Assessing calibration issues and intrinsic limits of a convection parameterization using machine learning

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Context and motivations

New atmospheric physics in CNRM-CM6-1** (Roehrig et al. 2020):

- Calibration over ~4-5 years (back and forth with model developments)
- Calibration "by hand", one or two parameters at the same time, combining 1D and 3D configurations
- New convection parameterization, "unified" (single plume) for both shallow and deep convection
  - ➢ ***Difficulties to calibrate this physics and make it work for both regimes***

Recent developments** (High-Tune project):

- Use of statistical (**machine learning**) tools from the *Uncertainty Quantification* community
- Rigorously explore the sensitivity of a physics/parameterization to its internal parameters
- Framework to identify which model errors are related to **calibration issues** and which are **structural** to the model

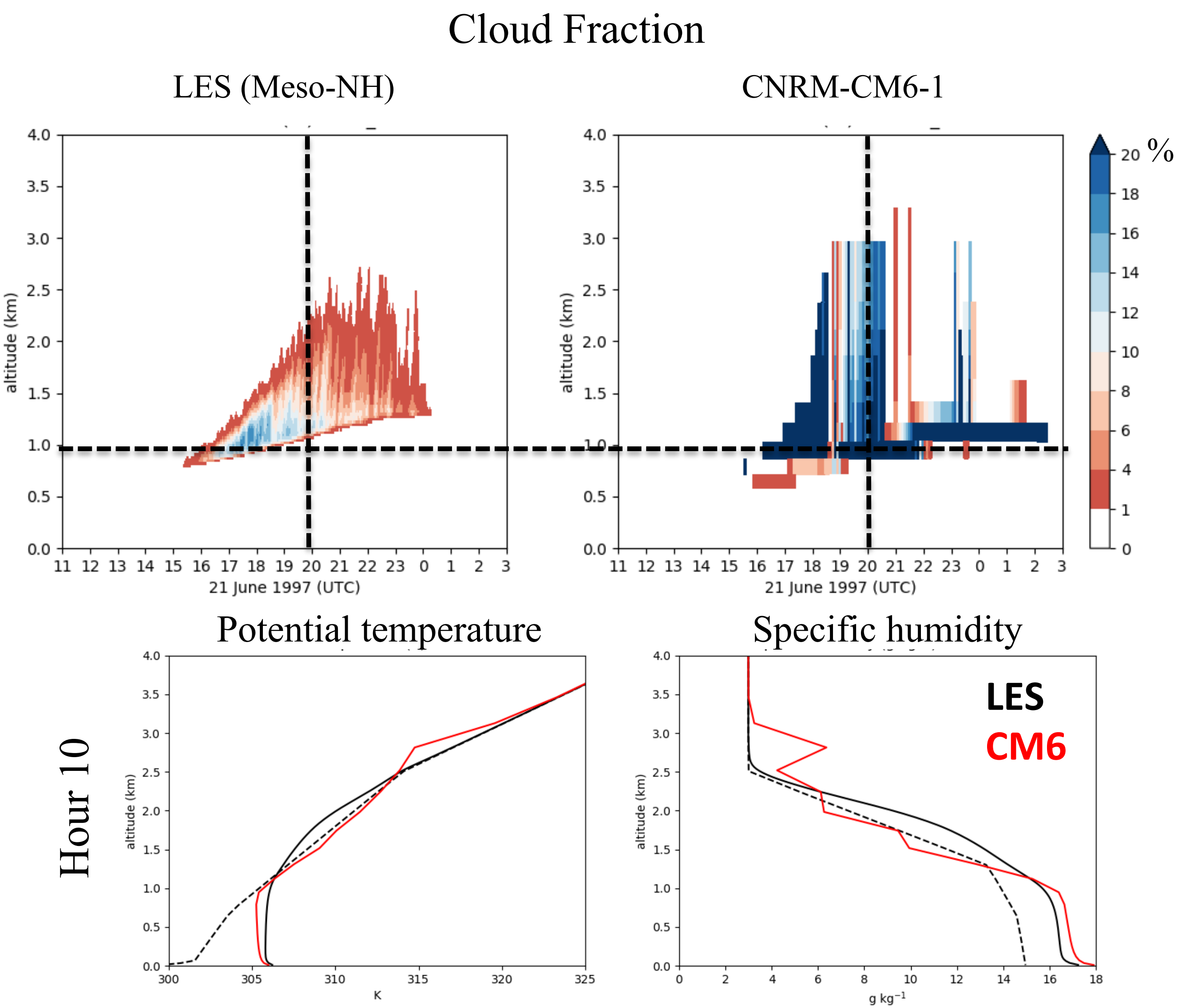
The 1D framework:

- Key step in the development of atmospheric parameterizations
- **Keep the fundamental processes right**, **reduce the risks for error compensations**
- Comparison to LES/CRM and observations : a wealth for parameterization development/evaluation
- A **wide diversity** of regimes is needed, and already partly available, with **references**.
  - ➢ ***Necessary condition for a parameterization to be validated?***

All these provide a rigorous framework to address questions such as:

- For a given model physics, and independently of calibration issues, is parameterization **A** better than parameterization **B** ?
- Can a unified convection parameterization (such as the one used in CNRM-CM6-1) really capture shallow and deep convection?

ARM-Cumulus : diurnal cycle of continental cumulus



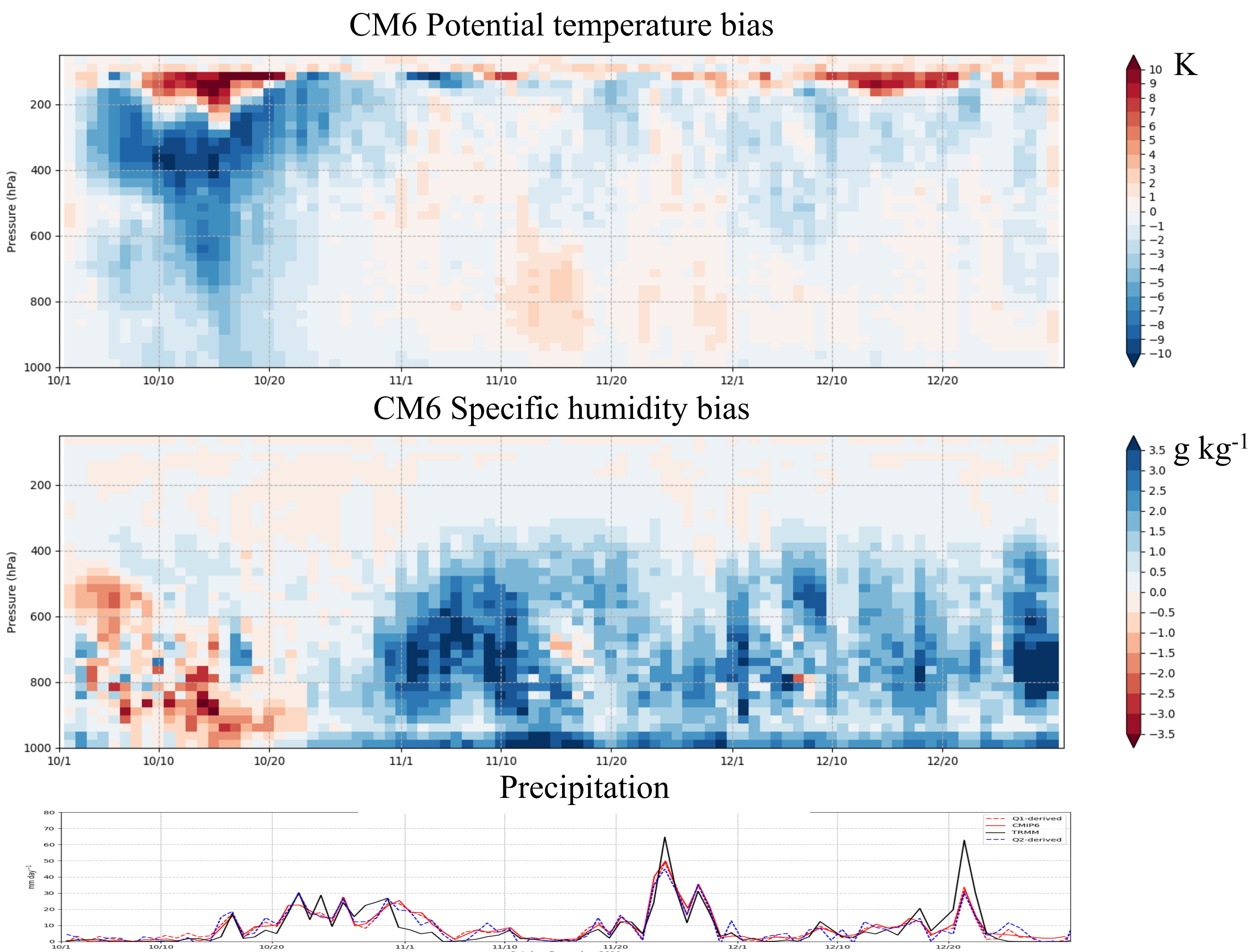
- Overestimate of cloud fraction
- Cloud base too low
- BL not deep enough, mixing too weak
- Intermittency and numerical issues

Convection during CINDY2011/DYNAMO

Field campaign in OND 2011, documenting energy and moisture budget over two arrays in the Indian Ocean

(Johnson and Ciesielski, 2013)

Northern Sounding Array (NSA)



Objectives and Framework

Objectives

- Explore the parametric uncertainty of the CNRM-CM6-1 convection parameterization for the ARM-Cumulus (Brown et al. 2002) et CINDY2011/DYNAMO-NSA (Abdel-Lathif et al. 2018) cases
- Which errors are **calibration issues** ? Which are **structural** ?

Framework : *Iterative refocusing*

(Williamson et al. 2017, Salter et al. 2018, Couvreux et al. 2020, Hourdin et al. 2020)

- Define target **metrics** f_k and associated **references**
- Identify relevant **parameters** $\boldsymbol{\lambda}$ and their uncertainty ranges (**input parameter space** $\boldsymbol{\Lambda}$)
- Build an experimental design (learning dataset)
- Build **emulators** $f_k(\boldsymbol{\lambda})$ for each metrics (Gaussian Processes)
- Identify the subset of $\boldsymbol{\Lambda}$ which cannot be ruled out yet (**NROY space**) knowing (***implausibility***) :
  - Reference uncertainties,
  - Emulator uncertainties,
  - Some **tolerance-to-error** quantifying how close to the reference we think our model can/should be.
  - **Cutoff** ***T*** on implausibility to define NROY

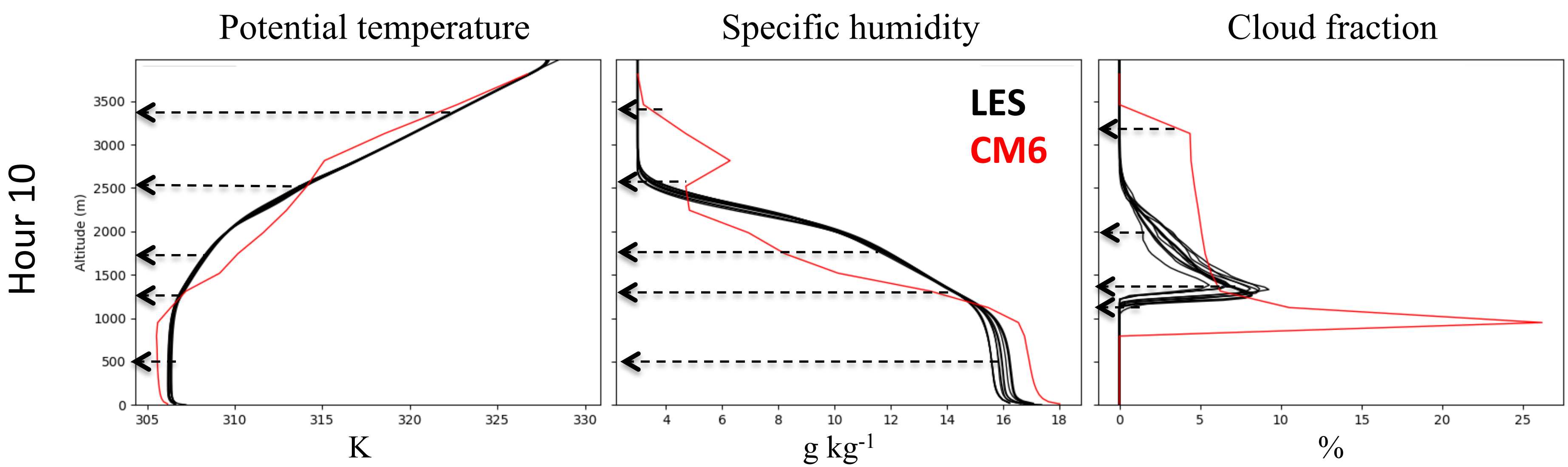
$$I_f(\boldsymbol{\lambda}) = \frac{|r_f - \mathrm{E}\left[f(\boldsymbol{\lambda})\right]|}{\sqrt{\sigma_{r,f}^2 + \sigma_{d,f}^2 + \mathrm{Var}\left[f(\boldsymbol{\lambda})\right]}}.$$

$$\mathrm{NROY}^n = \bigcap_k \mathrm{NROY}^n_{f_k} = \{\boldsymbol{\lambda} \mid \#\{k \mid I^n_{f_k}(\boldsymbol{\lambda}) > T\} \leq 0\}$$

- Continue with a 2nd, 3rd, … **wave**, as long as we need to improve the emulator forecasts (but only where it is needed), until convergence towards the true NROY is approximately achieved

Metrics, parameters and experimental design

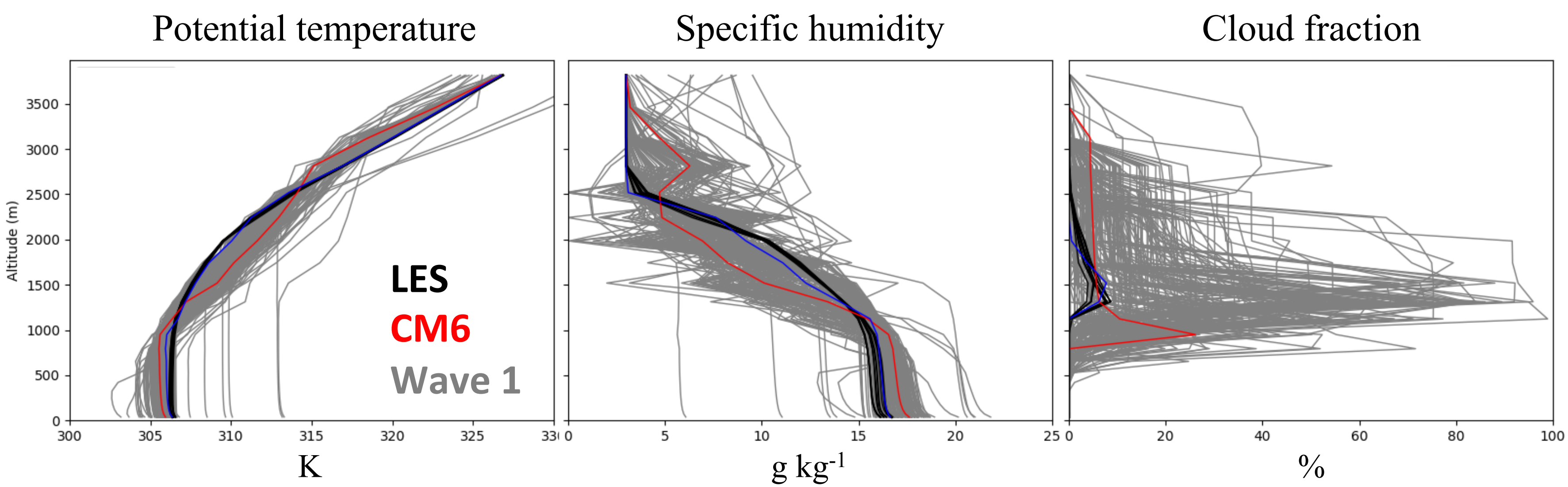
- **Metrics** (14): temperature, specific humidity and cloud fraction at a few levels (Hour 10)
- **Reference**: LES simulation with Meso-NH, uncertainty from an ensemble of LES simulations



- **Parameters** (24):
  - 11 related to convective transport (entrainment/detrainment, drag, buoyancy parameter)
  - 2 related with convective closure
  - 1 related to convective cloudiness
  - 6 related with liquid water microphysics
  - 4 related to turbulence

- Wave 1: 200 simulations, sampling based on a Latin hypercube
- Next waves: 200 simulations (within $NROY^{W-1}$)

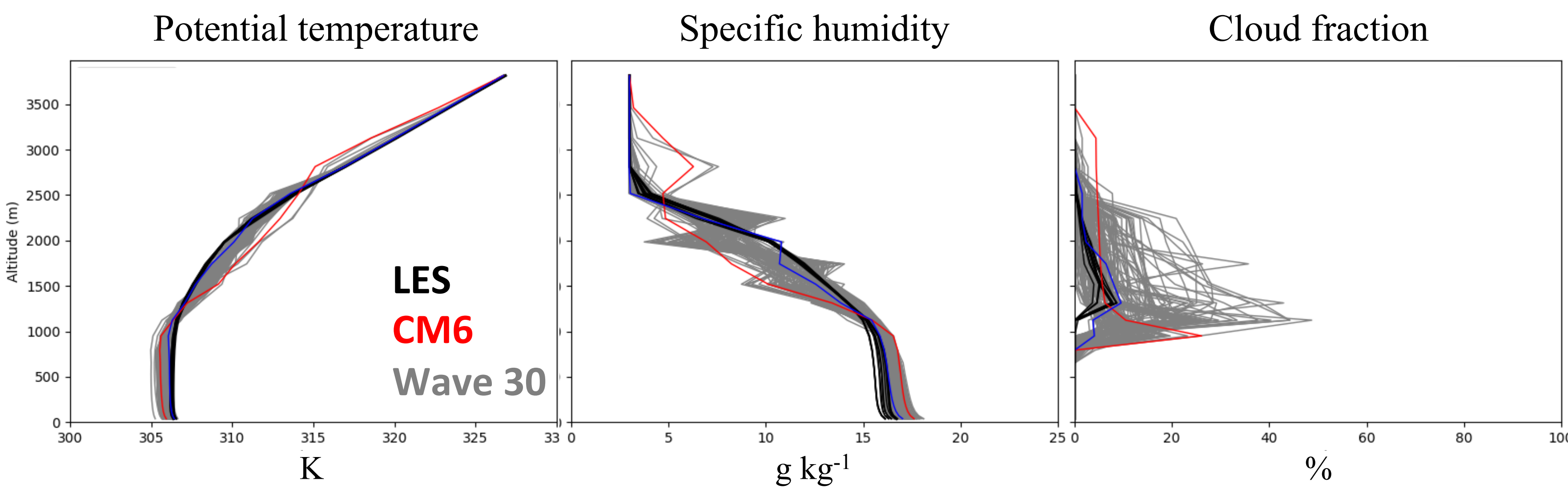
Wave 1: 200 simulations



Tolerance-to-error

- Potential temperature: 0.5 K except at 3400 m (0.1 K)
- Specific humidity: 0.5 g kg^{-1}
- Cloud fraction: 5 %

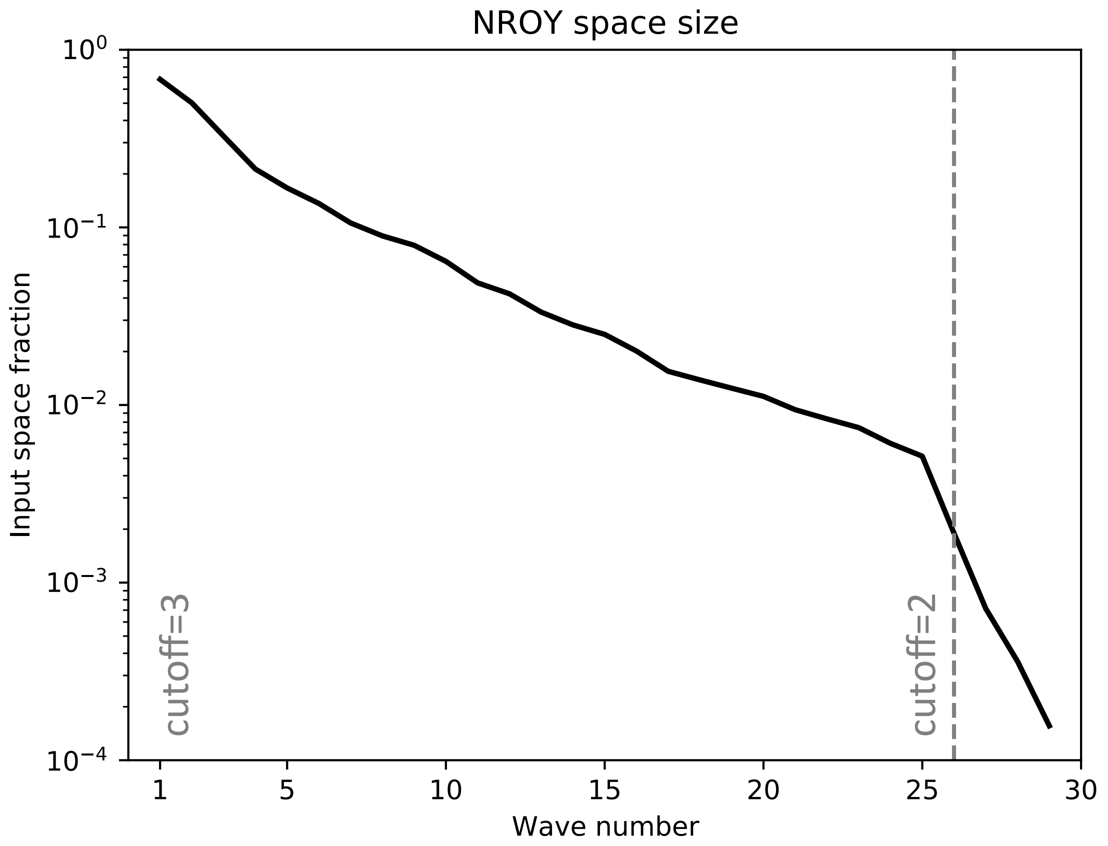
Wave 30: 200 simulations



First results

- Several calibrations much better than default.
- Convergence not fully achieved (especially for cf).
- **Intrinsic limits of the model physics**:
  - Some irregularities in the profile seem intrinsic (in q_v especially)
  - Cloud base systematically one level too low

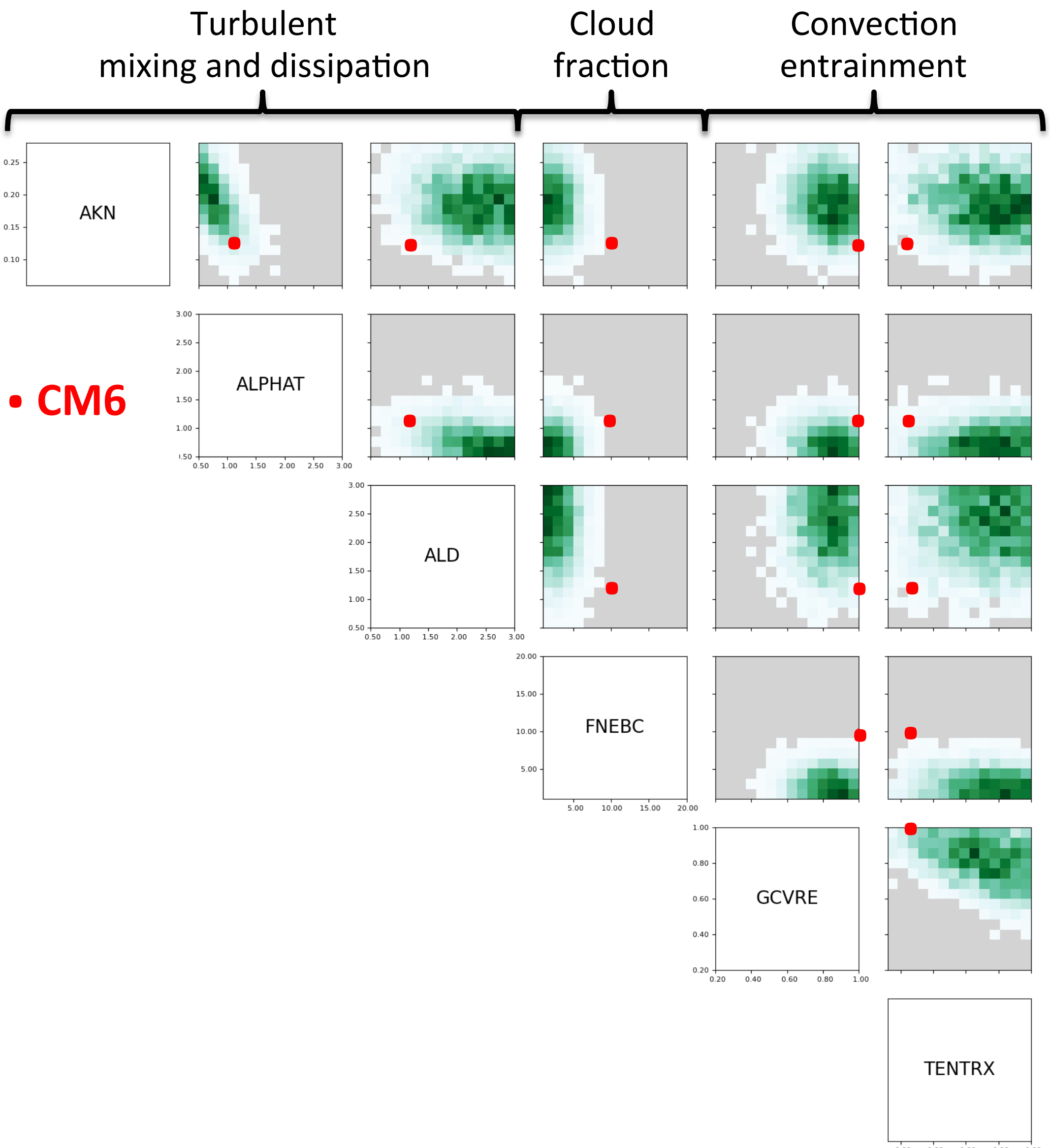
Evolution of the Not-Ruled-Out-Yet space



First results

- Decrease of cutoff when emulator uncertainty lower than reference uncertainty/tolerance-to-error
- After 30 waves, NROY ~0.015% of the input parameter space (~150 over 10^6 simulations)

Dominant parameters



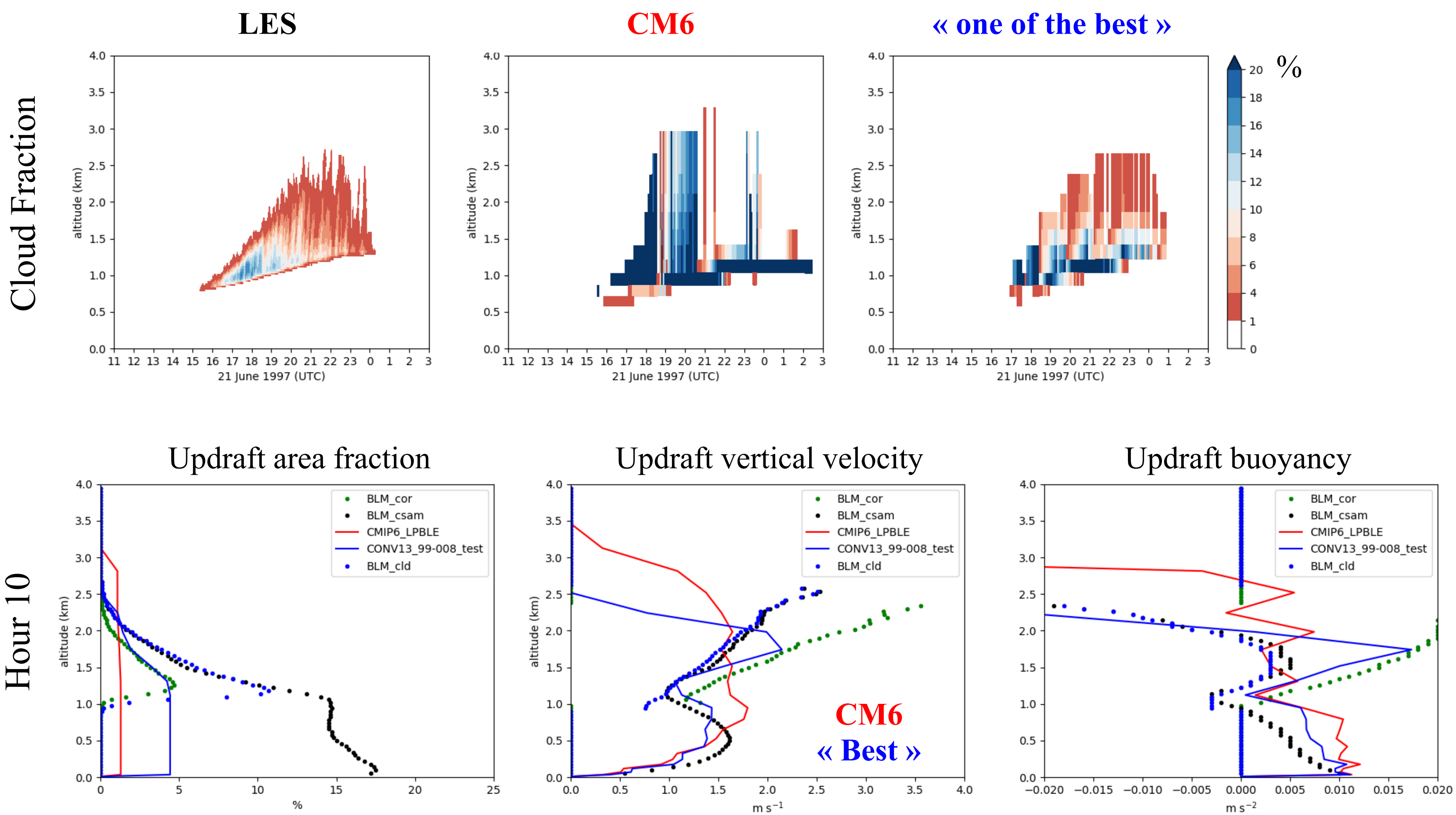
Dominant parameters

- Turbulent mixing (AKN and ALPHAT)
- TKE dissipation (ALD)
- Convective cloud fraction (FNEBC)
- Organized entrainement modulation factor (GCVRE)
- Maximum turbulent entrainment (TENTRX)

Reduced turbulent mixing required: balance between turbulent and mass-flux mixing ?

High entrainment rates required

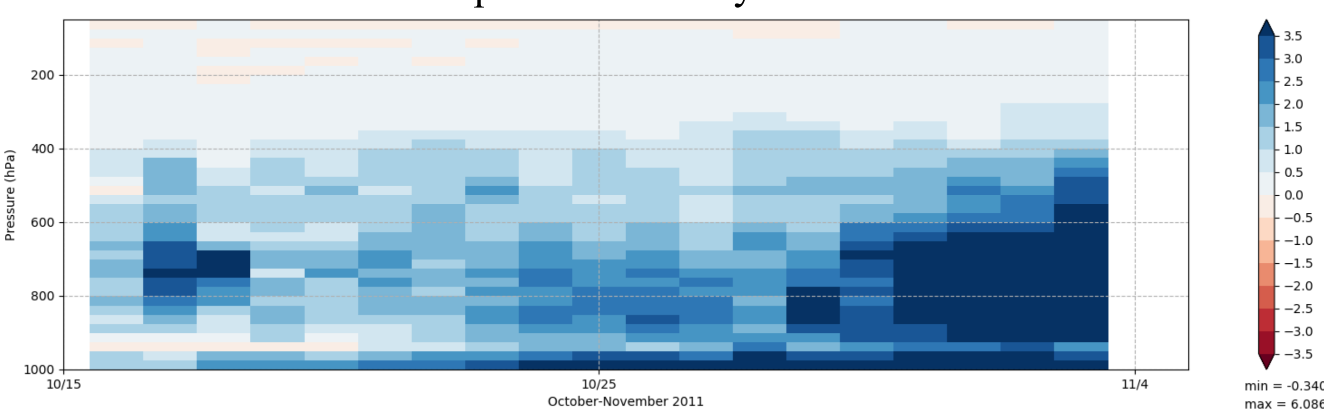
An example of calibration within NROY?



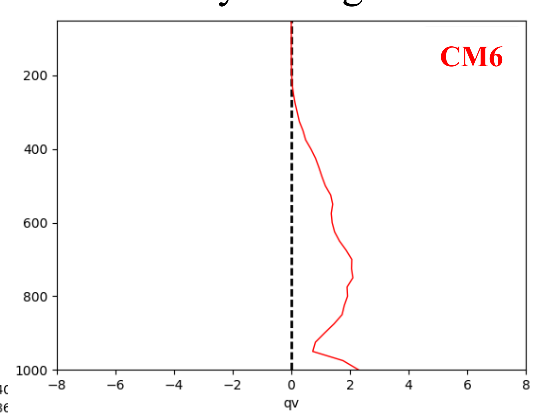
Metrics, parameters and experimental design

- Focus on the first MJO event (15 October to 4 November 2011)
- Consider temperature and specific humidity average profiles
- **Metrics**:
  - 3 levels for θ: 925, 600 and 200 hPa
  - 2 for q_v: 925 and 700 hPa
- **Reference**: field campaign observations (radiosounding array),
  - temperature uncertainty ~0.1 K; tolerance 0.5 K
  - humidity uncertainty ~0.1 g kg^{-1}; tolerance 0.2/0.1 g kg^{-1}

Specific humidity bias



20-day average bias



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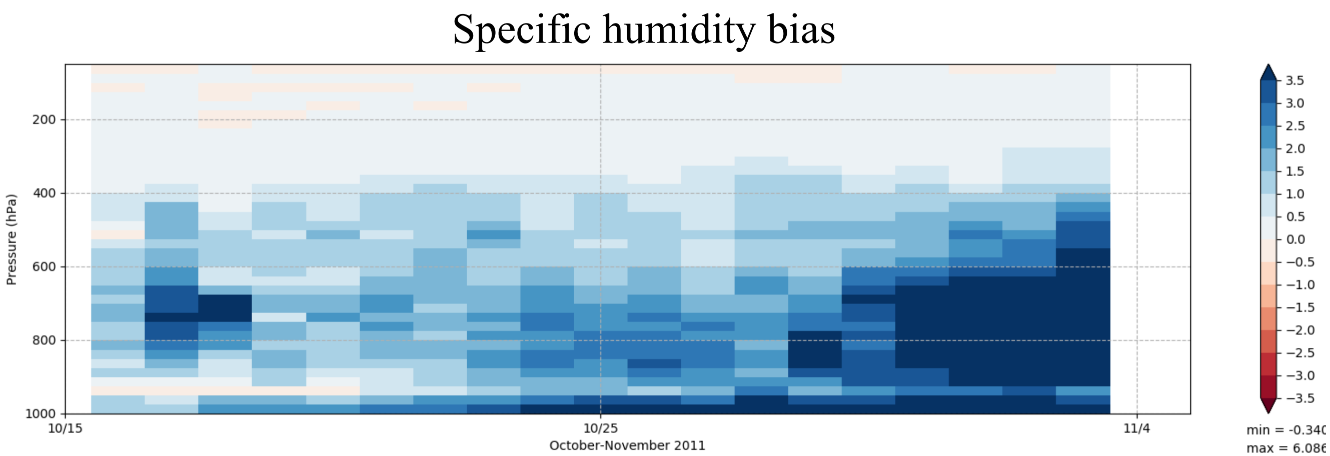
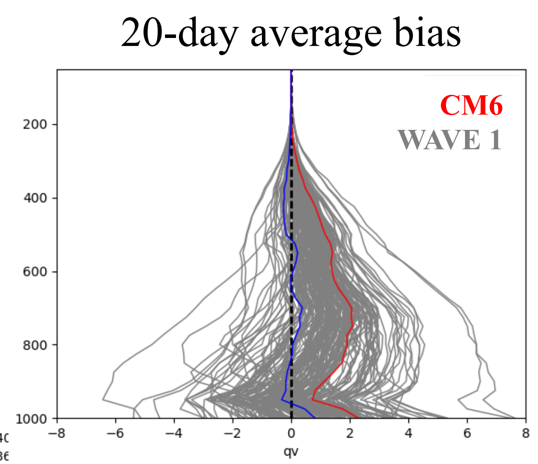
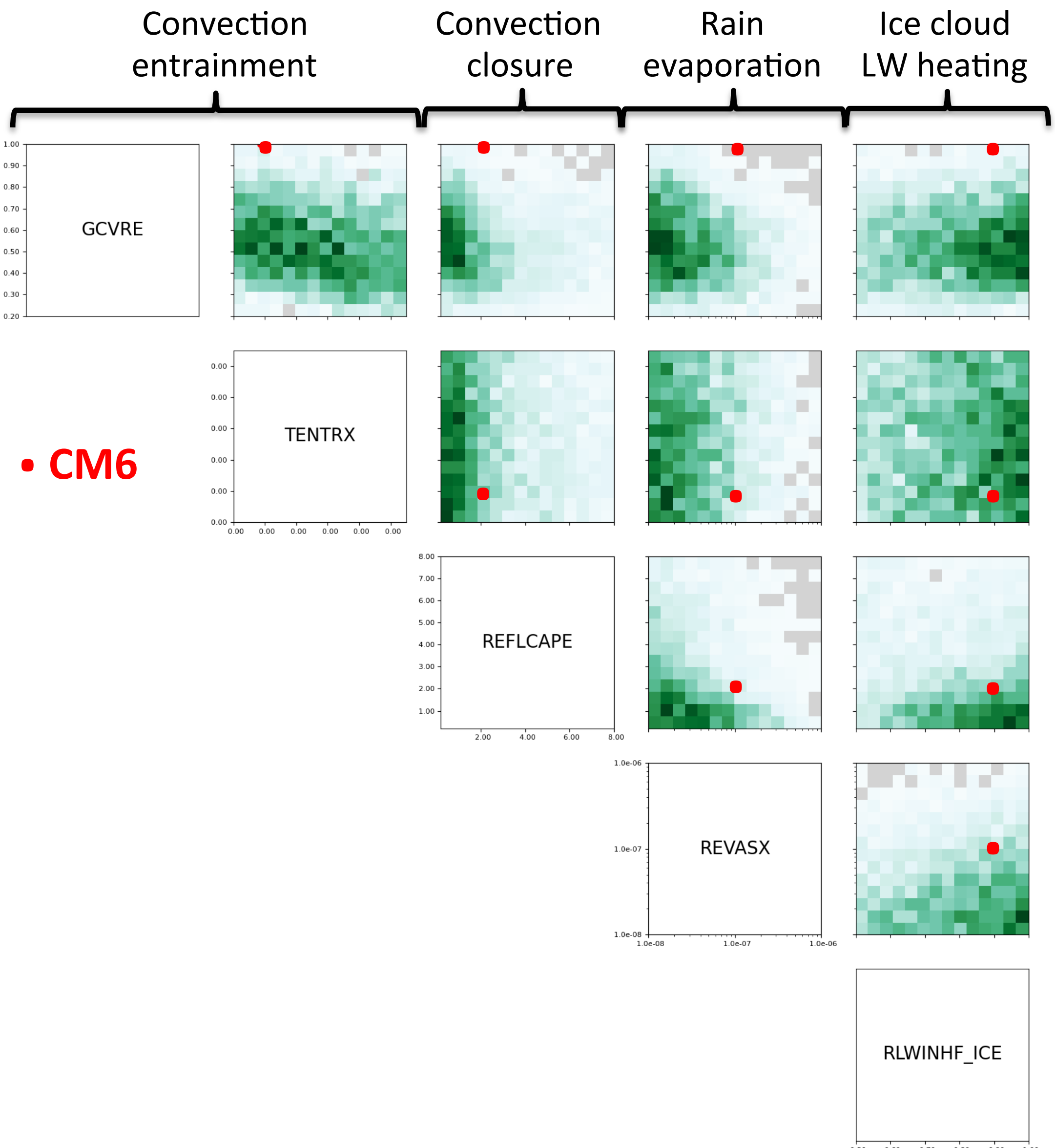
  - temperature uncertainty ~0.1 K; tolerance 0.5 K
  - humidity uncertainty ~0.1 g kg^{-1}; tolerance 0.2/0.1 g kg^{-1}
- **Parameters**: same 24 parameters for ARM-Cumulus
  - + 12 for ice microphysics
  - + 4 for cloud radiative properties
- Wave 1 and following: 200 simulations





Not-Ruled-Out-Yet space - Wave 5



• CM6

Wave convergence not yet achieved, so still preliminary results.

NROY[5] ~0.3% of the input space

Dominant parameters:

- **Rain evaporation** rate key to get the moisture vertical profile right
- Some role of **LW heating by ice cloud**
- **Convection intensity** (closure) is critical
- **Entrainment** still key, but towards more moderate values compared to shallow convection.

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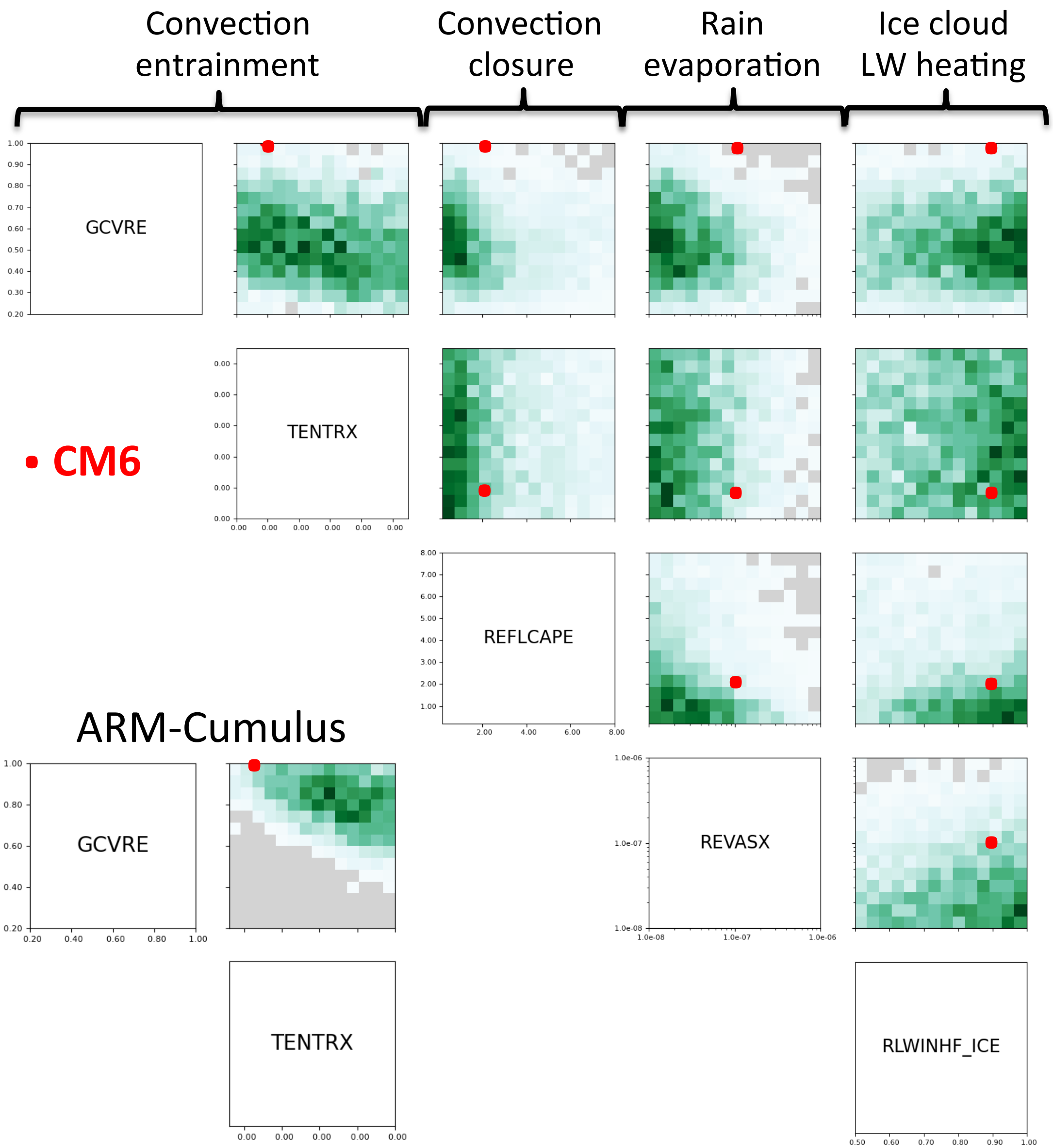

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- **Rain evaporation** rate key to get the moisture vertical profile right
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- **Convection intensity** (closure) is critical
- **Entrainment** still key, but towards more moderate values compared to shallow convection.
- Almost disjoint entrainment parameter spaces between shallow and deep cases

Conclusions and perspectives

Conclusions

- ***History Matching with Iterative refocusing***: framework to rigorously explore the parametric calibration of a parameterization/model physics, and identify its structural limits

- Better tuning of the CNRM convective parameterization (in fact the CNRM physics) can be achieved for each of the two 1D cases addressed here.

- The combination of a shallow convection case and a deep convection case (re-)emphasize the difficulty to make the CNRM "unified" convection parameterization work for both. **Single-plume mass-flux approach is structurally limited**.

- Shallow and deep convection regimes require significantly different entrainment rates.

Perspectives

- Choice of **metrics** (or the "eye of the expert") is crucial to define and analyse the NROY space, and avoid compensations of errors. Ideally, emulate directly the profile/timeseries would be interesting (ongoing).

- **Tolerance-to-error** is critical. A priori based on modellers' experience, but the present framework should help to better define it.

- Large and easy access to a **wide 1D case library** is key, to constrain the models as much as possible at the process level.

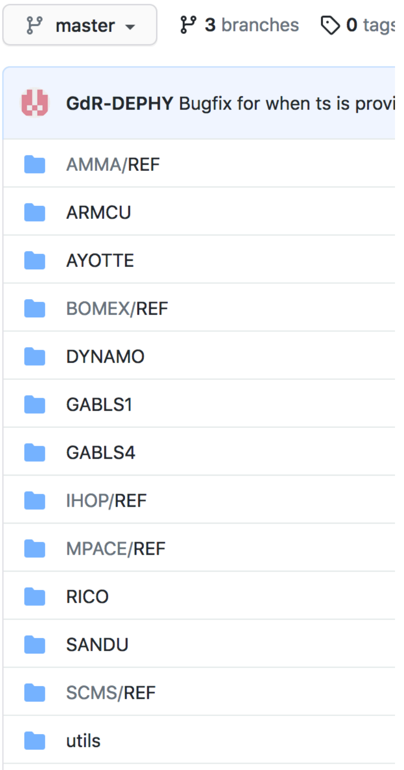
DEPHY common SCM/LES standard

Motivations

- Ease **sharing and traceability** of the available library of 1D cases among the modeling community
- Accelerate implementation and diffusion of new cases in each SCM/LES
    - ➢ easily **increase the diversity of cases**
- Ensure **reliability** of SCM/LES comparisons; gather the process and modeling communities
- …
- ***Formalize the ways of forcing a single-column model*** *(and to some extent LES)*

➢ All the details of a SCM/LES case in **one self-documented file**

➢ Library of SCM/LES cases well-identified, and well-documented



So far

- Version 0 presented during a dedicated virtual workshop in June 2020
  https://www.lmd.jussieu.fr/~hourdin/Workshop1Dstd.html
  https://github.com/GdR-DEPHY/DEPHY-SCM/tree/master
- Version 1 discussed in a second smaller-scale workshop in January 2021
  https://app.slack.com/client/T013CN4Q8TX/C01KG8N9RNV/
- **Version 1 to be shared in the coming weeks**
  https://docs.google.com/document/d/1UktLjFMRZnM-kmb_XYU6Io82n4FCGGRmI4bwx6uWHHk

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