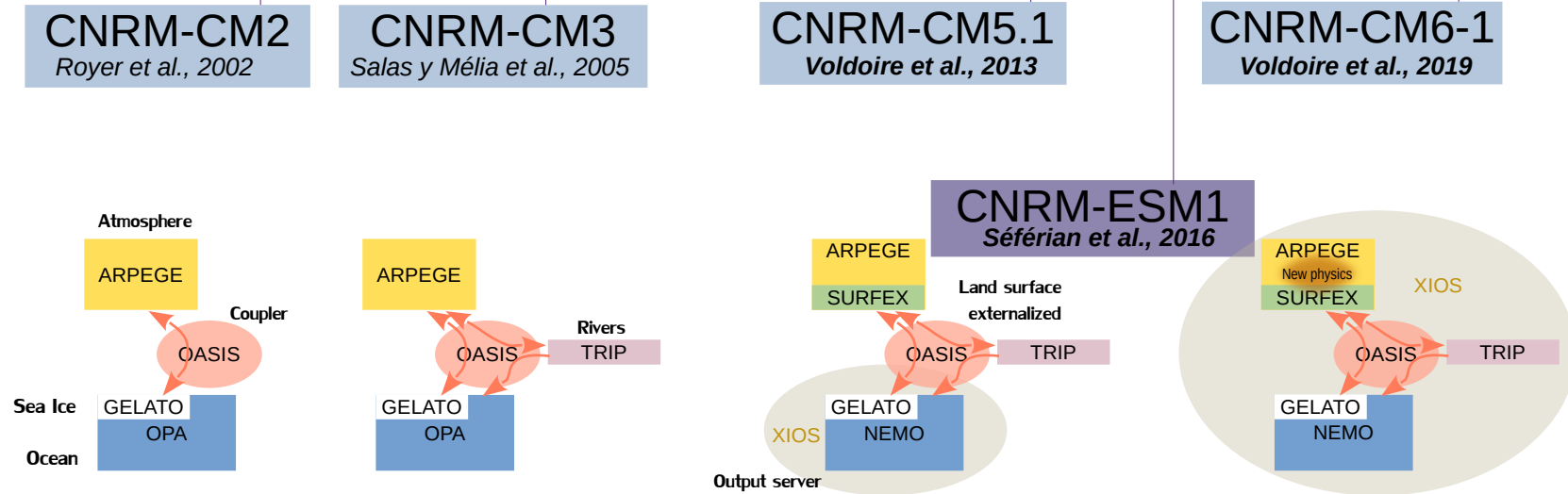
CNRM-CM development history



CMIP Phases



CNRM-CM development history



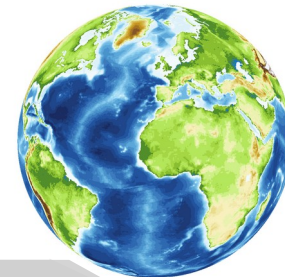
CMIP Phases

CMIP2

CMIP3

CMIP5

CMIP6



2002

2005

2013

2016

2019

280 km / 2°
ATM OCE

140km / 1°
ATM OCE

50km / 0,25°

CNRM-CM2
Royer et al., 2002

CNRM-CM3
Salas y Mélia et al., 2005

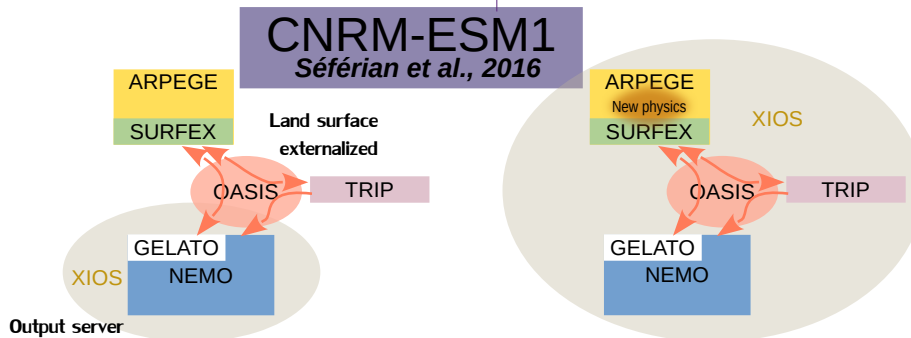
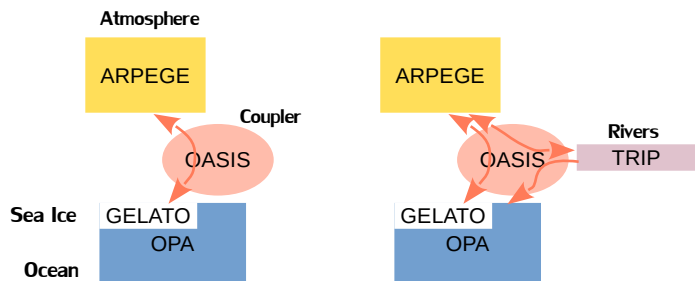
CNRM-CM5.1
Voltaire et al., 2013

CNRM-CM6-1
Voltaire et al., 2019

CNRM-CM6-1-HR
Saint-Martin et al., 2020

CNRM-ESM2-1
Séférian et al., 2019

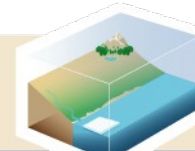
CNRM-ESM1
Séférian et al., 2016



CNRM-CM development history

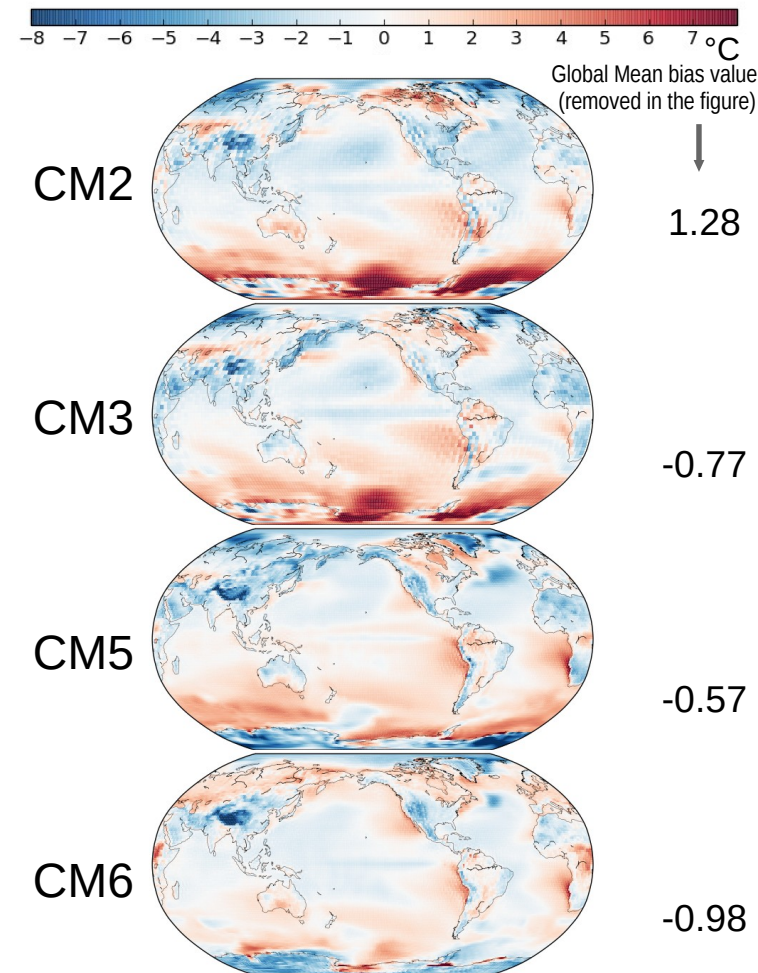
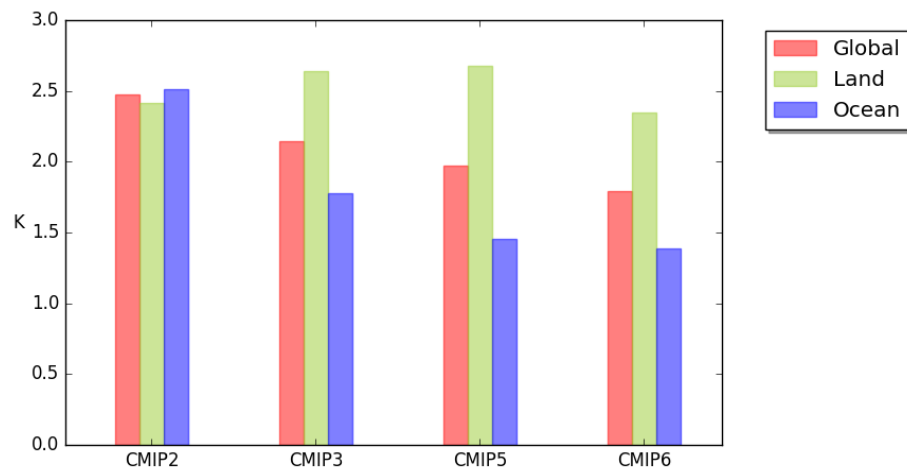
1 Long term evolution of the model realism

CNRM
CM



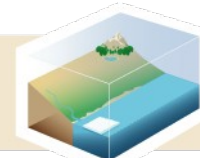
Surface **temperature** bias evolution

- Tuning aims at limiting the global mean surface temperature bias (thus it should be close to zero by construction, and it is removed in the figures)
- A progressive reduction of RMSE that is less systematic over land



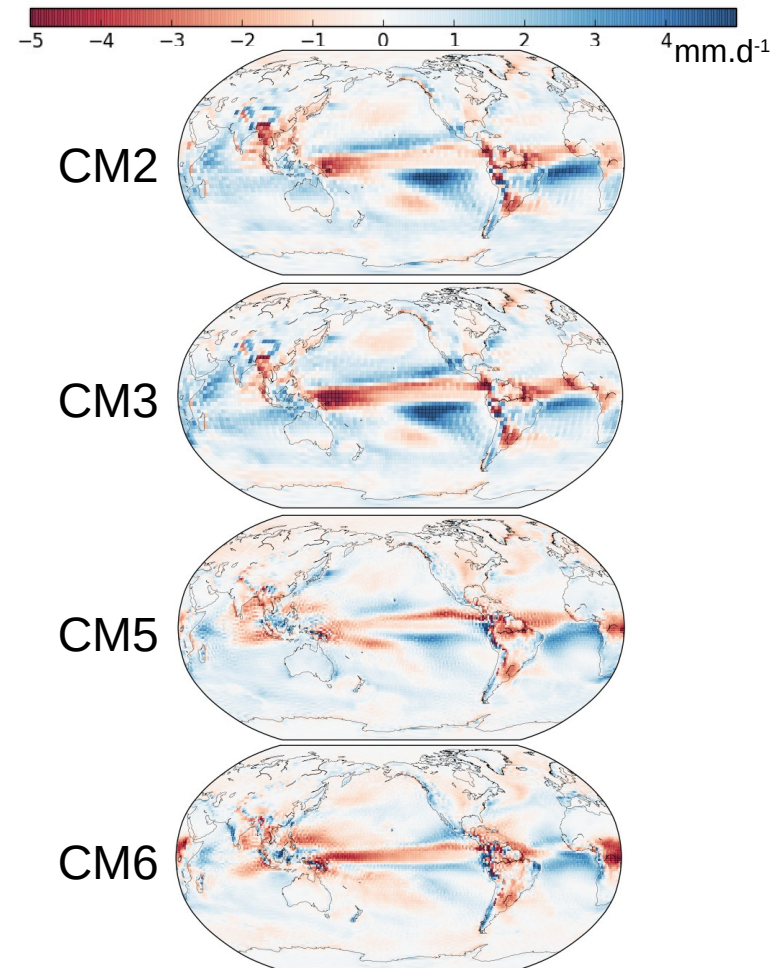
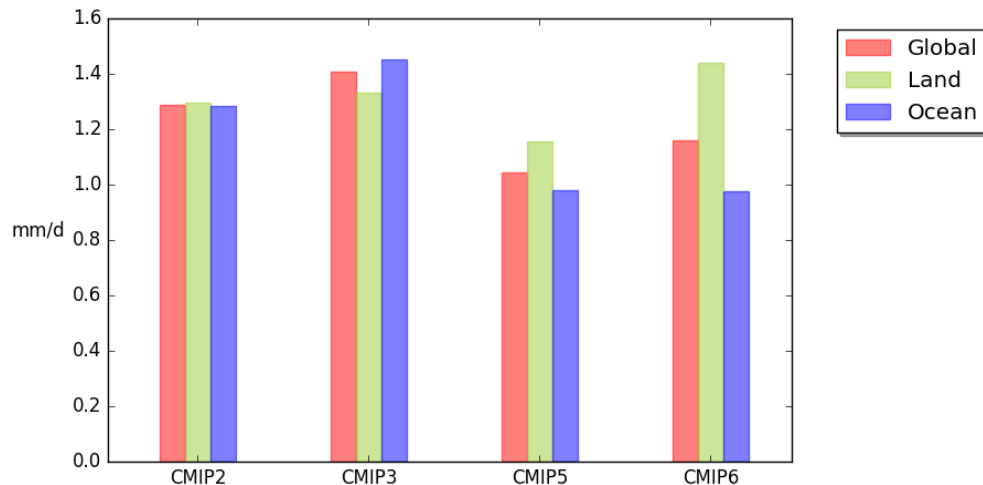
1 Long term evolution of the model realism

CNRM
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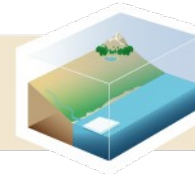


Precipitation bias evolution

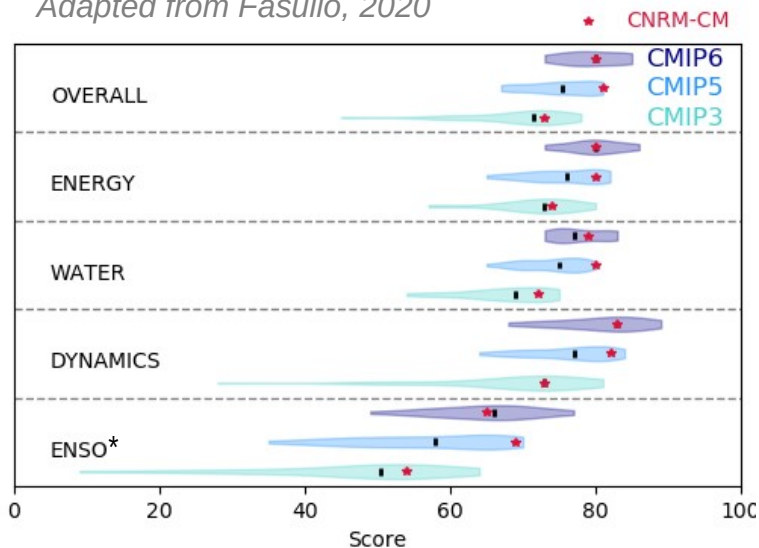
- Less well observed
- Long term evolution less progressive, improvement in specific regions whereas others are worsening.
- How to keep benefit of former improvement?



1 In the CMIP multi-model context

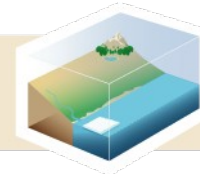


Adapted from Fasullo, 2020

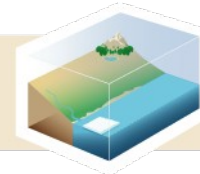


- CMIP ensemble
 - ▶ Progressive improvement of the best models from CMIP3 to CMIP6
 - ▶ Progressive reduction of score spread among models
- CNRM-CM case
 - ▶ General improvement from CNRM-CM3 to CNRM-CM5 : no major development but long tuning phase
 - ▶ No improvement from CNRM-CM5 à CNRM-CM6 : major change of the set of land and atmospheric parameterisation
- Compared to the multi-model, CNRM-CM6 is less performant
 - ▶ Need more time to adapt the new set of parameterisation ?
 - ▶ Is tuning insufficient?

*ENSO : El Nino Southern Oscillation



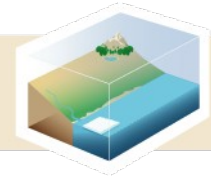
1. The CNRM-CM climate model : a complex system
2. Understanding the emergent properties of a climate model
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4. Conclusion



- Climate model development steps :
 - ▶ Develop/improve parameterisation in each component
 - ▶ Assemble components
 - ▶ Run the full model → « discover the emergent properties », ie how « climate » is simulated
 - Mean climate : Walker/Hadley circulation, Pole-Equator contrasts, energy transports
 - Climate variability, ENSO, monsoons, AMOC, ...
 - Extremes, etc...
- In the end :
 - ▶ Many metrics to monitor
 - ▶ How to relate unrealistic emergent features to model ingredients (ie parameterisations) ?

3 Why ENSO is less realistic in CM6?

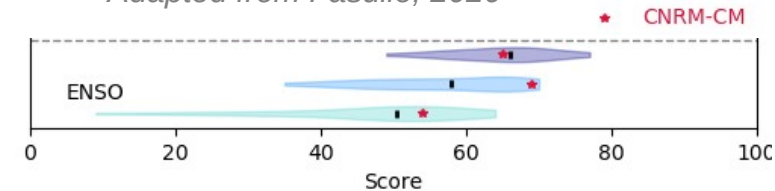
CNRM
CM



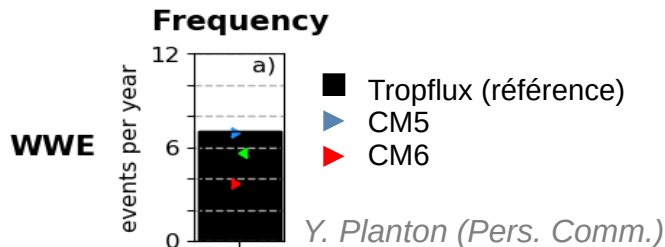
In CNRM-CM, ENSO representation

- ▶ Has been deteriorated from CMIP5 to CMIP6
- ▶ Does not follow the models general improvement from CMIP5 to CMIP6

Adapted from Fasullo, 2020

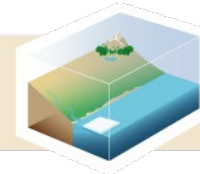


CNRM-CM5 strength: **Puy et al. 2017** have shown a very realistic representation of westerly wind events in CNRM-CM5 (frequency, seasonality, localization)

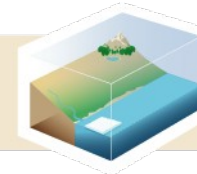


- ▶ Westerly Wind Events frequency is underestimated CM6 whereas it was “perfect” in CM5

Why such a degradation in between CM5 and CM6?



Methodology (M2 internship T. Manni, co-supervised with G. Bellon, 2021)

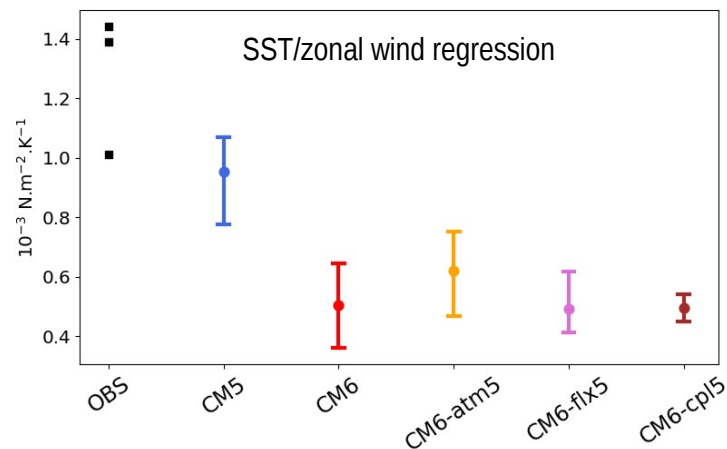


Methodology (M2 internship T. Manni, co-supervised with G. Bellon, 2021)

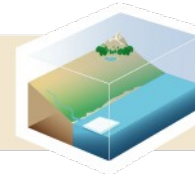
- Deactivate progressively changes made in between CM5 and CM6

- ▶ Back to former **atmospheric parameterisations set**
- ▶ Back to former **ocean-atmosphere bulk flux parameterization**
- ▶ Back to former **coupling frequency (1hour → 1day)**

⊗ Change not linked to atmospheric nor coupling changes
→ Is it due to the ocean component ?



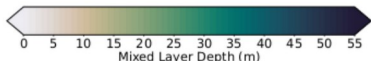
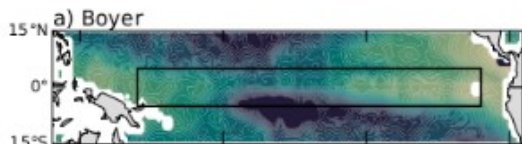
3 Ocean changes from CM5 to CM6



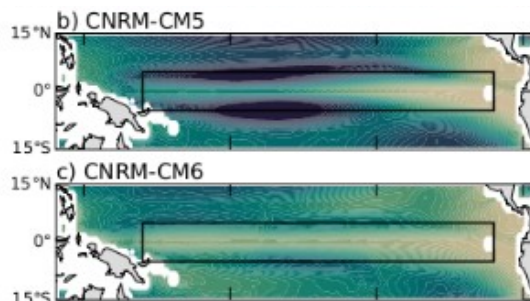
- Search for emergent properties that have been modified in between CM5 and CM6 :
 - ▶ Very clear modification of the ocean Mixed Layer Depth (MLD) mean pattern: zonal and meridional gradients weakened in the equatorial Pacific
 - ▶ Weaker MLD anomalies related to ENSO events

Mean state

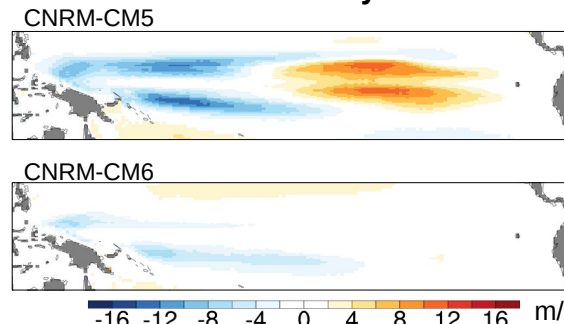
Référence



Mixed layer depth (annual mean, density criteria)

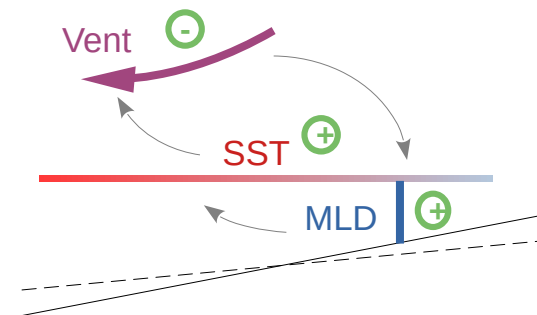


Variability

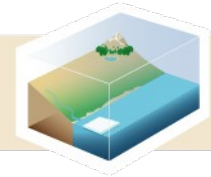


MLD regressed onto Nino3.4 SST anomaly to the mean seasonal cycle

➡ Bjerknes feedback less intense in CM6, why?



3 Intrinsic ocean component behavior

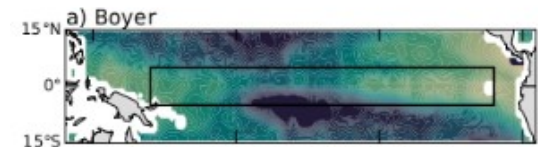
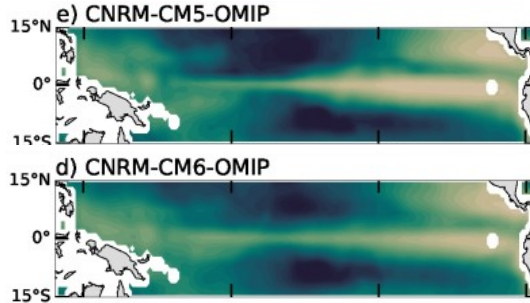
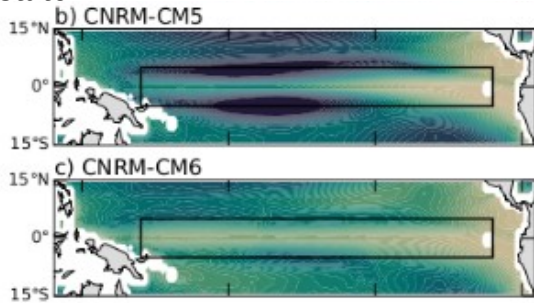
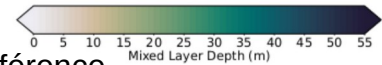


- Decouple the system and run the ocean component in forced mode:

Mean state

Fully coupled

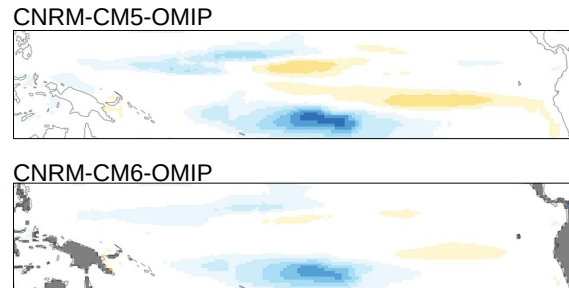
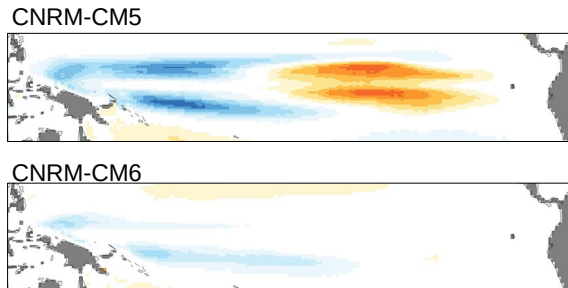
Ocean forced



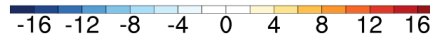
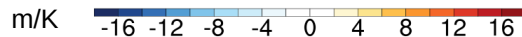
Mixed layer depth (annual mean, density criteria)

Difficult to conclude has ocean forced behavior is very different from the coupled system

Variability

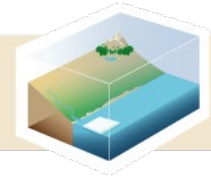


An imprint of degradation in term of variability in forced mode

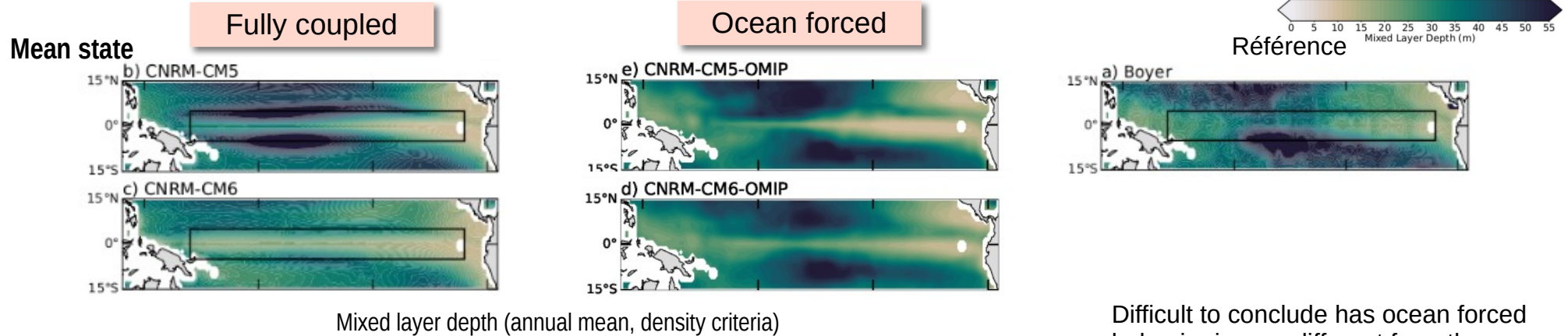


MLD regressed onto SST anomaly to the mean seasonal cycle

3 Intrinsic ocean component behavior



- Decouple the system and run the ocean component in forced mode:

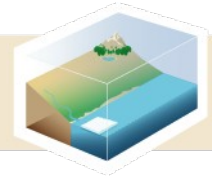


Difficult to conclude has ocean forced behavior is very different from the coupled system

Variability

Investigation to be pursued yet few lessons :

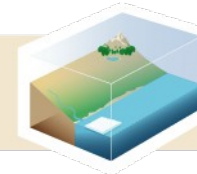
- Ocean forced configuration not always informative on the full system emergent behavior
- Hard to disentangle the impact of changing components from the mean state change due to coupled feedbacks
- Develop intermediate configurations more constrained (nudging in some components, Simplified Atmospheric Boundary Layer over the ocean (ABL1D, Lemarié et al., 2021), etc...



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2 Parameterisation development example

CNRM
CM




DOI: 10.1002/qj.3804

RESEARCH ARTICLE

Quarterly Journal of the
Royal Meteorological Society 

2020

Meso-scale contribution to air–sea turbulent fluxes at GCM scale

Sébastien Blein  | Romain Roehrig | Aurore Voldoire | Ghislain Faure

ANR COCOA


DOI: 10.1002/qj.4273

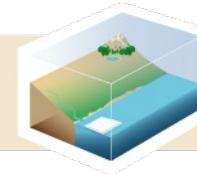
RESEARCH ARTICLE

Quarterly Journal of the
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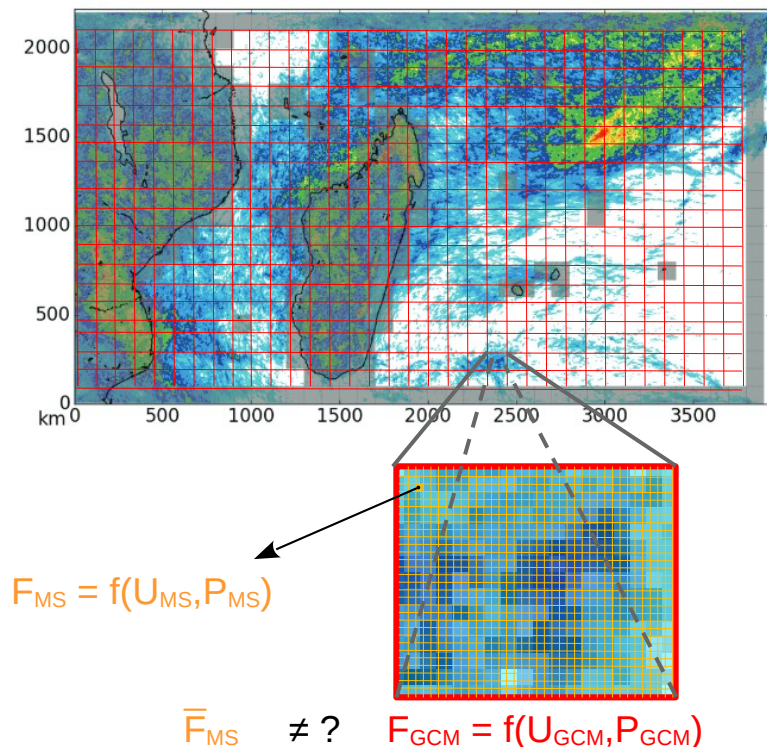
2022

Parametrizing the mesoscale enhancement of oceanic surface turbulent fluxes: A physical–statistical approach

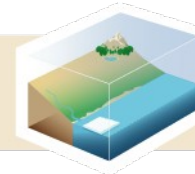
Sébastien Blein  | Romain Roehrig | Aurore Voldoire



Coarse-graining approach (MS res. 2.5 km, GCM res. 100 km).



- **High resolution** = AROME (convection permitting). Provides:
 - ▶ the **reference variables** to be parameterized
 - ▶ **parameters/diagnostics** characterizing features (e.g. convection or large scale circulation) which potentially impact the surface wind variabilities
- **Two domains** during one month: *Indien* ($\sim 360 \cdot 10^3$ samples) and *Antilles* ($\sim 110 \cdot 10^3$ samples) used as:
 - ▶ **Training** on $\mathcal{D}_{Indien}^{\text{Training}}$ (75% of *Indien* random samples)
 - ▶ **Test** on $\mathcal{D}^{\text{Test}} = \mathcal{D}_{Indien}^{\text{Test}} \cup \mathcal{D}_{Antilles}^{\text{All}}$

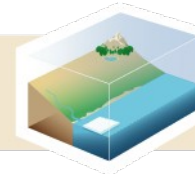


- Many former studies have addressed the impact of meso-scale $\geq \sim 10$ km:

- ▶ Jabouille et al. 1996, MWR
- ▶ Emanuel and Zivkovic-Rothman 1999, JAS
- ▶ Redelsperger et al. 2000, JC
- ▶ Williams 2001, QJRMS
- ▶ Zeng et al. 2002, JC
- ▶ Bessac et al. 2019, MWR

All based on the « gustiness approach », 3 main potential caveats :

- **1. Gustiness approach** is assumed as valid
- **2. Convective activity** is considered as the only driver
- **3. Predictors** are chosen in a rather **heuristic and univariate manner**



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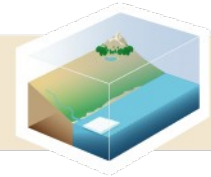
- Blein et al. 2020, QJRMS addressed point 1 and part of 2:

- ▶ Wind stress flux : $\bar{\tau}_{MS} \approx f_U (U_{GCM} + \delta U) + \rho_a C_D (U_{GCM} + \delta U) \sigma^2_U$
- ▶ Sensible heat flux : $\bar{H}_{MS} \approx f_\theta (U_{GCM} + \delta U, \theta_{GCM})$
- ▶ Latent heat flux : $\bar{LE}_{MS} \approx f_q (U_{GCM} + \delta U, q_{GCM})$

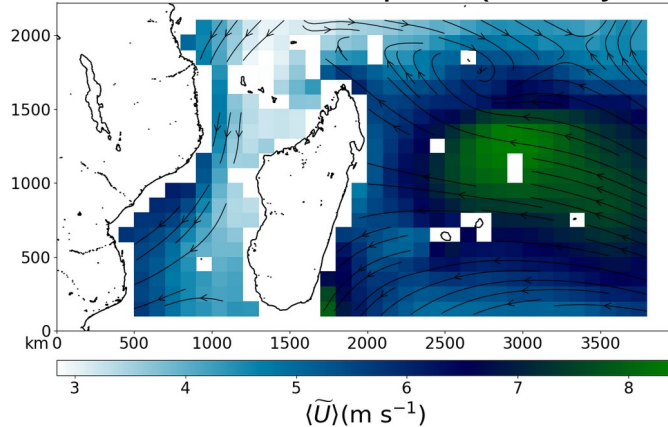
$\delta U = \bar{U}_{MS} - U_{GCM}$ missing wind contribution
at the GCM scale from the meso-scale
 σ^2_U meso-scale wind speed variance

Take into account the meso-scale enhancement = parameterize δU and σ^2_U

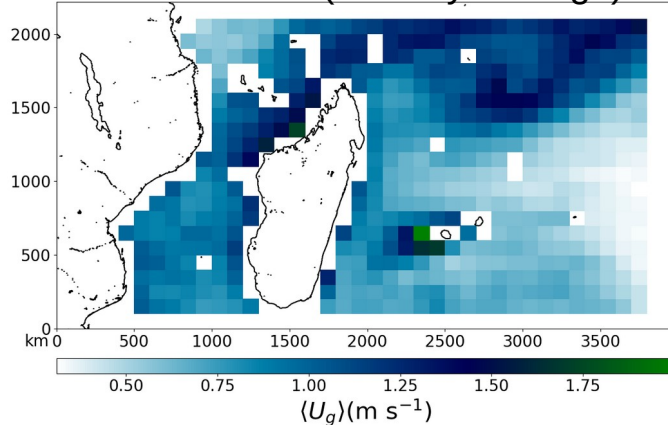
2 Wind speed variability characteristics



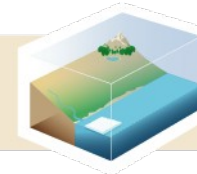
GCM-scale wind speed (monthly average)



Reference δU (monthly average)



- Wide variety of situations
- Variability not only due to deep convection
 - ▶ Shallow convection
 - ▶ Fronts
 - ▶ Wind shear
- Processes often interplay → a **statistical approach** retained rather a physical-mechanical approach
- To construct a parameterisation $\delta U = f(P_1, P_2, \dots, P_n)$ need to establish potential predictors, 2 categories of predictors :
 - ▶ Convection-related (8)
 - ▶ Dynamics-related (4)
- Select relevant predictors following a LASSO procedure, **5 predictors retained** :
 - ▶ Updraft mass flux, cold pool velocity
 - ▶ GCM scale wind speed, horizontal wind shear and horizontal wind divergence

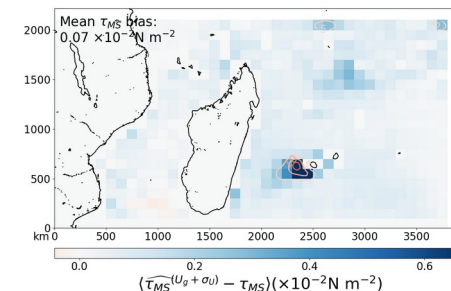
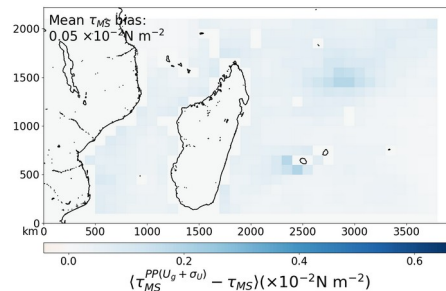
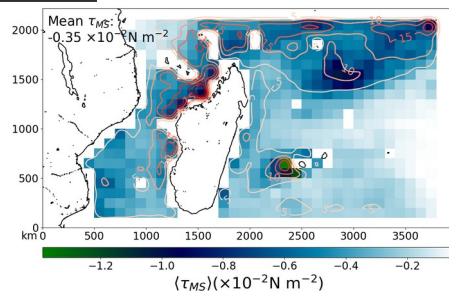


Ref. meso-scale flux enhancement

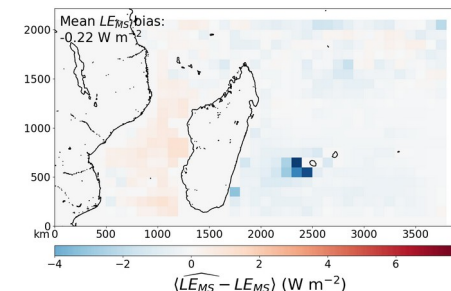
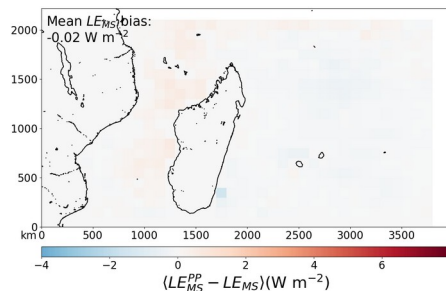
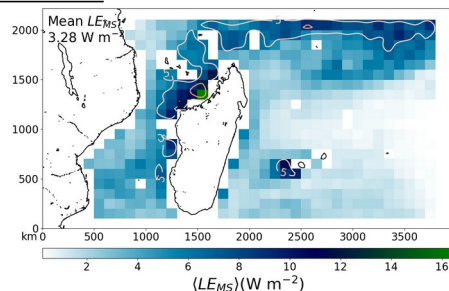
“Perfect Param.” meso-scale enhancement bias

Param. meso-scale enhancement bias

Momentum flux



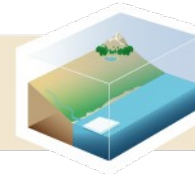
Latent heat flux:



Blein et al. 2020
Gustiness concept verified

Blein et al. 2022
Parameterisation check

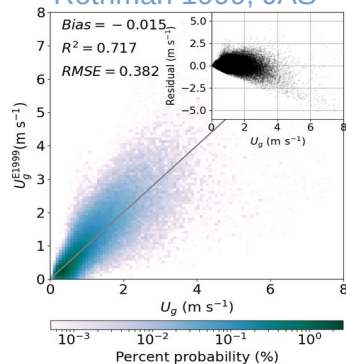
Comparison with previous parameterisations



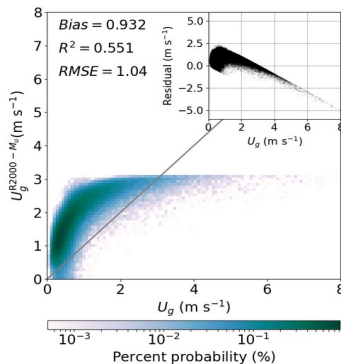
$$\mathcal{D}^{\text{Test}} = \mathcal{D}_{\text{Indien}}^{\text{Test}} \cup \mathcal{D}_{\text{Antilles}}^{\text{All}}$$

Testing dataset does not contain the training dataset

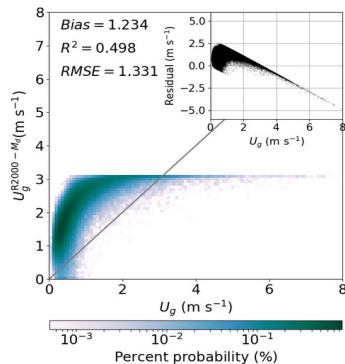
Emanuel and Zivkovic-Rothman 1999, JAS



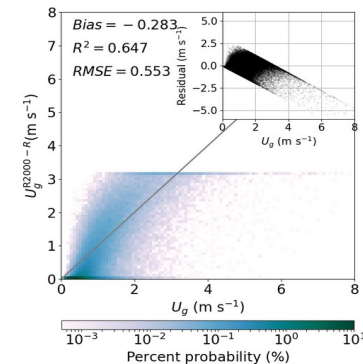
Redelsperger et al. 2000, JC



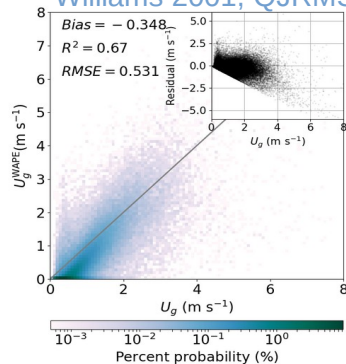
Redelsperger et al. 2000, JC



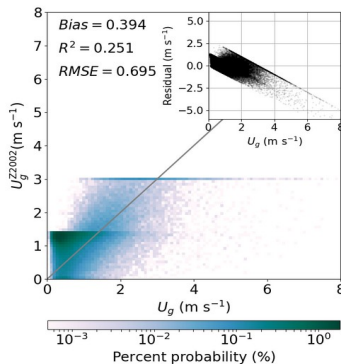
Redelsperger et al. 2000, JC



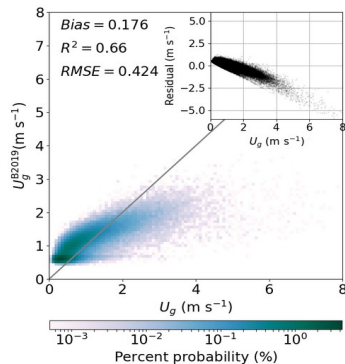
Jabouille et al. 1996, MWR
Williams 2001, QJRMS



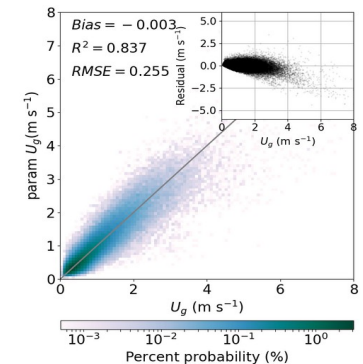
Zeng 2002, JC

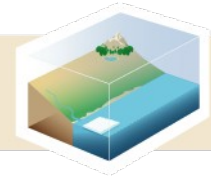


Bessac et al. 2019, MWR



Blein et al. 2022, QJRMS



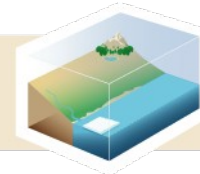


● Summary

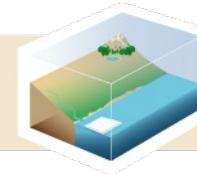
- ▶ δU parameterization = **multivariate linear model** involving: the **updraft mass flux**, the **cold-pool spreading velocity**, the **large-scale shear**, the **large-scale divergence** and the **GCM-scale wind speed**
- ▶ σ_U parameterization: addition of the **cold-pool objects aggregation index**
- ▶ Both **convection**-related and **large-scale dynamics**-related predictors are relevant
- ▶ **Skilful** param. (residual only deviate from Gaussian distribution due to specific region of orographic perturbation).
- ▶ **Simpler** param (fewer predictors) also proposed for GCM-implementation perspective

● Next steps

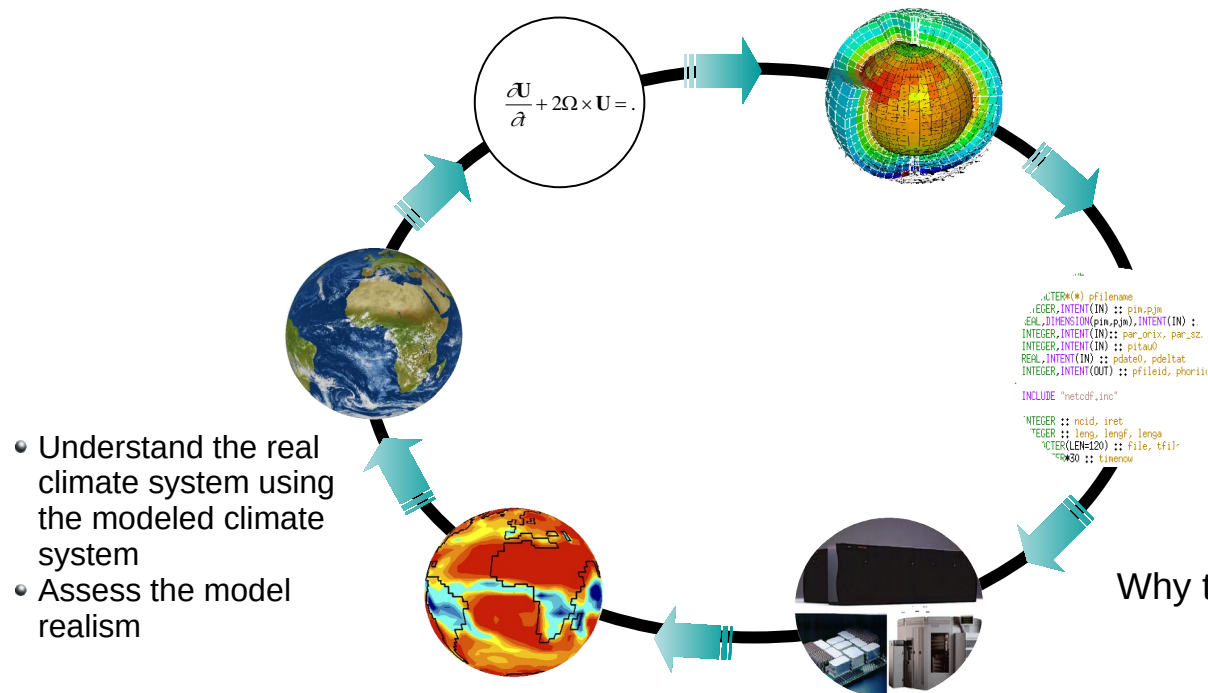
- ▶ GCM implementation under way (predictor choice, validation of input parameters as simulated by the GCM, tuning...)
- ▶ Address smaller scales? Deep learning approach ?



1. The CNRM-CM climate model : a complex system
2. Understanding the emergent properties of a climate model
3. An example of model improvement : parameterising the ocean-atmosphere flux enhancement due to meso-scale variability
4. Conclusion



Is the modelisation a positive feedback loop a reality ?



- Understand the real climate system using the modeled climate system
- Assess the model realism

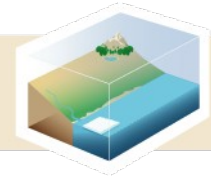
The loop does not feature well two Bottlenecks :

- The difficulty to link model errors to parametrisations, **tracking model error source** is painful and unattractive
- The **tuning** necessity, which is a long back and forth process

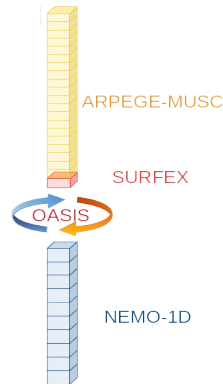
Why tuning necessary ?
(sea Hourdin et al., 2017, BAMS)

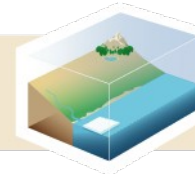
- Emergent properties are largely « unpredictable »
- Compensating errors are unavoidable
- Need to ensure energy budget closure to avoid large SST drifts and unrealistic mean climate

4 Improve the source tracking error



- Pursue the effort of **modularity** to be able to assess each component separately and decompose the full system
- Develop new intermediate configurations more representative of the full system
 - ▶ Column 1D-model (Voldoire et al., 2022, GMD) : a practical tool to work on improving the ocean-atmosphere interface
 - ▶ Simplified Atmospheric Boundary Layer (Lemarié et al., 2021, GMD) over the ocean
- Develop dedicated protocols
 - ▶ Transpose-AMIP (Brient et al., 2019, JAMES), Transpose-CMIP (Voldoire et al., 2019, Clim. Dyn.)
 - ▶ Nudging, Flux-correction, ...





- Use an objective and semi-automatic tuning procedure (Couvreur et al., 2021)
 - ▶ Based on the « History Matching » method (Williamson et al., 2017)
 - ▶ Advantages of this method
 - Tuned model emergent properties listed
 - Avoid over-fitting and error-compensation
 - Take in to account observation uncertainties
 - A way to explore the model structural error
- Method already well established for the atmospheric component (Hourdin et al., 2023, Sci. Adv.)
 - ↪ How to extend it to the full system ?
 - ↪ How to deal with long-term memory time-scale of other components ?

Objectives of the QUINTET project as part of the TRACCS PEPR

