

(Two) Ongoing efforts in the French NWP/climate modelling community

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the High-Tune and DEPHY communities...

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Legacy of the High-Tune project (2018-2021)

Initial motivations

- Model **calibration/tuning**: bottleneck in NWP/climate modelling
- Critical role of **boundary-layer clouds** in the Earth system
- Lack of references to benchmark boundary-layer **cloud radiative effects**

➤ Process-based climate model development harnessing machine learning

A new philosophy for climate (and NWP) model calibration

- **Formalized** calibration process (transparent, reproducible)
- Starting at the **process level** (1D / LES or Observations)
- Natural articulation between 1D and 3D (and coupled) configurations
- Accounting for sources of **uncertainties**
- Rather than optimize, **identify sets of parameters compatible** with a set of given constraints

A statistical framework to better address the complexity of the calibration process, and to accelerate it

- **History matching** with iterative refocusing (Williamson et al. 2015, 2017)
- Use statistical **emulators** to explore the whole space of parameters, at quasi-null computational cost
- Be **parsimonious** in terms of "true", expensive simulations

Game changer in climate modelling

- Separation of concerns between development of model physical content and parameter calibration
- Increased efficiency in implementing new developments and quantify their true benefit
- Rigorous comparison between parameterizations or between model physics
- Exploring model parametric uncertainty, and thereby the model emergent properties



History matching with iterative refocusing

Framework

- Define targeted **metrics** f_k , their **references** and their **uncertainties**
- Identify the relevant model **parameters** λ and their "acceptable" ranges (**input parameter space** Λ)
- Build an experimental design (learning dataset)
- Build an **emulator** $f_k(\lambda)$ for each metrics (Gaussian Processes)
- Identify the sub-space of Λ which is not compatible with the chosen constraints (**Not-Ruled-Out-Yet - NROY - space**) knowing:
 - The reference uncertainty,
 - The uncertainty due to the emulator,
 - The model structural uncertainty (interpreted so far as a tolerance to error)
- **Implausibility, cutoff** ($T=3$)

$$I_f(\lambda) = \frac{|r_f - \mathbb{E}[f(\lambda)]|}{\sqrt{\sigma_{r,f}^2 + \sigma_{d,f}^2 + \text{Var}[f(\lambda)]}}$$

$$\text{NROY}_f^1 = \{\lambda \mid I_f(\lambda) < T\}$$

$$\text{NROY}^1 = \bigcap_f \text{NROY}_f^1 = \{\lambda \mid I_f(\lambda) < T, \text{ for all } f\}$$

- Iterate over several **waves** to reduce the emulator uncertainty in NROY^{N-1} , until convergence

Proof of concept: from 1D to 3D with LMDZ

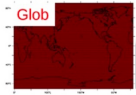
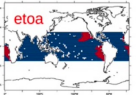
Multi 1D case approach (focus on boundary-layer clouds)

- Dry convective boundary layer (IHOP, Couvreux et al. 1996)
- Continental cumulus (ARMCU, Brown et al. 2002)
- Marine cumulus (RICO, van Zanten et al. 2011)
- Stratocumulus-cumulus transition (SANDU, Sandu et al. 2011)
- Reference LES: Meso-NH or UCLA

Case	IHOP	ARMCU	RICO	SANDU	SANDU	SANDU
Subcase	REF	REF	REF	REF	SLOW	FAST
Time	7-9	7-9	19-25	50-60	50-60	50-60
$\theta_{400-600\text{ m}}$	X	X	-	-	-	-
$Q_{v,400-600\text{ m}}$	-	X	-	-	-	-
$\alpha_{\text{cld,max}}$	-	X	X	-	-	-
$z_{\text{cld,ave}}$	-	X	-	X	-	-
$z_{\text{cld,max}}$	-	X	-	X	X	X

Metrics

- 11 metrics in 1D: potential temperature, moisture averaged in the boundary layer, cloud cover
- 11 metrics in 3D: TOA radiative budget components, global/regional averages

Mask	Variable	Metrics	target W m^{-2}	error W m^{-2}
	Total rad. TOA (rt) Swup TOA (rsut)	glob.rt glob.rsut	2.5 99.6	0.2 5
Convective, intermediate, subsiding, Circum Antact. anomaly	SWup TOA (rsut) LWup TOA (rlut)	conv.rsut weak.rsut subs.rsut circAa.rsut	103.2 81.8 84.9 -48.6	5 5 5 5
	SWup TOA (rsut)	conv.rlut etoa.rsut	235.8 11.0	5 5

Parameters

- 9 parameters from the cloud, shallow convection and microphysics parameterizations

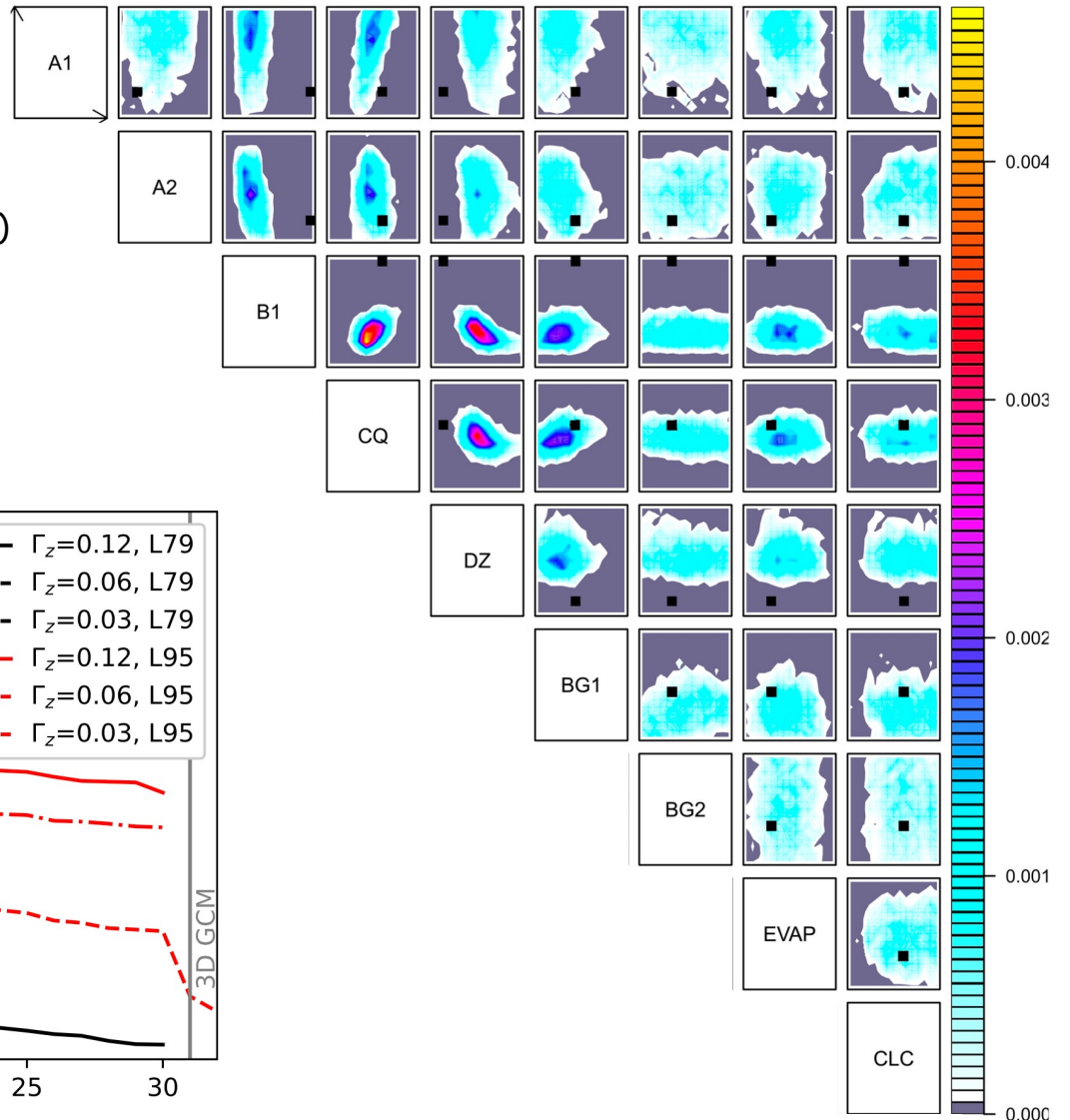
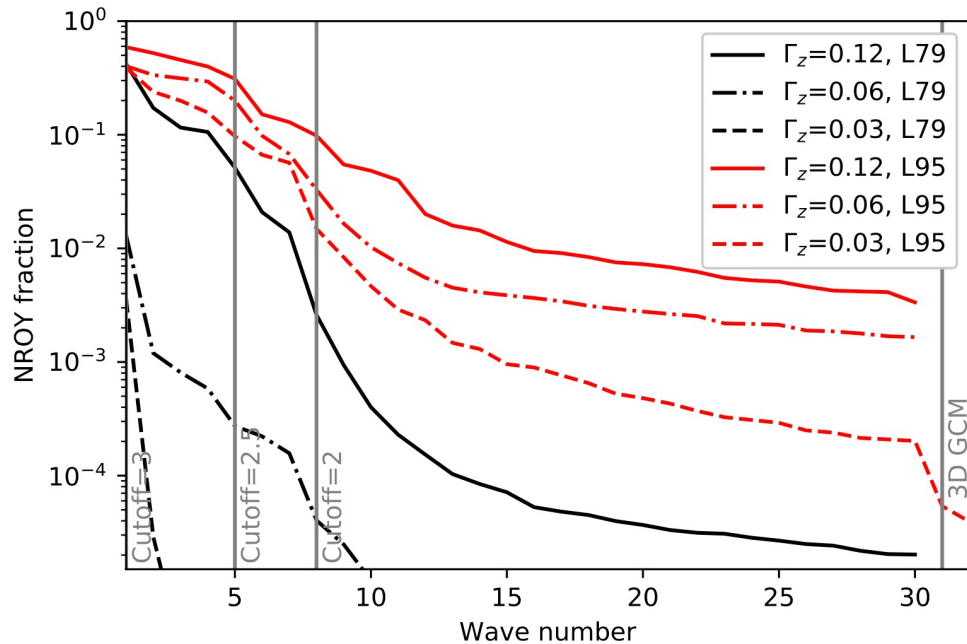
Waves

- 30 waves in 1D, with a progressive reduction of the implausibility cutoff (de 3 à 2)
- 2 waves then in 3D

After 30 waves in 1D

NROY space - Implausibility matrix

- Algorithm convergence
- Non-empty space (0.02% from the *input space*)
- LMDZ6 tuning non-optimal



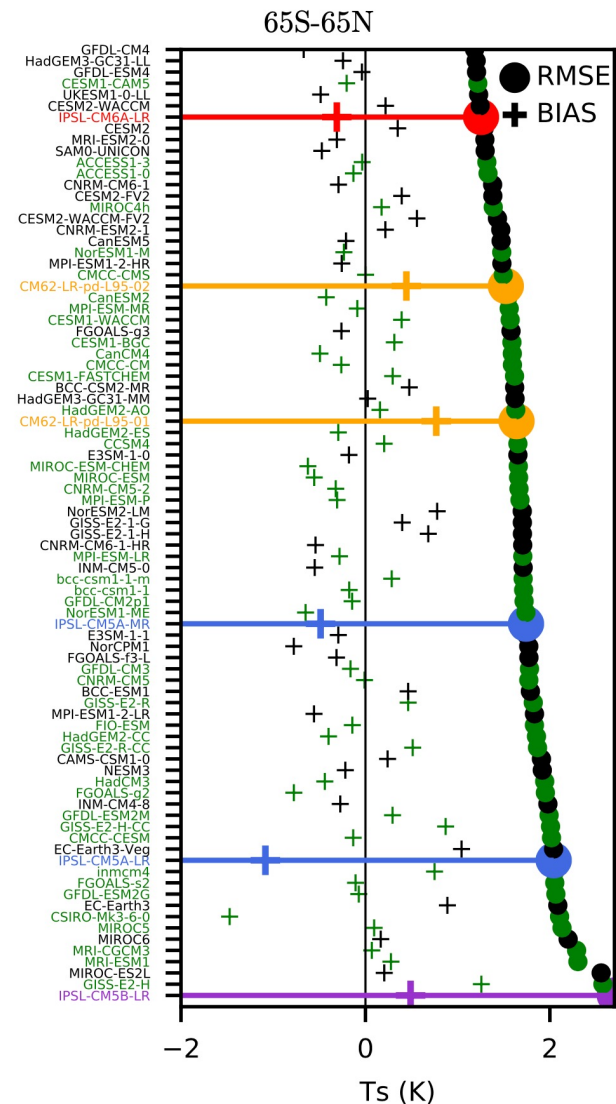
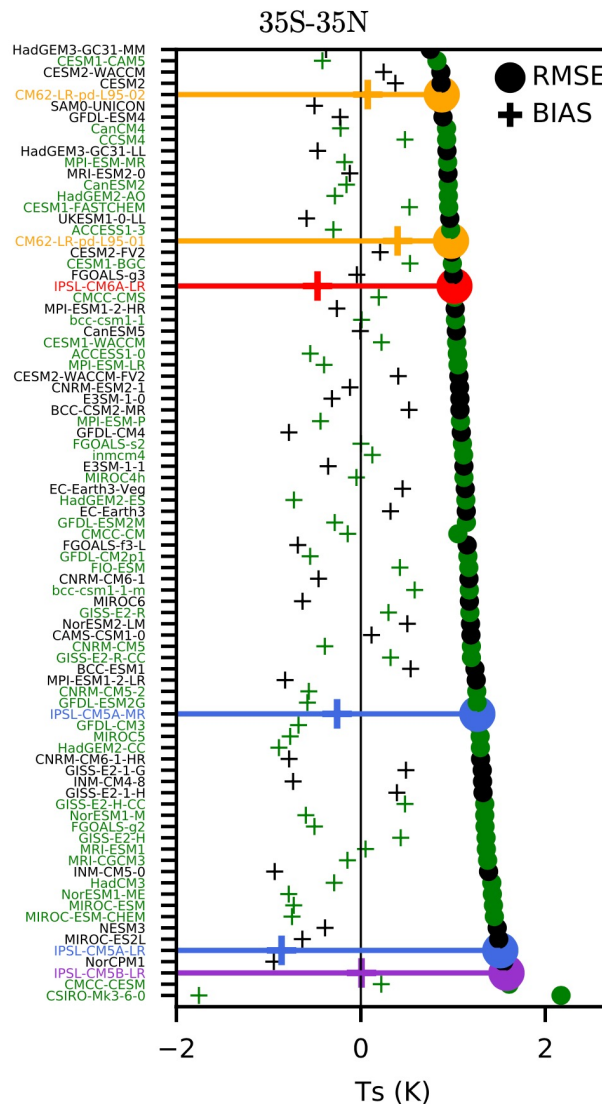
From 1D to 3D to coupled

3D model calibration starting from the 1D NROY space

- Non-empty space (0.004% from the input space)
- The 1D setup has efficiently provided pre-conditioning of the 3D configuration
- LMDZ6 tuning "by hand" good, though slight not optimal
- Probably a need to add a few further waves

From 3D to coupled

- Recalibration by hand of the TOA radiation budget (1 parameter)
- Behaviour ~similar the version tuned "by hand" during 2-3 years.

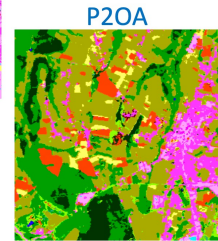
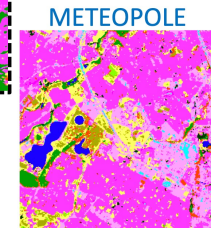
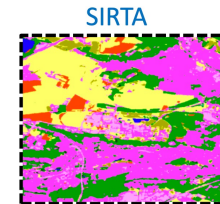
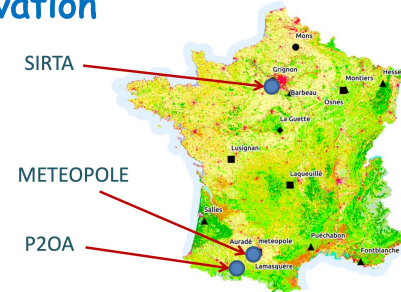
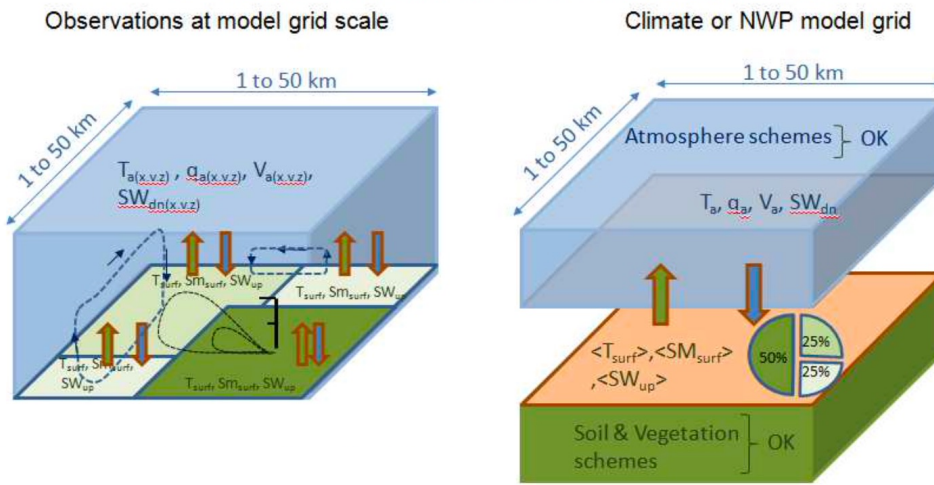


MOSAI (2021-2024)

Models and Observations for Surface-Atmosphere Interactions



➤ Better account for surface heterogeneities in the observation and modelling of land-atmosphere coupling



WP1: Uncertainty and representativeness of L-A exchanges measured over heterogeneous landscapes

WP2: Model evaluation using long-term measurements

WP3: Better account for the sub-grid landscape heterogeneities in the coupling between LSM and atmospheric models. Assess the impact of current simplifications.

Enhanced Observing Periods

- METEOPOLE: 06/2020 - 07/2021
- Sirta: 12/2021 - 10/2022
- P2OA: 12/2022 - 10/2023