Harnessing Machine Learning to Improve Cloud Radiative Effect Predictions in Large-Scale Models

Najda Villefranque, HIGH-TUNE team, Robin Hogan

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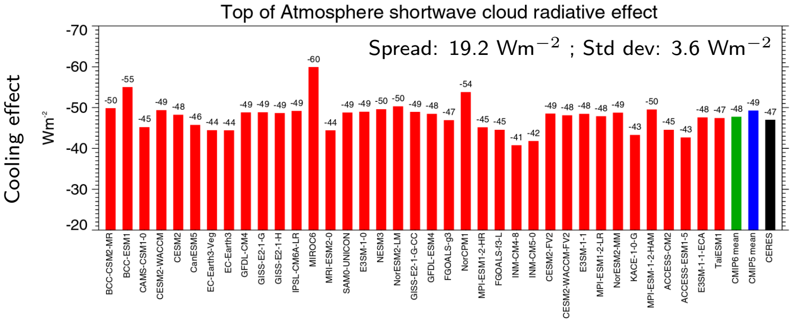
Villefranque, N., Blanco, S., Couvreux, F., Fournier, R., Gautrais, J., Hogan, R. J., et al. (2021). Process-based climate model development harnessing machine learning: III. The Representation of Cumulus Geometry and their 3D Radiative Effects. *Journal of Advances in Modeling Earth Systems*, 13. https://doi.org/10.1029/2020MS002423

Cloud radiative effect to measure model quality

The global energy balance as represented in CMIP6 climate models

M. Wild (2020)



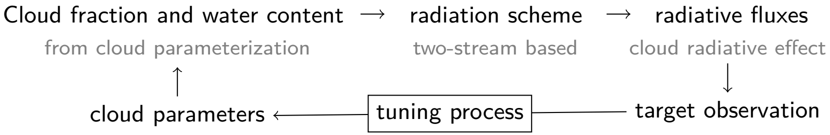
… but a common tuning practice (Hourdin et al. 2017):
adjusting cloud parameters to match observed radiation

Wrong radiation will lead to wrong clouds

Cloud fraction and water content → radiation scheme → radiative fluxes

from cloud parameterization   two-stream based   cloud radiative effect

Wrong radiation will lead to wrong clouds



Cloud fraction and water content → radiation scheme → radiative fluxes

from cloud parameterization

two-stream based

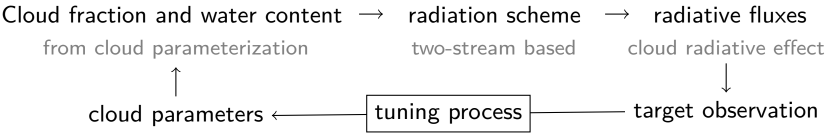
cloud radiative effect

cloud parameters

tuning process

target observation

Wrong radiation will lead to wrong clouds



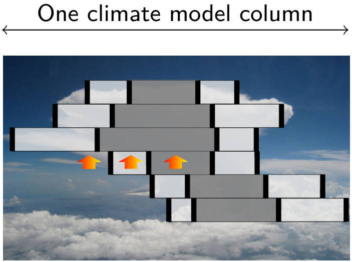
Cloud fraction and water content → radiation scheme → radiative fluxes

from cloud parameterization ↑ cloud parameters

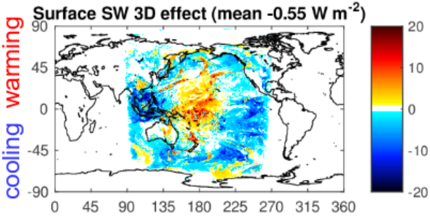
two-stream based

cloud radiative effect ↓ target observation

cloud parameters ← **tuning process** — target observation



Subgrid clouds as seen from a radiation scheme



These 3D effects are usually neglected in climate models

(Conceptual scheme and figure from Robin Hogan (2018?))

The HIGH-TUNE project

Process-based calibration to avoid compensation errors

Single Column Models vs. Large-Eddy Simulations

The HIGH-TUNE project

Process-based calibration to avoid compensation errors

Single Column Models vs. Large-Eddy Simulations

Using ~~machine learning~~ statistics to do this efficiently

Emulating SCMs to rule out unacceptable parameter space

The HIGH-TUNE project

Process-based calibration to avoid compensation errors

Single Column Models vs. Large-Eddy Simulations

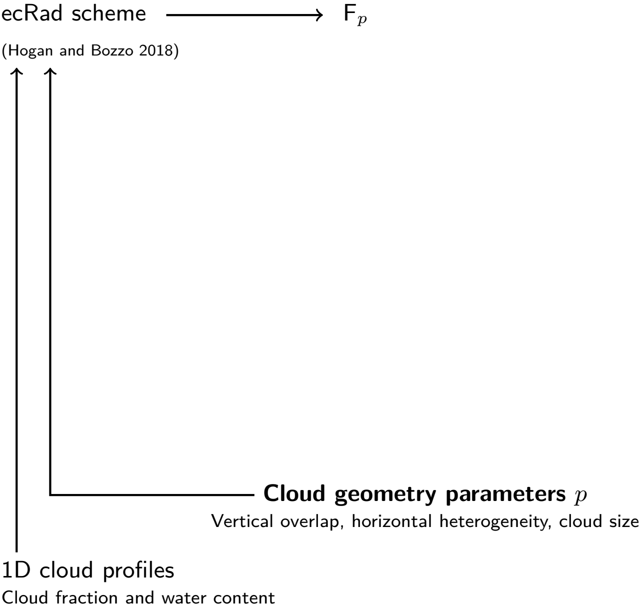
Using ~~machine learning~~ statistics to do this efficiently

Emulating SCMs to rule out unacceptable parameter space

Here: **focus on the radiation scheme**

More in the next six slides!

Offline radiation scheme evaluation in cumulus clouds



ecRad scheme $\longrightarrow$ F_p

(Hogan and Bozzo 2018)

Cloud geometry parameters p

Vertical overlap, horizontal heterogeneity, cloud size

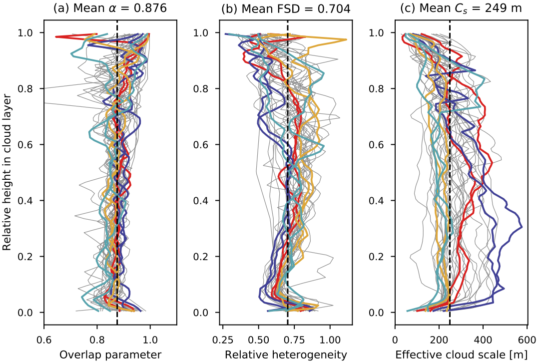
1D cloud profiles

Cloud fraction and water content

Offline radiation scheme evaluation in cumulus clouds

ecRad scheme ⟶ F_p

(Hogan and Bozzo 2018)



Cloud geometry parameters p

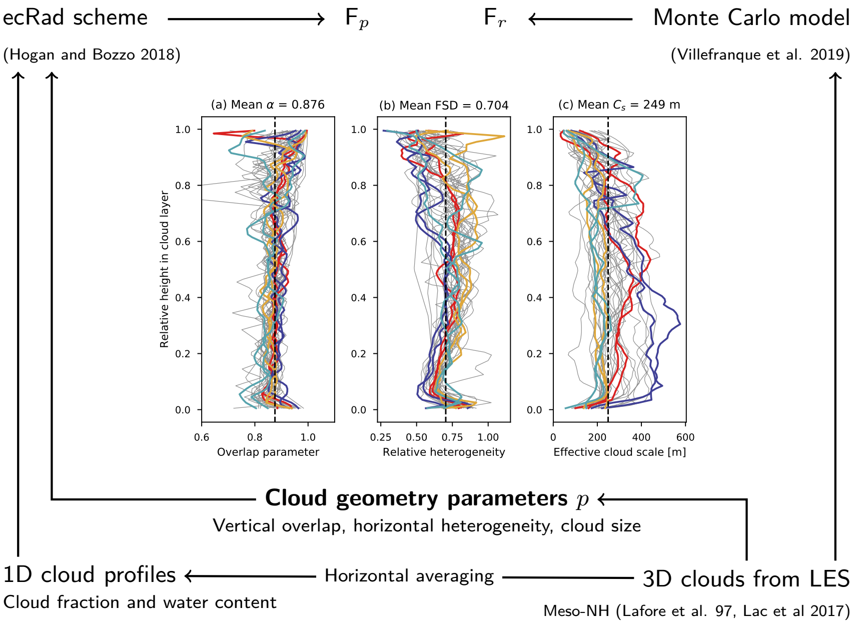
Vertical overlap, horizontal heterogeneity, cloud size

1D cloud profiles ⟵ Horizontal averaging ⟵ 3D clouds from LES

Cloud fraction and water content

Meso-NH (Lafore et al. 97, Lac et al 2017)

Offline radiation scheme evaluation in cumulus clouds



ecRad scheme → F$_p$

F$_r$ ← Monte Carlo model

(Hogan and Bozzo 2018)

(Villefranque et al. 2019)

Cloud geometry parameters p

Vertical overlap, horizontal heterogeneity, cloud size

1D cloud profiles ← Horizontal averaging — 3D clouds from LES

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Offline radiation scheme evaluation in cumulus clouds

ecRad scheme $\longrightarrow$ $\mathrm{F}_p \xleftrightarrow{} \mathrm{F}_r$ $\longleftarrow$ Monte Carlo model

Δ_p

(Hogan and Bozzo 2018)

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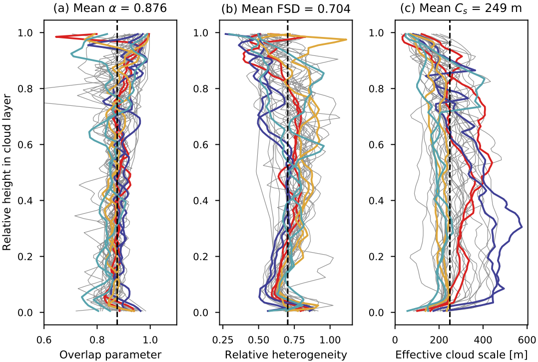

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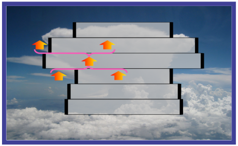
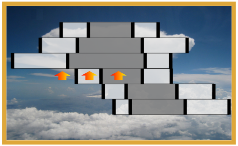
Different levels of complexity in cloud representation

1D homogeneous



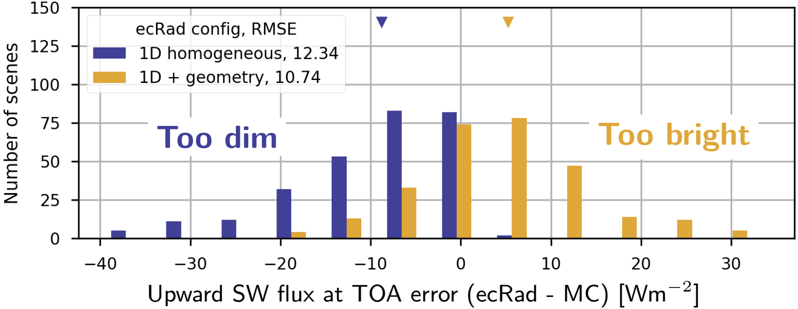
Tripleclouds[1]
$\alpha = 1$, FSD=0

1D + geometry



Tripleclouds[1]
α, FSD from LES

One histogram = 280 scenes = 35 cumulus fields × 8 solar angles



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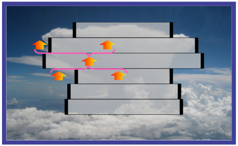
[1] Shonk and Hogan, 2008 ; [2] Schäfer et al., 2016, Hogan et al., 2016, 2019

Different levels of complexity in cloud representation

1D homogeneous



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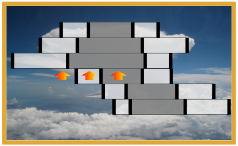
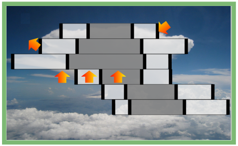


Tripleclouds[1]

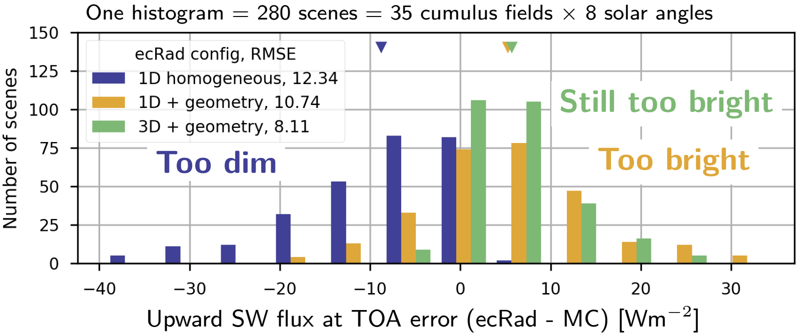
α, FSD from LES

3D + geometry



SPARTACUS[2]

α, FSD, C_s from LES



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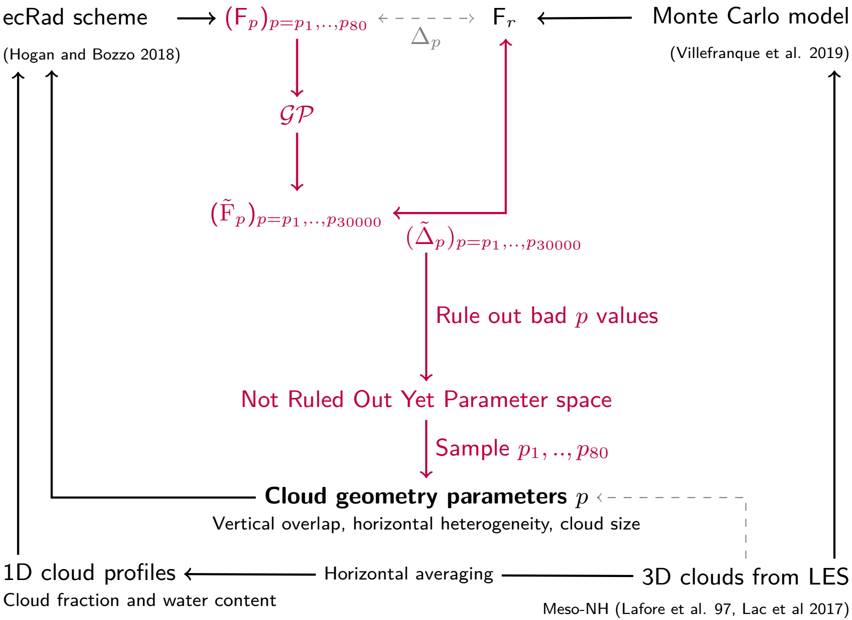
Introducing the High-Tune:Explorer tool

(Couvreux et al., 2020,
Hourdin et al., 2020,
Villefranque et al. 2021)



ecRad scheme $\longrightarrow$ $(\mathsf{F}_p)_{p=p_1,..,p_{80}}$ $\xleftarrow{\quad\Delta_p\quad}\!\!\!\rightarrow$ F_r $\longleftarrow$ Monte Carlo model

(Hogan and Bozzo 2018)

(Villefranque et al. 2019)

$\mathcal{GP}$

$(\tilde{\mathrm{F}}_p)_{p=p_1,..,p_{30000}}$

$(\tilde{\Delta}_p)_{p=p_1,..,p_{30000}}$

Rule out bad p values

Not Ruled Out Yet Parameter space

Sample $p_1, .., p_{80}$

Cloud geometry parameters p

Vertical overlap, horizontal heterogeneity, cloud size

1D cloud profiles $\longleftarrow$ Horizontal averaging — 3D clouds from LES

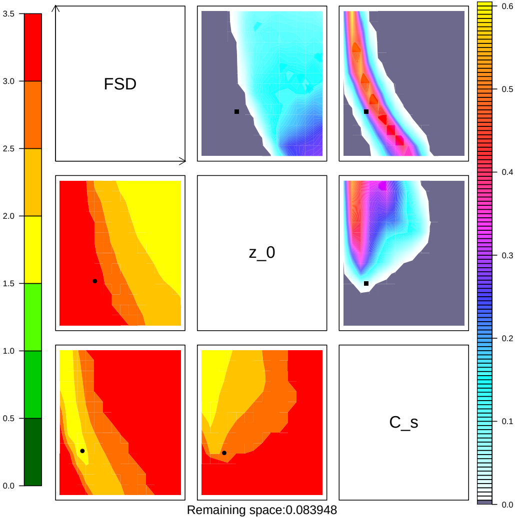
Cloud fraction and water content

Meso-NH (Lafore et al. 97, Lac et al 2017)

Not Ruled Out Yet space after 13 iterations

72 metrics: upward TOA, downward surface, absorbed × 8 cumulus field × 3 solar angles

3 parameters: FSD=horizontal heterogeneity; z_0=overlap decorrelation length; C$_s$=cloud size



- Reject parameters if at least one metric is bad

- Large FSD = less reflective clouds

- Small z_0 = overlap → maximum (cloud cover too small)

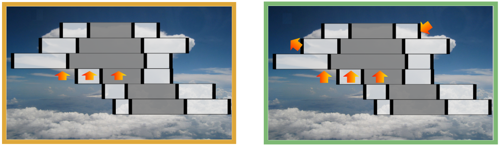
- Small C$_s$ = more 3D effects

- Heterogeneity and 3D effects compensate each other

- LES-derived values (black dots) not in NROY space

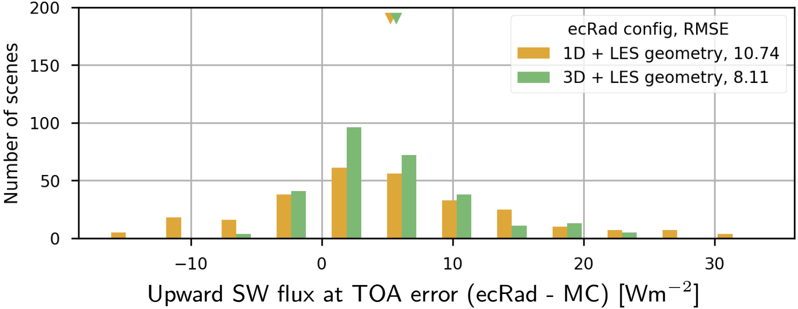
Testing one good configuration (FSD, z_0, C$_s$)

1D + LES geometry

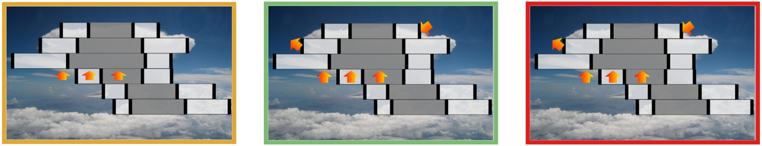


Mean LES-derived: (0.7, 187 m, 247 m)

One histogram = 280 scenes = 35 cumulus fields × 8 solar angles



Testing one good configuration (FSD, z_0, C$_s$)



1D + LES geometry

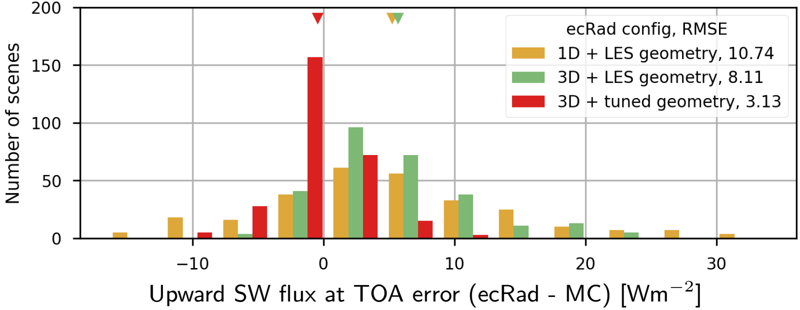
3D + LES geometry

3D + tuned geometry

Mean LES-derived: (0.7, 187 m, 247 m)

htexplo: (1.1, 436 m, 155 m)

One histogram = 280 scenes = 35 cumulus fields × 8 solar angles



Conclusions, remaining questions and further work

- Parameterizations need *effective* parameter values rather than observed
- 3D effects are a big deal and SPARTACUS is doing quite well
- Tuning using only a few fields and solar zenith angles works
- Even using bulk parameters instead of case-dependent vertical profiles

- Remaining errors = “structural errors”?
- Outside the cumulus regime?
- Parameterize the parameters?
  $\Rightarrow$ **More parameters to tune? No longer a bad news!**

- Next: tuning clouds and radiation together in SCM/LES/MC framework

Conclusions, remaining questions and further work

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Thanks! Questions?