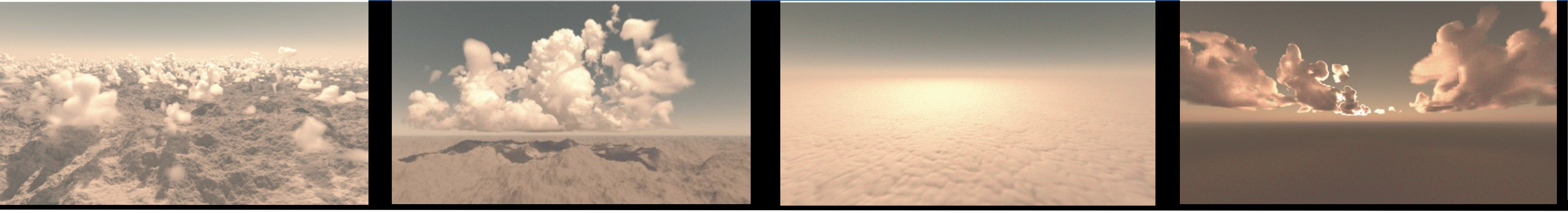
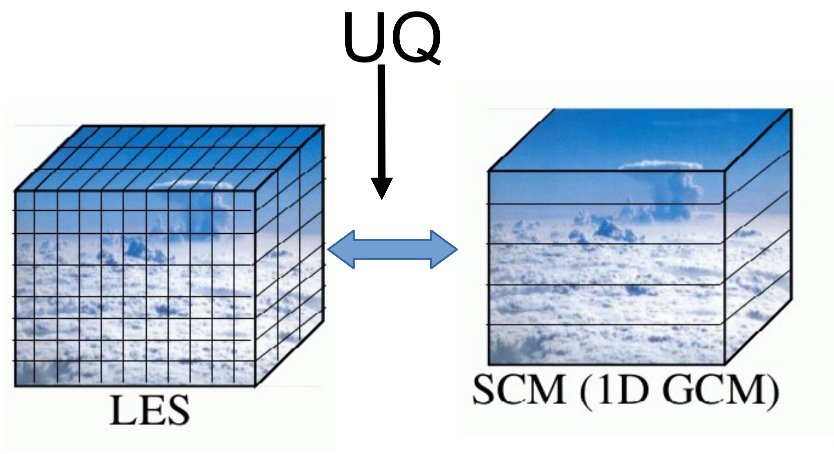
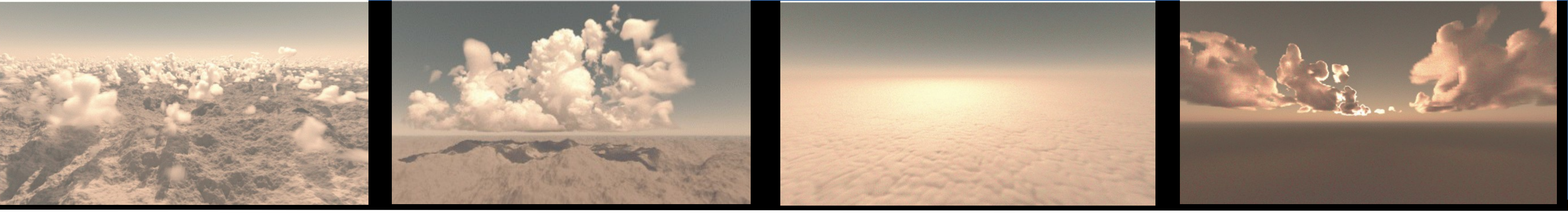


High-Tune Explorer : a calibration tool for parameterization improvement

F Couvreux, F Hourdin, D Williamson, R Roehrig, N Villefranque,
and the HIGH-TUNE team (CNRM, LMD, Exeter University)





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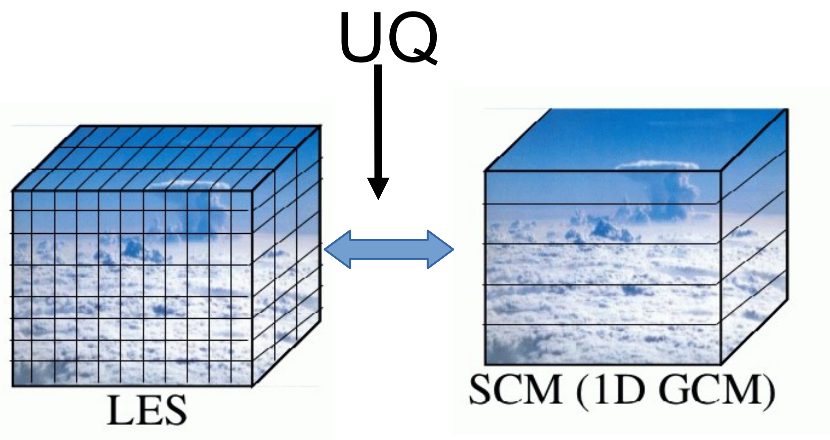
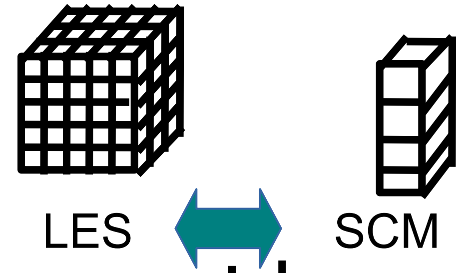


Calibrating an atmospheric model

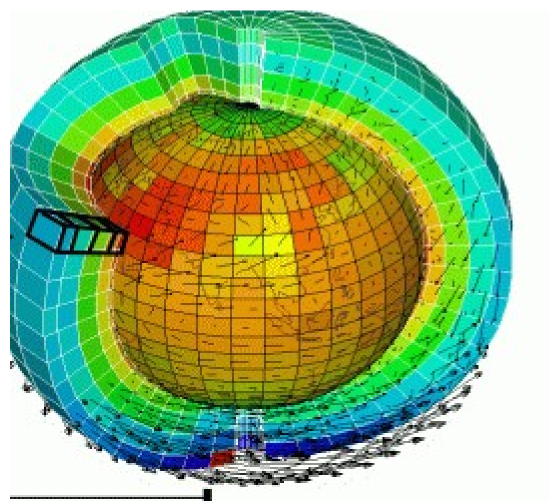
An atmospheric model

Dynamical Core **parametrizations**

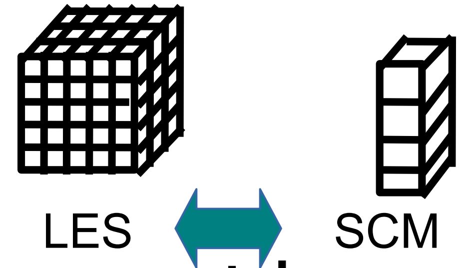
$$\frac{\partial \boldsymbol{x}}{\partial t} = \mathcal{D}(\boldsymbol{x}) + \sum_p \mathcal{P}_p(\boldsymbol{x}, \boldsymbol{\lambda}_p)$$



Pp : reflect our process understanding
λp= free parameter to tune



Calibrating an atmospheric model



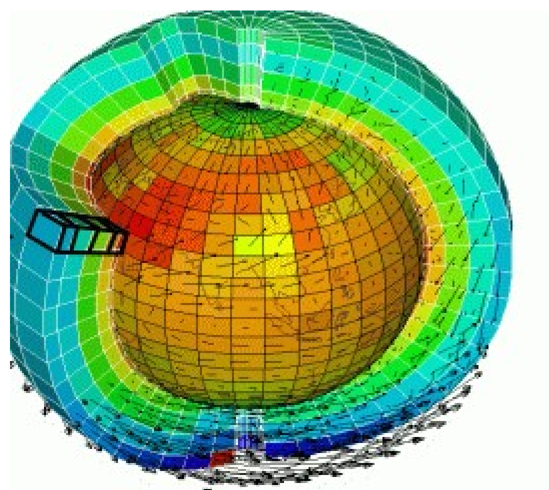
An atmospheric model

Dynamical Core **parametrizations**

$$\frac{\partial \boldsymbol{x}}{\partial t} = \mathcal{D}(\boldsymbol{x}) + \sum_p \mathcal{P}_p(\boldsymbol{x}, \boldsymbol{\lambda}_p)$$

Pp : reflect our process understanding
λp= free parameter to tune

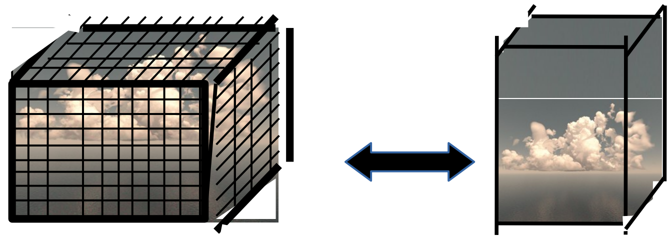
Global Calibration:
- radiative metrics
- key step of model dvlpt
- not well documented (Hourdin et al 2017)
- often through an optimization procedure



Approach

To build a calibration tool that serves parameterization development based on the LES/SCM comparison => process-oriented
Use methods of the community of Uncertainty Quantification (History Matching)
Tackle jointly calibration & parameterization development

The SCM/LES comparison



LES   1D

3D

$$\frac{\partial \boldsymbol{x}}{\partial t} = \mathcal{D}(\boldsymbol{x}) + \sum_p \mathcal{P}_p(\boldsymbol{x}, \boldsymbol{\lambda}_p)$$

y   **x** $_c$

$$\frac{\partial \boldsymbol{y}}{\partial t} = \mathcal{L}(\boldsymbol{y}) + \mathcal{F}_c(\overline{\boldsymbol{y}})$$

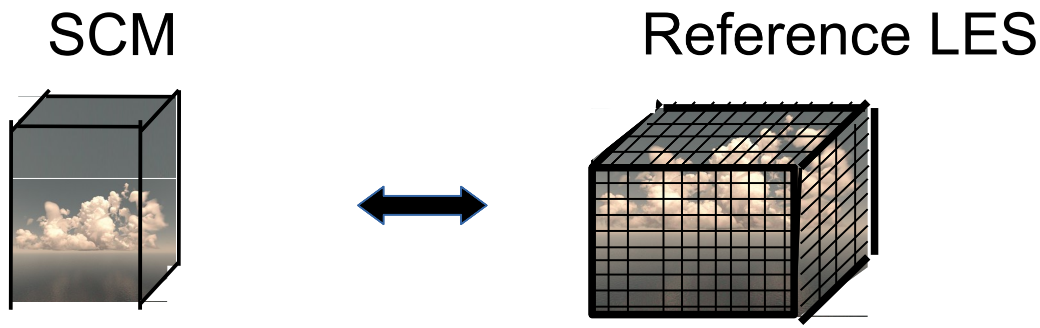
$$\frac{\partial \boldsymbol{x}_c}{\partial t} = \sum_{p_{\text{activated}}} \mathcal{P}_p(\boldsymbol{x}_c, \boldsymbol{\lambda}_p) + \mathcal{F}_c(\boldsymbol{x}_c)$$

$$\boldsymbol{x}_c(t=0) = \overline{\boldsymbol{y}}(t=0)$$

Advantages

An exact comparison : same forcing & initial conditions, no coupling with LS dynamics
Focus on parameterization
A framework largely used for model evaluation and development promoted by GCSS/GASS (Browning 1993 ; Randall et al 1996)
1D : very cheap, still representative of main biases of 3D model (Neggers 2015 ; Gettleman et al 2019)
LES : reference + provide parameterization-oriented diagnostics (Couvreux et al 2010)

A process-based calibration tool



History matching with iterative refocusing (Williamson et al 2013)

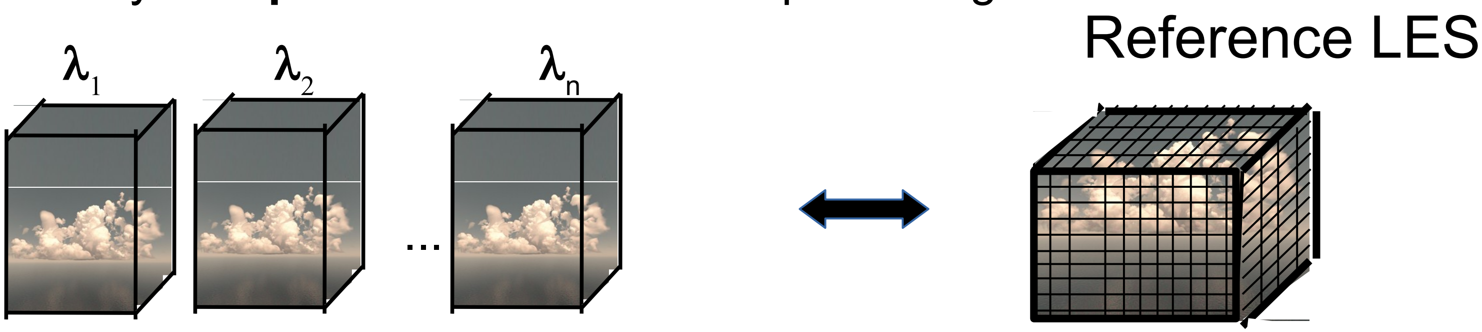
- Machine learning approaches for tuning (UQ)

To define the sub-space of the <u>parameter values</u> for which <u>SCM</u> matches <u>LES</u> on <u>selected metrics</u> for <u>a series of cases</u> within a given <u>uncertainty</u>

A process-based calibration tool

Selection of **metrics** [can combine different cases and metrics]

Identify **free parameters** and their a-priori ranges



History matching with iterative refocusing (Williamson et al 2013)

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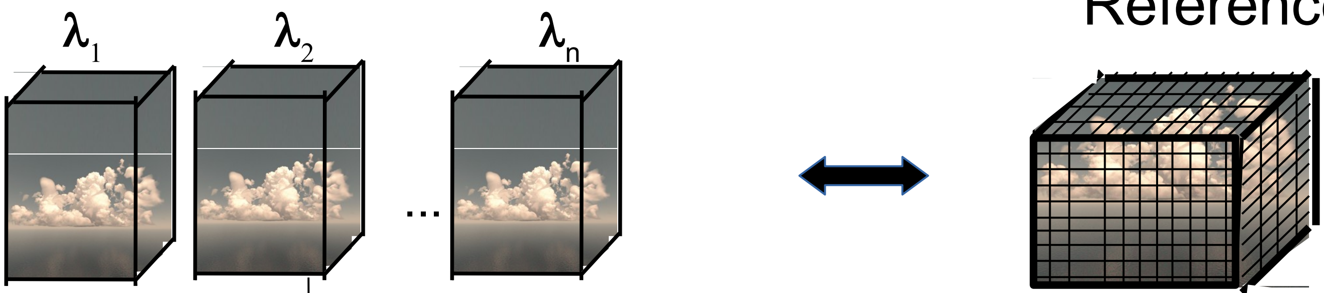
A process-based calibration tool

Selection of **metrics** [can combine different cases and metrics]

Identify **free parameters** and their a-priori ranges

Reference LES



SCM metrics = training dataset

↓ emulator

metrics for any λ ± uncertainty

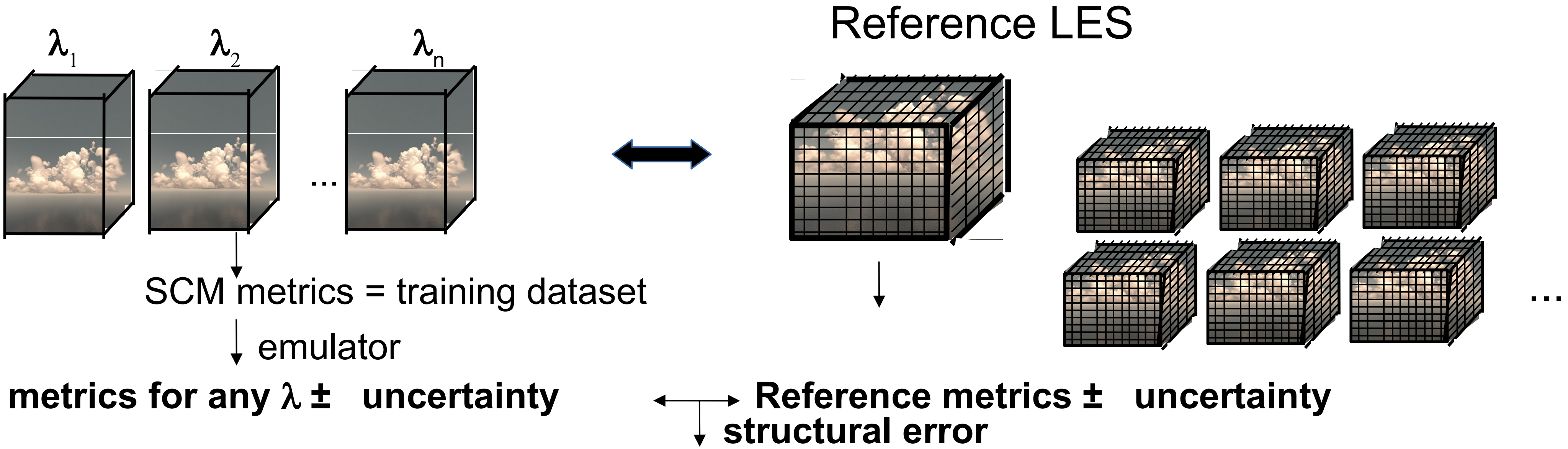
History matching with iterative refocusing (Williamson et al 2013)

- Machine learning approaches for tuning (UQ)
- Extensive exploration of parameter space with emulator

A process-based calibration tool

Selection of **metrics** [can combine different cases and metrics]

Identify **free parameters** and their a-priori ranges



Discard **impossible values of parameters**

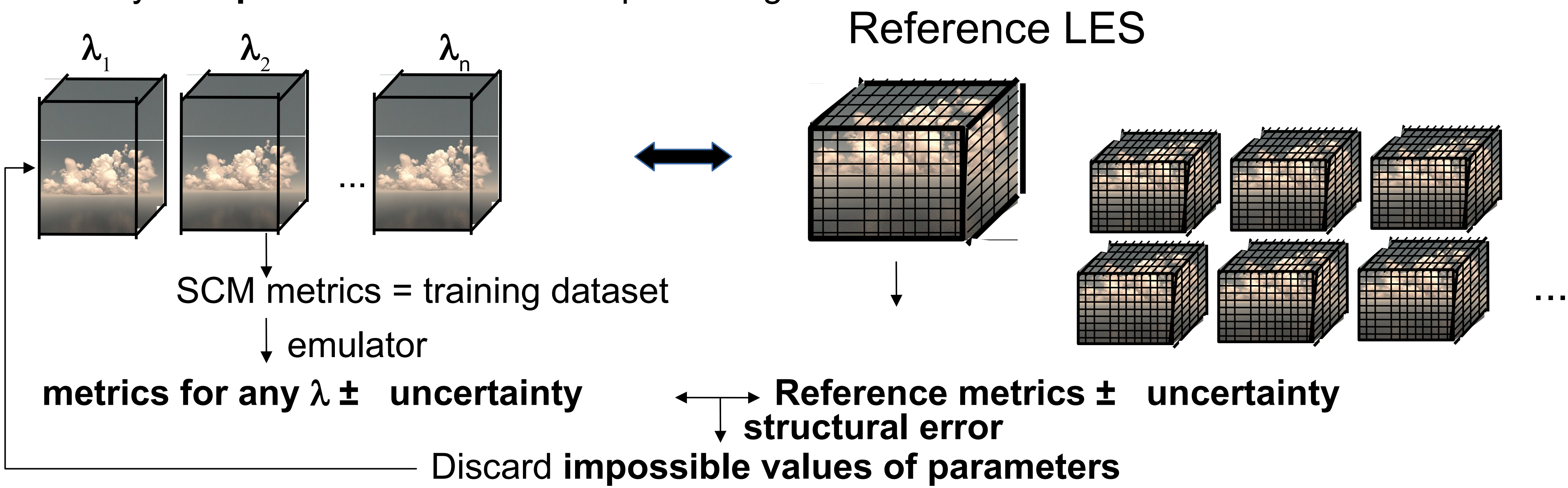
History matching with iterative refocusing (Williamson et al 2013)

- Machine learning approaches for tuning (UQ)
- Extensive exploration of parameter space with emulator
- Taking into account different sources of uncertainties : a/observation error, b/ emulator error and c/ an error tolerance or structural error to avoid error compensation

A process-based calibration tool

Selection of **metrics** [can combine different cases and metrics]

Identify **free parameters** and their a-priori ranges



History matching with iterative refocusing (Williamson et al 2013)

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- Removing progressively implausible values

A process-based calibration tool

Selection of **metrics** [can combine different cases and metrics]

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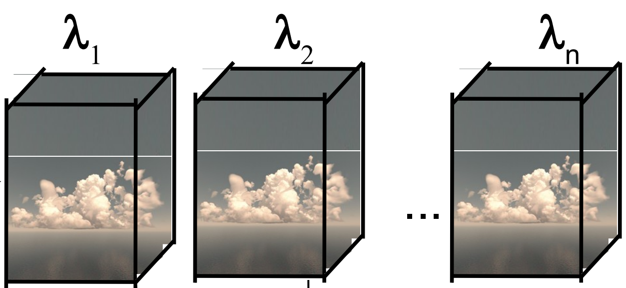
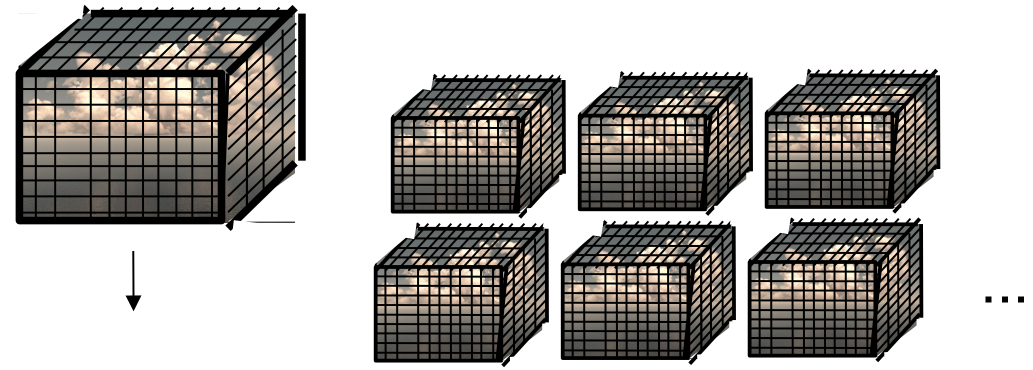


Reference LES



SCM metrics = training dataset

emulator

metrics for any λ ± uncertainty ↔ **Reference metrics ± uncertainty**

structural error

Discard **impossible values of parameters**

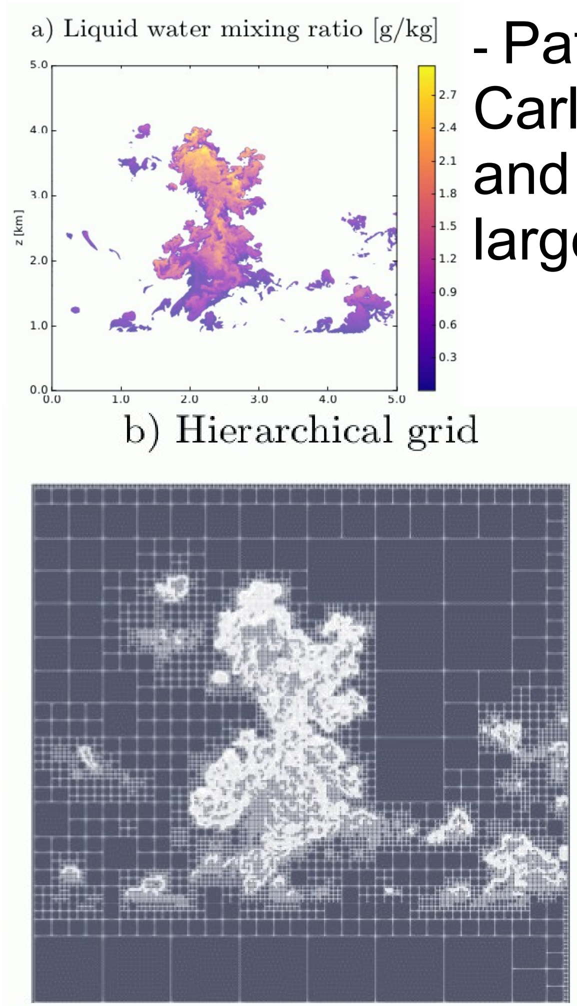
History matching with iterative refocusing (Williamson et al 2013)

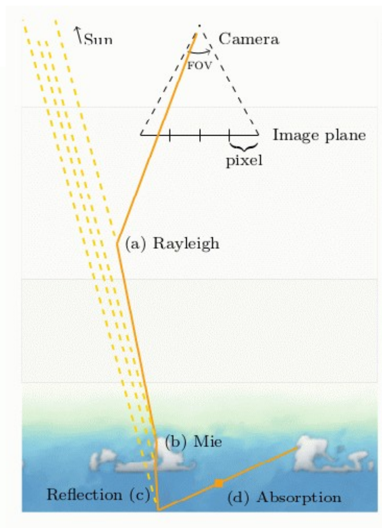
- Machine learning approaches for tuning (UQ)
- Extensive exploration of parameters space with emulator
- Taking into account different sources of uncertainties : a/ observation error, b/ emulator error and c/an error tolerance or structural error to avoid error compensation
- Removing progressively implausible values
- Can be used for other configurations than SCM (Hourdin et al 2021)

Couvreux et al, 2021

Calibration of a parameterization

- Path-tracing library for flexible implementation of Monte-Carlo algorithms in cloudy atmosphere : use of null-collision and hierarchical grids to accelerate ray-tracing computation in large 3D data + virtual synthetic images

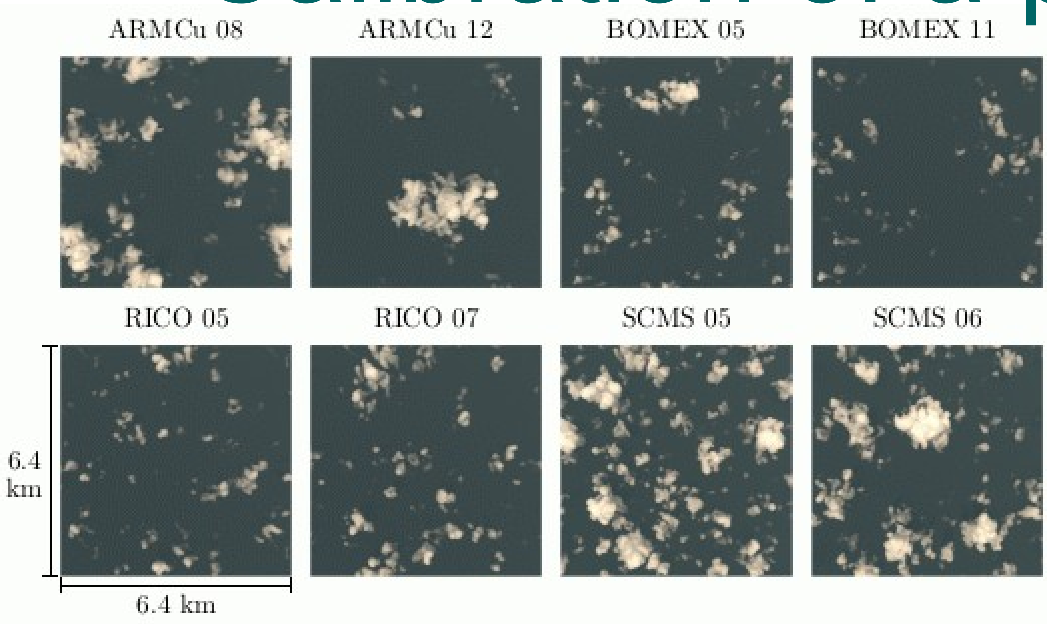




- Apply offline on 3D LES fields
- Provide reference computation of 3D radiative effects => metrics for the evaluation of the ecRad parameterization code

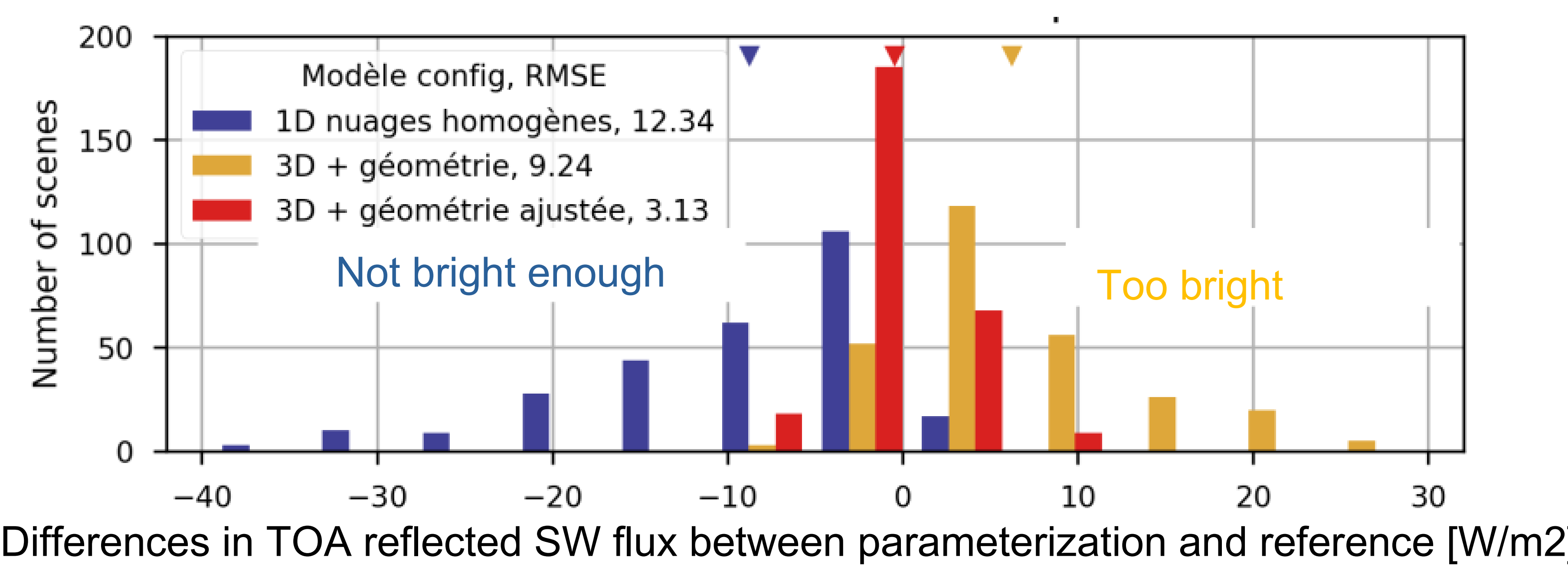
Villefranque et al, JAMES, 2019

Calibration of a parameterization



LES :
Monte-Carlo radiative computation applied offline on LES cloud scenes (+ uncertainty) => ref metrics

derived 1D cloud profiles to run EcRad offline with the right cloud information



Villefranque et al, 2021

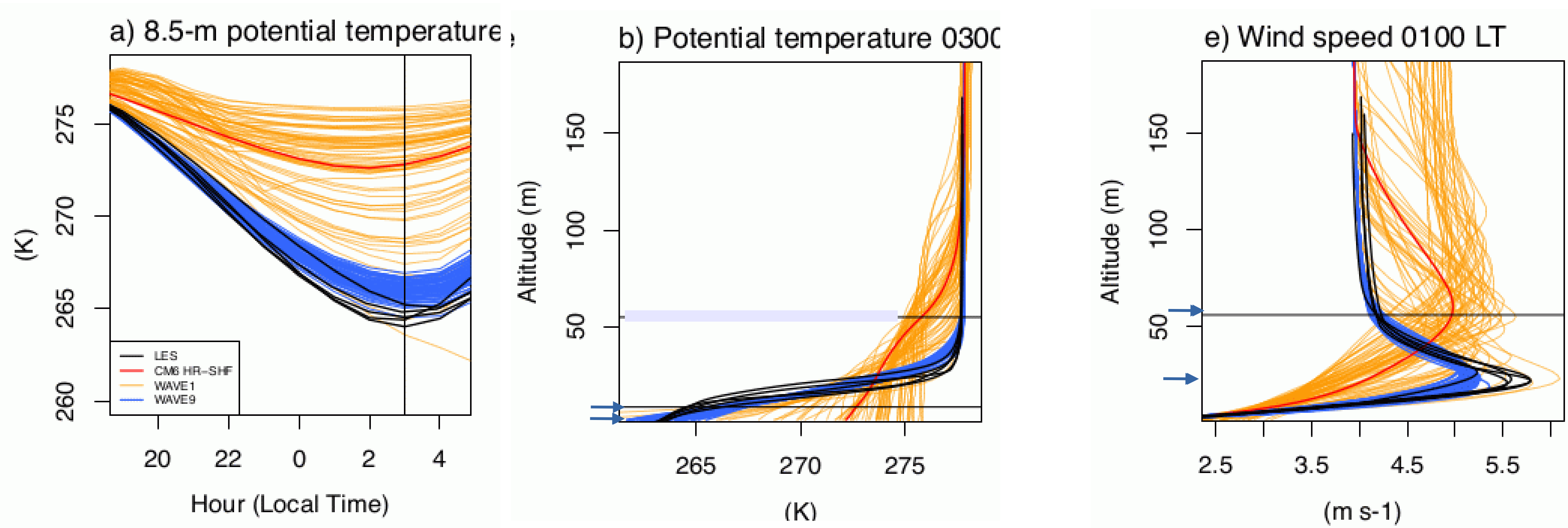
Disentangling calibration issues and structural errors

ARPEGE-Climat (Roehrig et al 2020) – SCM-HR-SHF [Dz=2m ->400m]
GABLS4 [only turbulence and surface scheme]
Metrics: θ_2m θ_8m ws_max ws_55m
7 Parameters : Cm, Ce, Lmin, α_{eps}, α_T, Kozmin. Kozmax

$$K_\psi = \alpha_\psi \mathbf{CM} L_m \sqrt{\bar{e}} \phi_\psi \qquad L_m = \max\left[L_m^{\mathrm{BL89}}, \min(\mathbf{LMIN}, \kappa z)\right]$$

$$L_\epsilon = \mathbf{CE} L_m$$

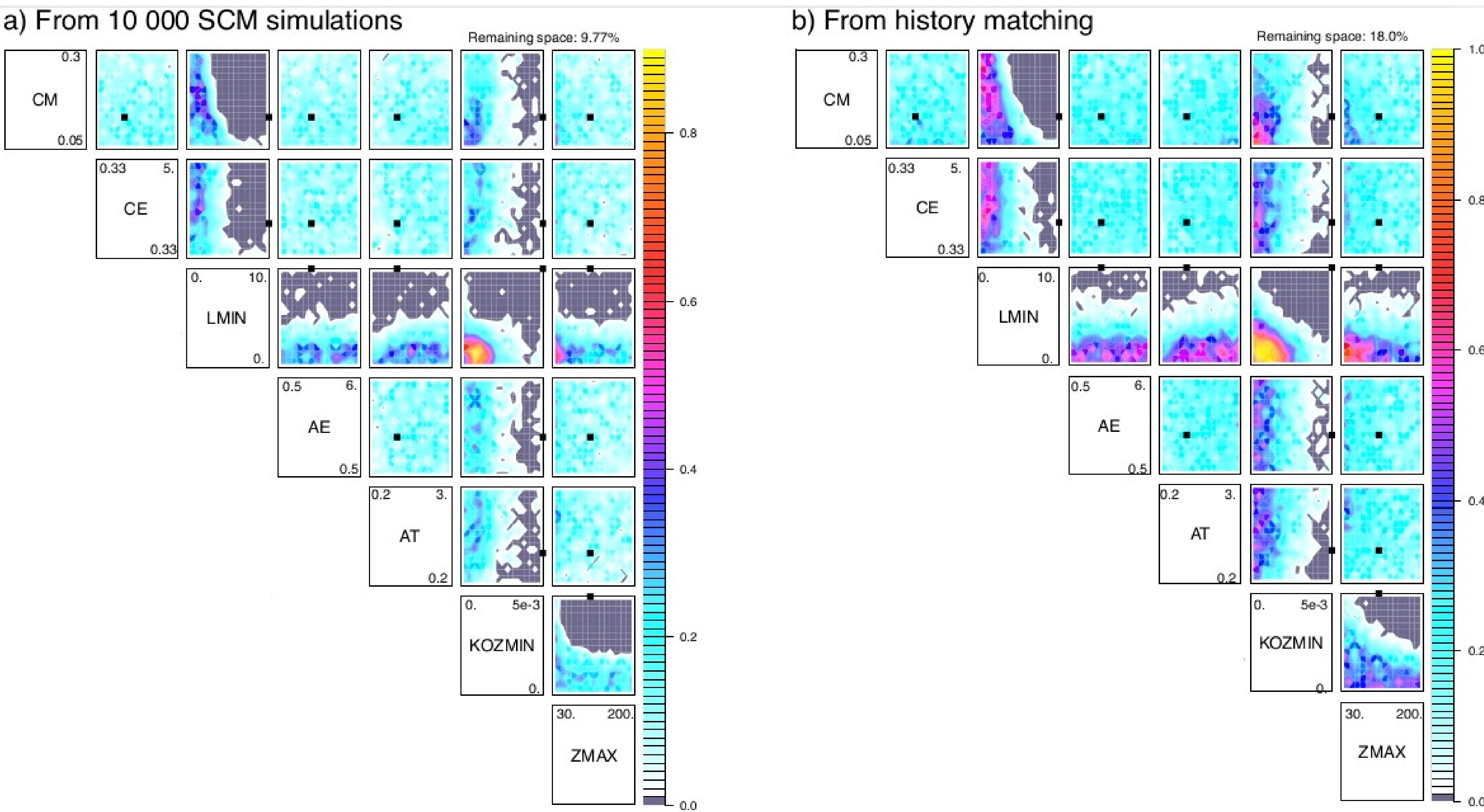
LES – GABLS4
ARPEGE-Climat-CM6
Wave 1
Wave 9



- Only 4 instantaneous metrics that constrain the behaviour of the stable boundary layer throughout the night

Audouin et al, 2021

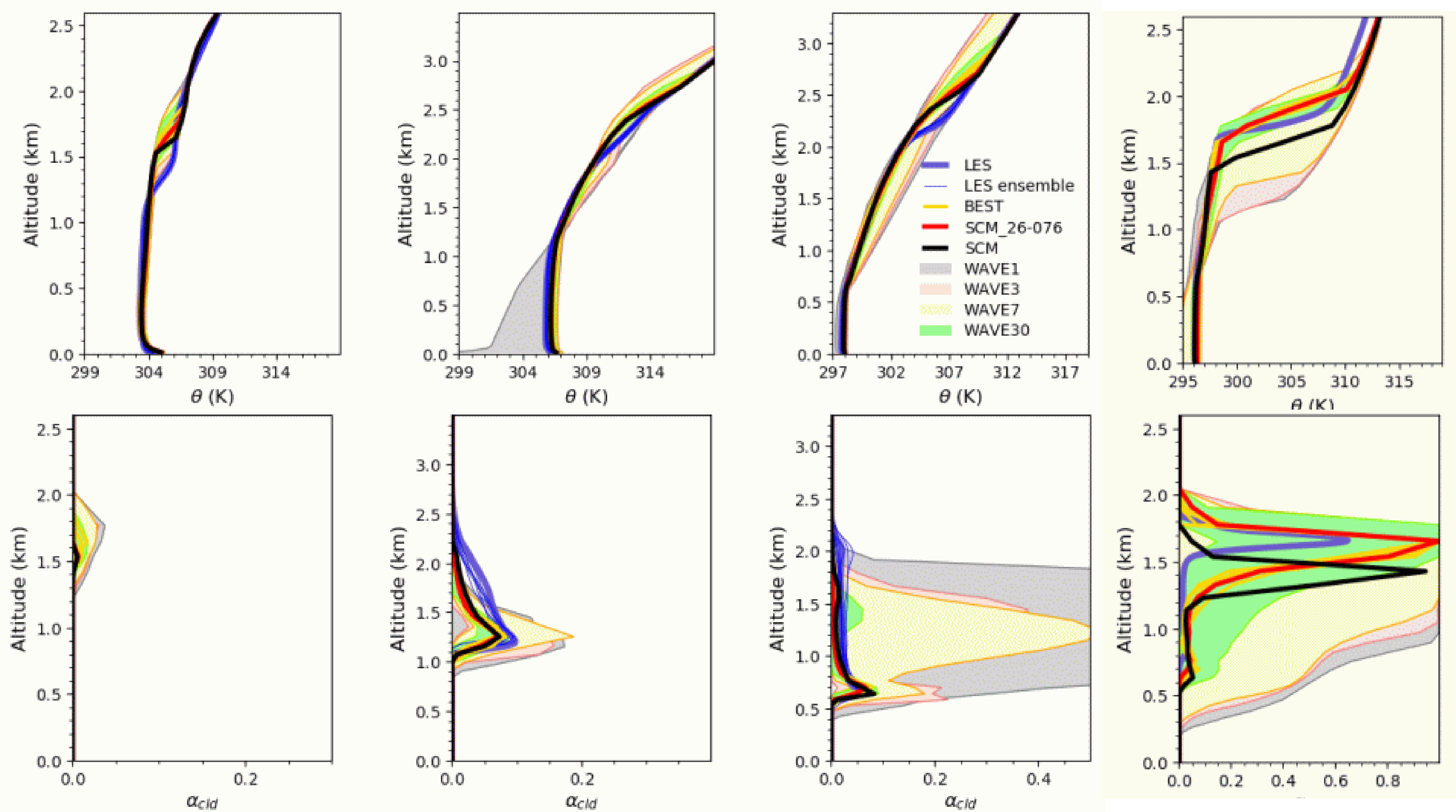
Verification of the emulator ability



- SCM=cheap => test for a not too constraining metrics
Very similar results

From 1D calibration to 3D calibration

Dry convective BL IHOP | Continental shallow cu ARMCU | Oceanic shallow cu RICO | Transition Stocu to Cu SANDU



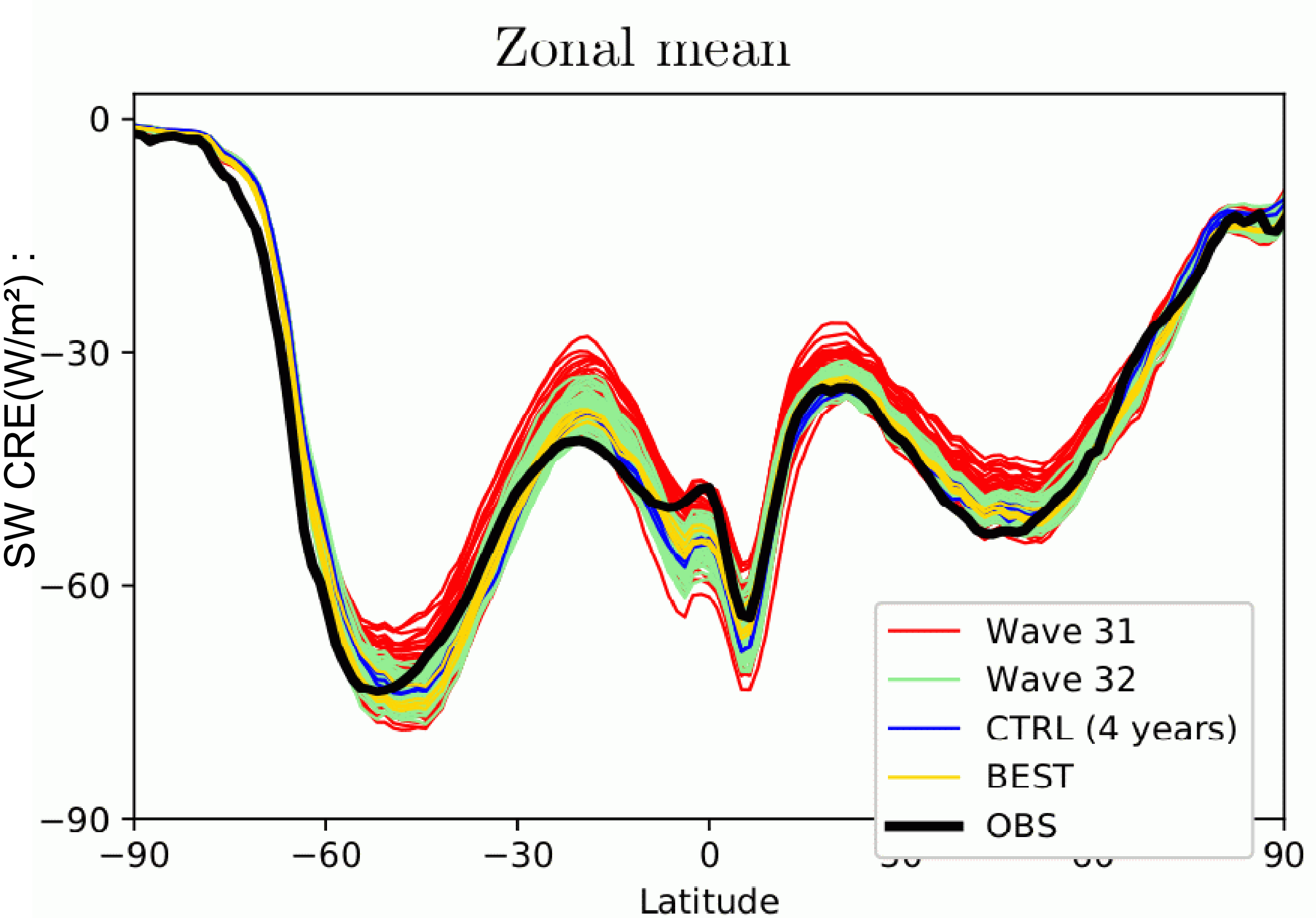
Hourdin et al, 2021

LMDZ

Metrics $:= \int \theta(z)\,dz\theta \quad \bar{q}\,v = \int qv(z)\,dz \qquad \bar{q}\,v = \int qv(z)\,dz \qquad z_{cld,ave} = \frac{\int cf(z)\,z\,dz}{\int cf(z)\,dz} \qquad cld_{max} = max(cf(z))$

9 Parameters : Mass-flux scheme+ Cloud scheme +autoconversion+ reevaporation of rain

From 1D calibration to 3D calibration



After 30 1D waves :
combining 1D and 3D metrics

3D radiative metrics :
Global or masked regions TOA upfluxes
[9 parameters]

- Already good behaviour of the 3D model after 1D calibration
- More reduction through the 3D Calibration

LMDZ
IHOP/ARMCU/RICO/SANDU
Metrics : $\theta = \int \theta(z)\,dz$ $\quad \bar{q}_v = \int q_v(z)\,dz$ $\quad \bar{q}_v = \int q_v(z)\,dz$ $\quad z_{cld,ave} = \frac{\int cf(z)\,z\,dz}{\int cf(z)\,dz}$ $\quad cld_{max} = max(cf(z))$
9 Parameters : Mass-flux scheme+ Cloud scheme +autoconversion+ reevaporation of rain
+ 3D GCM tuning with **radiative metrics**

Hourdin et al, 2021

Conclusions

A new tool to accelerate model development:

Harness machine learning to improve physical parameterizations
Exploit the LES/SCM comparison
Complementary use of multicases with various metrics

Available freely under https://svn.lmd.jussieu.fr/HighTune/HighTune
Easy to use if adopting the common format initiative (DEPHY)

Main use:

Sensitivity analysis
Quantify parametric uncertainty- Identify parameter that limit model performance
Disentangle model formulation deficiencies from calibration issues
Provide guidance for global tuning
Applied to individual parameterization or all of them

Towards a well-defined tuning strategy:

With solid physical (emphasis on processes) and statistical (UQ) basis
Hourdin et al (2017) => first phase on process-level calibration
Model development and calibration tackled together

Conclusions

Some aspects that desserve further attention when using the tool:

Definition of metrics => main biases
Determination of the tolerance to error
Still important need of modeler expertise
When to stop the iterative processes [evolution of emulator uncertainty]

Other aspects to be further explored:

Deep convection and high clouds => need of reference
Coupled models
Provide guidance for physically based initialization of ensemble forecast
...

References (http://www.umr-cnrm.fr/high-tune):

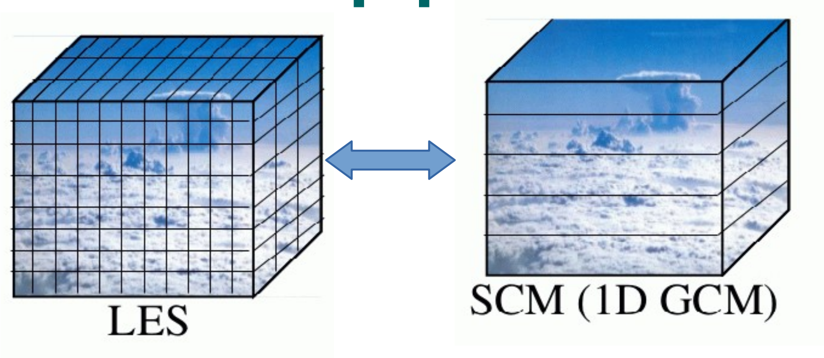
Couvreux F, F Hourdin, D Williamson, R Roehrig, V Volodina, N Villefranque, C Rio, O Audouin, J Salter, E Bazile, F Brient, F Favot, R Honnert, M-P Lefebvre, J-B Madeleine, Q Rodier, W Xu, 2021: Process-based climate model development harnessing machine learning: I A new tool for parameterization improvement, JAMES , 13

Hourdin F, D Williamson, C Rio, F Couvreux, R Roehrig, N Villefranque, I Musat, L Fairhead, F B Diallo, V Volodina, 2021: Process-based climate model development harnessing machine learning: II: model calibration from single column to global, JAMES,13

Audouin, 0., R. Roehrig, F. Couvreux, D. Williamson,2021: Modeling the GABLS4 strongly-stable boundary layer with a GCM turbulence parameterization: parametric sensitivity or intrinsic limits? JAMES, 13

Villefranque N, S Blanco, F Couvreux, R Fournier, J Gautrais, R Hogan, F Hourdin, V Volodina, D Williamson, 2021: Process-based climate model development harnessing machine learning: III: guiding the choice of cumulus geometry parameters in a radiative transfer scheme, JAMES, 13

Supplementary : SCM/LES cases



- Ensemble of cases covering the diversity of boundary-layer regimes

- Reference simulation +sensitivities to configuration and parameterization => provide uncertainty around this reference

Case name	grid resolution dx=dy, dz (m, m)	Domain Lx=Ly, H (km, km)	Specificity	Radiation	Reference	Observations
Academic cases of dry convective boundary layer						
AYOTTE-1	50, 40	10, 2	Varying inversion (strong/weak capping) and varying cst-in-time surface fluxes	No	Ayotte et al. 1996	No
AYOTTE-2	50, 40	10, 2		No		No
… 6	50, 40	10, 2		No		No
Cases of clear sky continental convective boundary layer						
IHOP	50, 40	10, 5	USA great plains	No	Couvreux et al., 2005	Yes
AMMA	50, 40	10, 5	Semi-arid, West-Africa	No	Canut et al., 2011	Yes
WANGARA	50, 40	10, 5	Semi-arid, Australia	No		Yes
Boundary layer cumulus						
ARM	50, 40	13, 4	Continental shallow, SGP	No	Brown et al., 2002	Yes
BOMEX	50, 40	13, 4	Oceanic shallow, Caraibes	No	Siebesma et al., 2003	Yes
RICO	50, 40	13, 4	Precipitating oceanic, Caraibes	No	Van Zanten et al., 2011	Yes
SCMS	50, 40	13, 4	Continental shallow, Florida	No	Neggers et al, 2002	Yes
CASS	50, 40	13,4	Composite cont. shallow, SGP	No	Zhang et al., 2017	Yes
Marine strato-cumulus clouds						
FIRE	25, 5-15	5, 1.2	Day and Nighttime stratocumulus	Yes	Duynkerke et al. 2004	Yes
DYCOMS2	25, 5-15	5, 1.5	Stratocumulus	Yes	Stevens et al., 2005	Yes
SANDU	35,5-15	9, 3.2	Transition to cumulus, Pacific	Yes	Sandu and Stevens, 2011	Yes
ASTEX	25, 5-15	5, 2	Transition to cumulus, Atlantic	Yes	Van Der Dussen et al., 2013	Yes
GreyZone	250,25-90	100, 5	Transition to cumulus,North Sea	Yes	De Roode et al, in prep	Yes
Stable boundary layer						
GABLS1	?	1000, 500	Academic case	No	Beare et al, 2006	No
GABLS4	1,1	500,200	Antarctica	No	Bazile etal, 2019; Couv et al 2019	Yes
Transition to deep convection						
AMMA	100, 50	100, 20	Niamey, initiation of local storm	No	Couvreux et al., 2012	Yes