Model error representations in the AROME model : focus on microphysics perturbations using parameter perturbations

ECMWF workshop on model uncertainty

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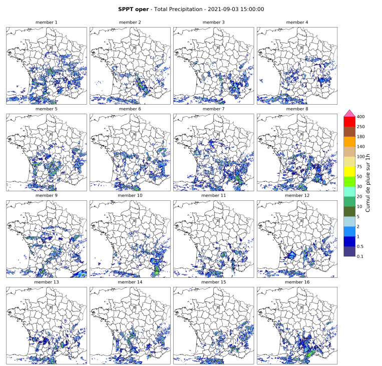
Context

Arome ensemble prediction system (AROME-EPS)

Current configuration

- 16 members, 2.5km resolution, 90 vertical levels
- coupling with members selected from ARPEGE-EPS
- initial conditions from AROME EDA
- perturbation of some surface variables
- model error representation with Stochastically Perturbed Parametrization Tendencies (SPPT)



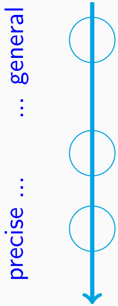
Main objective

Investigate alternative perturbation methods to SPPT to represent model uncertainty

Representing model uncertainty

Focus on the perturbation of the model parametrization schemes, which are an important source of uncertainty (Palmer et al., 2009).

Depending on the method, the perturbations are introduced at **different levels** of the parametrizations :

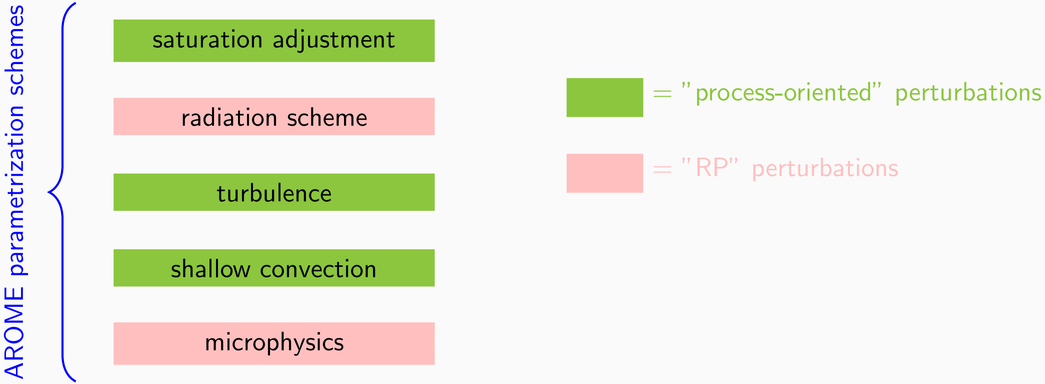


perturbation of tendencies: SPPT

perturbation of processes: "process-oriented" perturbation schemes

perturbation of parameters: Random parameters (RP),
Stochastically Perturbed Parameterizations (SPP)

Stochastic perturbations applied to AROME parametrizations



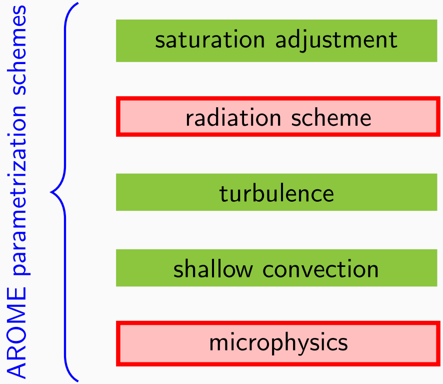
AROME parametrization schemes

- saturation adjustment
- radiation scheme
- turbulence
- shallow convection
- microphysics

🟩 = ”process-oriented” perturbations

🟥 = ”RP” perturbations

Stochastic perturbations applied to AROME parametrizations



AROME parametrization schemes

saturation adjustment

radiation scheme

turbulence

shallow convection

microphysics

🟩 = "process-oriented" perturbations

🟥 = "RP" perturbations

Methodology

AROME-1D model

Dynamical core not called

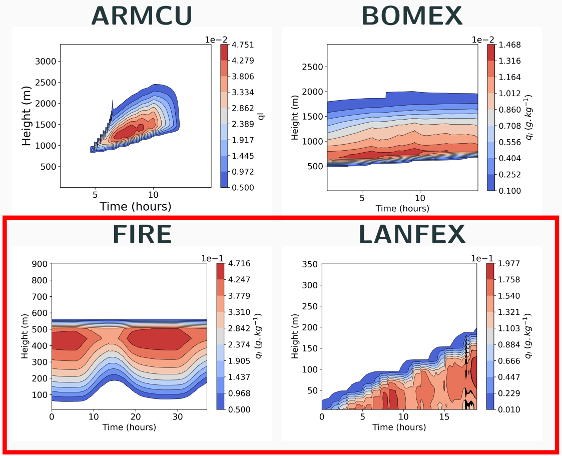
State evolution through forcing + tendencies from parametrization schemes

Idealized boundary-layer cases

Cumulus cases : ARMCu, BOMEX

Stratocumulus case : FIRE

Radiative fog case : LANFEX



Perturbation of the microphysics

Motivations

Numerous microphysical processes depend on the size of the hydrometeors. The various sizes are modeled by distribution functions.

Generalized gamma distribution used for liquid cloud droplets in ICE3:

$$n(D) = N_0 \frac{\alpha}{\Gamma(\nu)} \lambda^{\alpha\nu} D^{\alpha\nu - 1} e^{-(\lambda D)^{\alpha}} \tag{1}$$

In ICE3, N_0, α and ν have fixed values (Meso-NH Scientific Documentation, Part III: Physics):

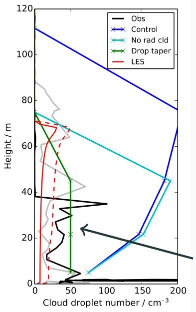
- on continental surfaces : $N_0 = 300$ drops/cm^3, $\alpha = 1$, $\nu = 3$
- on oceanic surfaces : $N_0 = 100$ drops/cm^3, $\alpha = 3$, $\nu = 1$

λ is computed so as to get the right liquid water content (LWC) in the grid box:

$$\rho_{dref} LWC = \int_0^{\infty} \frac{\pi}{6} D^3 \rho_w n(D) dD \quad \Rightarrow \quad \lambda = \left(\frac{\pi}{6} \rho_w \frac{\Gamma(\nu + \frac{3}{\alpha})}{\Gamma(\nu)} \frac{N_0}{\rho_d LWC} \right)^{1/3} \tag{2}$$

Motivations

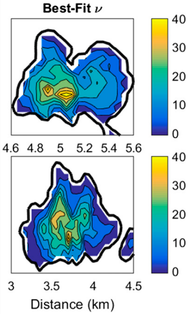
Cloud droplet number N_0



observed N_0 profile during LANFEX IOP1

Boutle et al. (2018)

Shape parameter ν



Igel and van den Heever (2017), Miles et al. (2000)

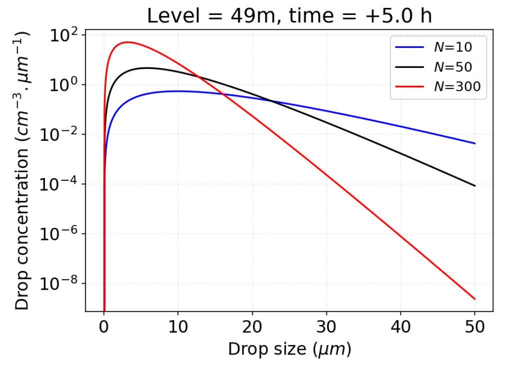
Perturbation of the droplet size distribution parameters (SPP):

Thompson et al. (2021)

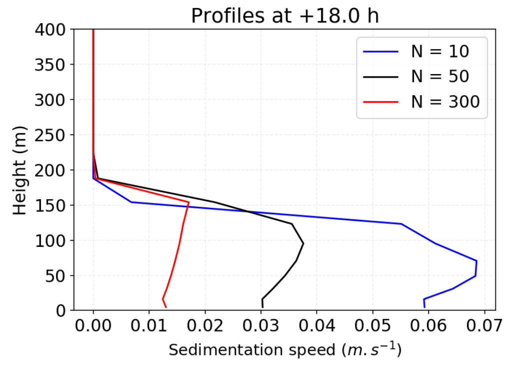
+ work in the Hirlam community: Tsiringakis et al. (2022)

Sensitivity study: impact of N_0 on the LANFEX simulation

Droplet size distribution



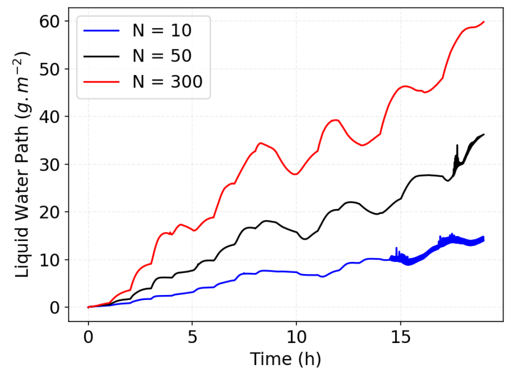
Sedimentation speed



Bigger drops with smaller N_0.

The sedimentation speed increases when N_0 decreases.

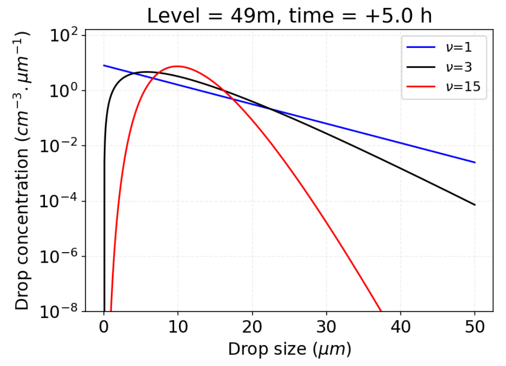
Sensitivity study: impact of N_0 on the LANFEX simulation



The fog is less developed and the liquid water content is reduced for smaller N_0.

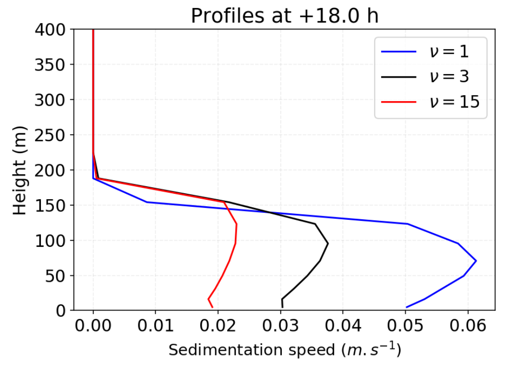
Sensitivity study: impact of ν on the LANFEX simulation

Droplet size distribution



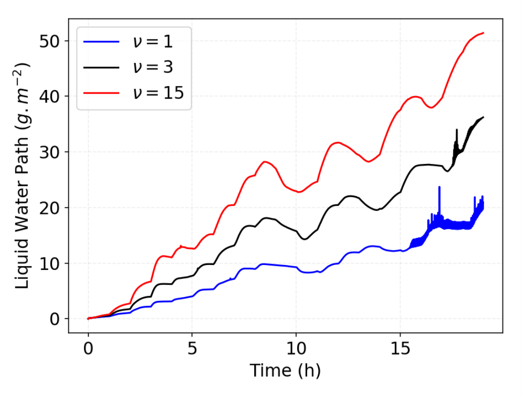
Distribution maximum increases with ν but the distribution tail is smaller ⇒ **the mean drop size decreases when ν increases**

Sedimentation speed



Mean drop size decreases ⇒ sedimentation speed decreases.

Sensitivity study: impact of N_0 on the LANFEX simulation



The liquid water content is reduced for smaller ν.

These results are consistent with Boutle et al. (2021)**.**

"RP" ensembles of LANFEX simulations

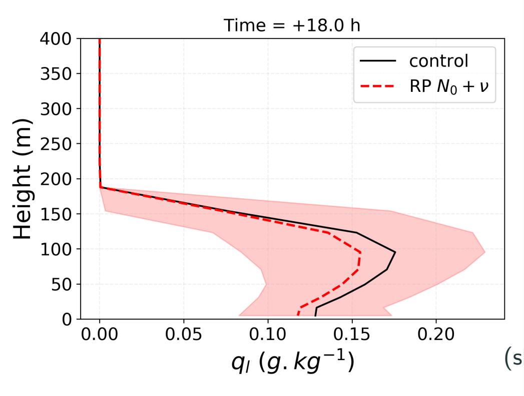
Parameter	Default value	Distribution	Clip
XCONC_LAND	5E7	lognormal	1E7 - 3.5E8
XNUC	3	lognormal	1.5 - 15

3 types of ensembles (each of 50 simulations) depending on the perturbed parameters :

- XCONC_LAND (N_0)
- XNUC (ν)
- XCONC_LAND + XNUC

The ensembles are biased

Cloud water profile



(shaded area = q10-q90 range)

The LANFEX simulation is very sensitive to changes in N_0 and ν (up to 90% change in the profile maximum).The ensembles are biased.

Can we reduce the bias ?

We have an **inverse problem** : we can define the desired **distribution of some measure** and we want to find the appropriate **parameters distribution** that will reproduce this distribution.

- y = a measure, e.g. $q_l(t,k)$ (liquid water content at time t and level k)
- λ = some parameters, e.g. N_0, ν

The parameters and the measure are linked by the **model**

$$\boxed{y = f(\lambda) \qquad (3)}$$

which is the AROME model in our case.

Inverse problem

We follow the **"Bayesian Push-forward based Inference"** method proposed by Butler et al. (2018). This method is designed precisely to get a posterior parameter distribution consistent with the distribution of the measure.

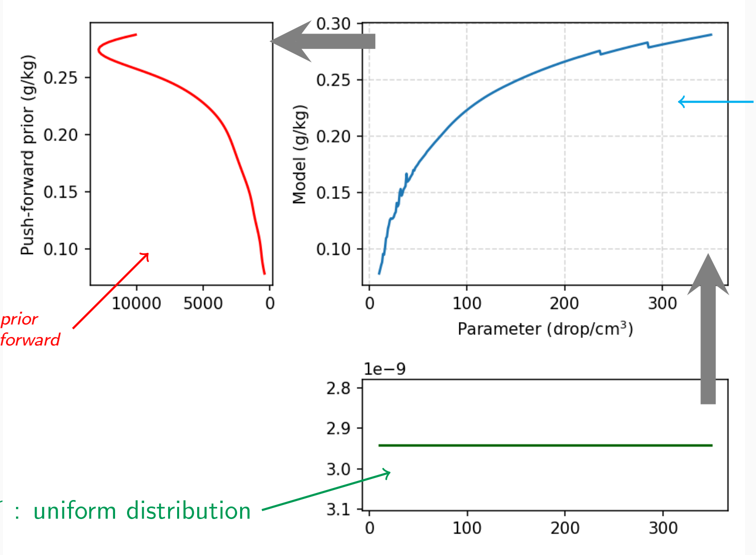
We have

- p^{prior} : the prior distribution of the parameters
- p^{obs} : the distribution of the measure, which is known
- $p^{prior}_{forward}$: the **"push-forward"** distribution, computed from p^{prior} and the model f

The posterior parameter distribution is given by

$$p^{post}(\lambda|y) = p^{prior}(\lambda)\frac{p^{obs}(f(\lambda))}{p^{prior}_{forward}(f(\lambda))} \tag{4}$$

Inverse problem: push-forward of the prior

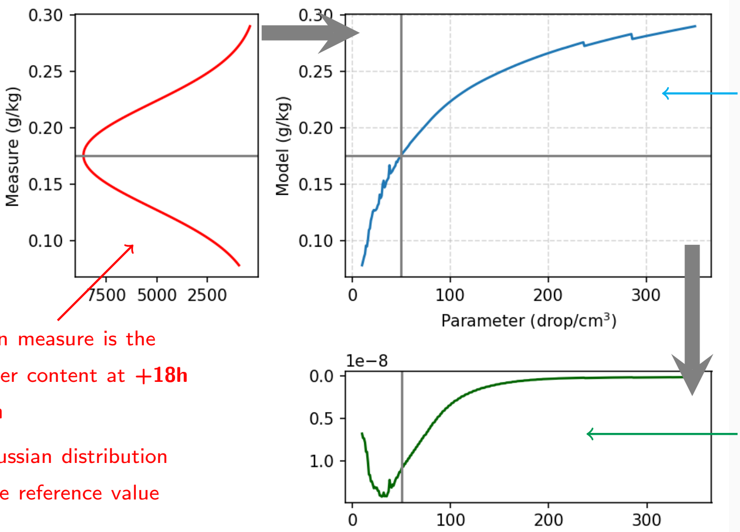


$f(\lambda)$: the model obtained from several LANFEX simulations with varying N_0

$p^{prior}_{forward}$

p^{prior} : uniform distribution

Inverse problem: posterior distribution



$f(\lambda)$: the model obtained from several LANFEX simulations with varying N_0

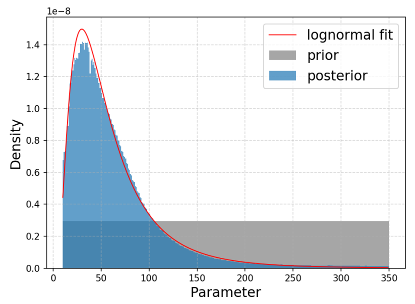
the chosen measure is the liquid water content at **+18h** and **100m**

p^{obs} : gaussian distribution around the reference value

p^{post}

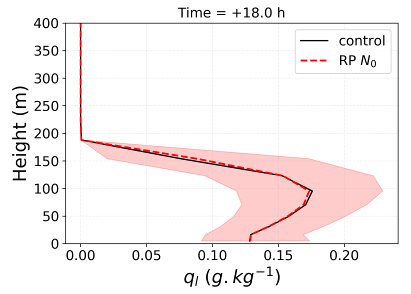
Inverse problem: resolution for $\lambda = N_0$

Posterior parameter distribution



Posterior distribution well fitted by a lognormal.

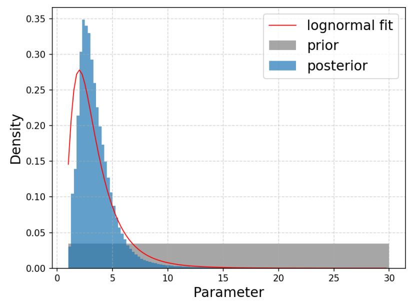
New "RP" ensemble



With the new distribution for N_0, the bias is significantly reduced.

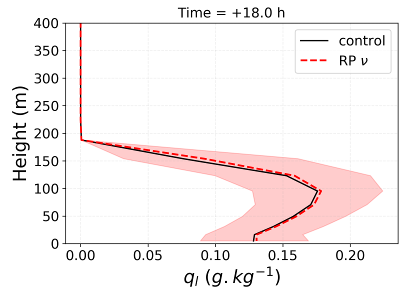
Inverse problem: resolution for $\lambda = \nu$

Posterior parameter distribution



Posterior distribution can be fitted by a lognormal.

New "RP" ensemble



With the new distribution for ν, the bias is significantly reduced.

Summary

- perturbing N_0 and ν seems justified since their value is not constant
- RP perturbations produce significant dispersion in a radiation fog case (LANFEX)
- the impact on the model of these parameters is non-linear, which implies to find appropriate distributions to make non-biased RP ensembles. This may be achieved with an inverse problem resolution.
- the resolution of the inverse problem depends on the meteorological situation and can be very computationally expensive with several parameters/measures (MCMC algorithms)

Link to the radiation scheme

Droplet size distribution in the radiation scheme

The computation of cloud optical properties relies on the determination of the effective radius:

$$r_{\text{eff}} = \frac{\int r^3 n(r) dr}{\int r^2 n(r) dr},$$

where r is the droplet radius and $n(r)$ the droplet size distribution.

In AROME, the parametrization of Martin et al. (1994) is used:

$$\boxed{r_{\text{eff}} = \left(\frac{1}{k}\right)^{1/3} \left(\frac{3LWC}{4\pi \rho_w N_0}\right)^{1/3} \qquad (5)}$$

k and N_0 values are fixed independently of the microphysics scheme. In this parametrization, r_{eff} does not depend on the droplet size distribution.

Droplet size distribution in the radiation scheme

With the droplet size distribution modeled as a generalized Gamma (equation 1), Jahangir et al. (2021) derive the expression of k (case $\alpha = 1$):

$$k = \frac{(\nu^2 + \nu)}{(\nu + 2)^2}, \tag{6}$$

where ν is the shape parameter of the droplet size distribution.

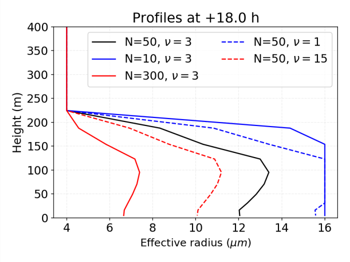
The general solution for $\alpha > 0$ is: $k = \dfrac{\Gamma(\nu + 2/\alpha)^3}{\Gamma(\nu)\Gamma(\nu + 3/\alpha)^2}$.

By using the same N_0 and ν as in the microphysics, the RP method can be easily extended to perturb the radiation scheme.

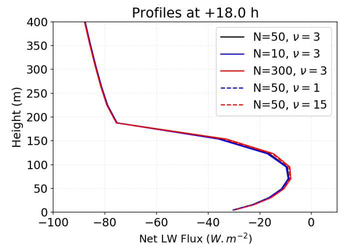
Sensitivity study

Sensitivity to the value of N_0 or ν (LANFEX case)

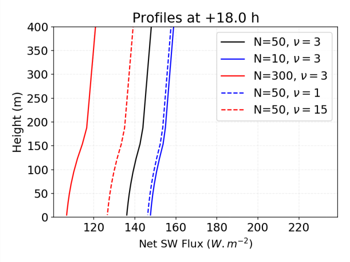
Effective radius



Long-wave net flux



Short-wave net flux

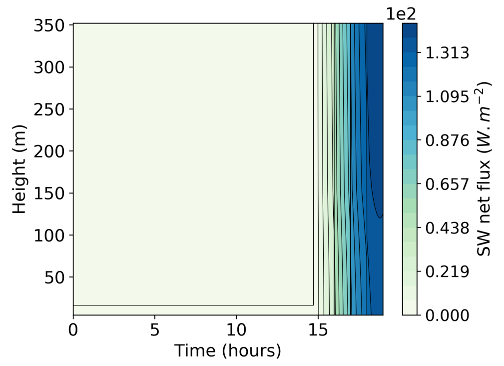


Negligible impact in the LW, significant impact in the SW.

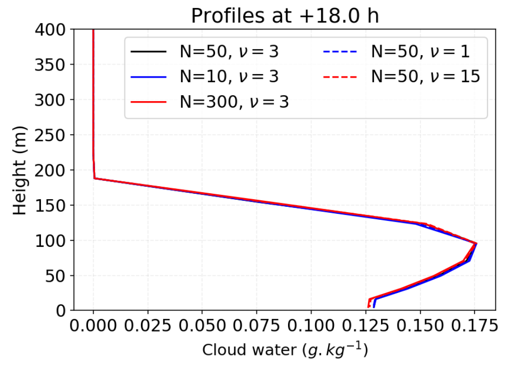
Sensitivity study

Sensitivity to the value of N_0 or ν (LANFEX case)

Short-wave net flux



Cloud water profile

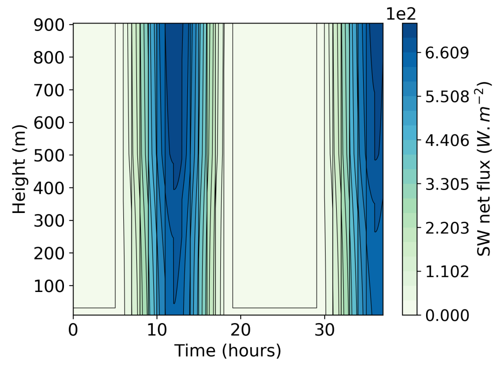


LANFEX is a fog case developing during the night ⇒ very little impact.

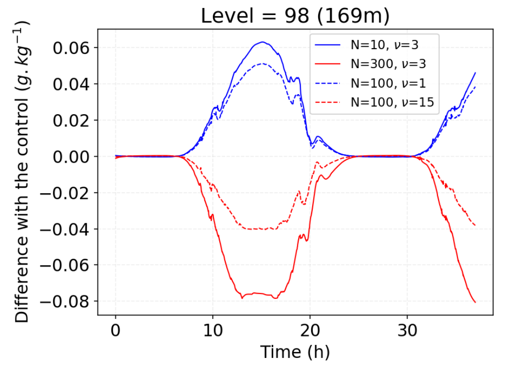
Sensitivity study

Sensitivity to the value of N_0 or ν (FIRE case)

Short-wave net flux



Cloud water evolution
(difference with the control)



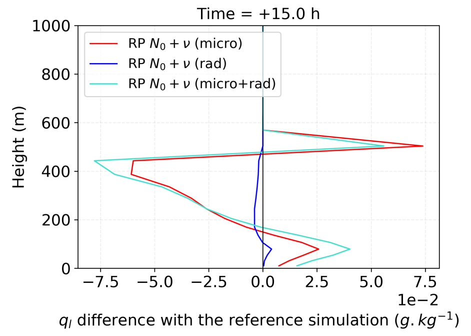
N_0: at 169m, difference up to $\sim$ 50%, and at profile maximum, difference up to $\sim$ 15%.

ν: at 169m difference up to $\sim$ 37%, and at profile maximum, difference up to $\sim$ 7%.

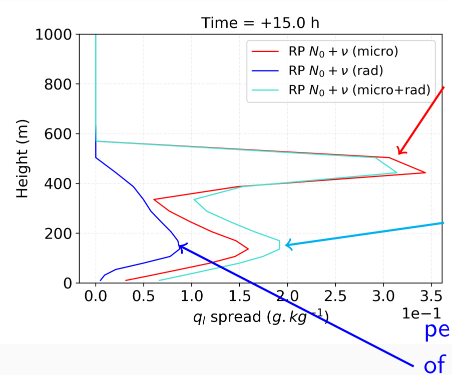
RP ensemble

Perturbation of N_0 and ν (FIRE simulations)

Cloud water bias



Cloud water ensemble spread



perturbation of micro-physics only

perturbation of radiation + micro-physics

perturbation of radiation only

Smaller impact in the radiation scheme than in the microphysics scheme.

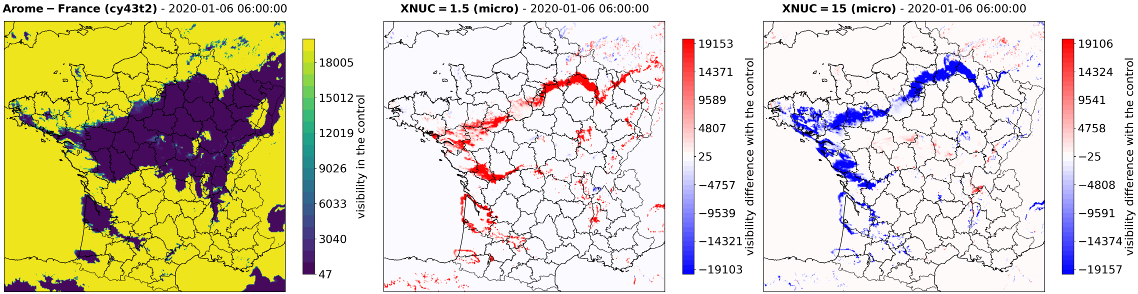
Conclusions

- using a revised parametrization of the effective radius enables to consistently perturb the microphysics and the radiation scheme
- perturbing N_0 and ν in the radiation scheme seems to have an impact only in the SW
- the main impact seems to come from the microphysics scheme for the two cases studied

3D simulations

ν in the microphysics scheme

06/01/2020 06:00 (local time) IOP6 from SoFoG3D campaign



visibility map

ν in the radiation scheme

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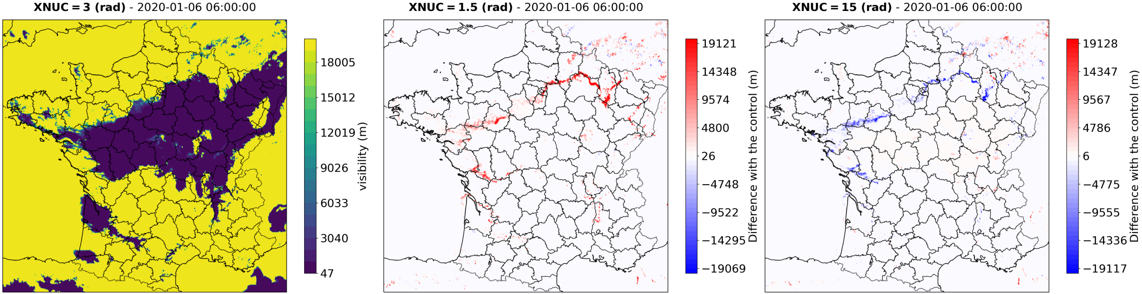

visibility map

Thank you!

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Appendix: assumptions in the radiation and microphysics schemes

Microphysics: generalized gamma distribution, with:

- $N_0 = 300$ gouttes/cm^3, $\alpha = 1$, $\nu = 3$ for land
- $N_0 = 100$ gouttes/cm^3, $\alpha = 3$, $\nu = 1$ for sea

Radiation: no assumption on the form of the distribution and:

- CCN=900 (aerosol concentration), d=0.43 (spectral dispersion) for land
- CCN=50 (aerosol concentration), d=0.33 (spectral dispersion) for sea

Appendix: assumptions in the radiation and microphysics schemes

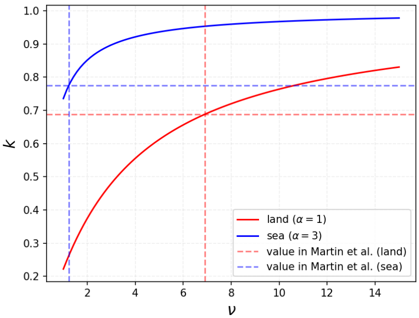
Relations between N_0 and CCN in Martin et al. (1994):

- $N_0 = -2.10 \times 10^{-4}\mathrm{CCN}^2 + 0.568\mathrm{CCN} - 27.9 \Rightarrow N_0 \sim 313$
- $N_0 = -1.15 \times 10^{-3}\mathrm{CCN}^2 + 0.963\mathrm{CCN} + 5.30 \Rightarrow N_0 \sim 50$

Relations between d and ν, α **assuming a generalized gamma distribution** for the droplet size spectra:

$$\frac{\left(1+d^2\right)^3}{\left(1+3d^2\right)^2} = k = \frac{\Gamma(\nu+2/\alpha)^3}{\Gamma(\nu)\Gamma(\nu+3/\alpha)^2}$$

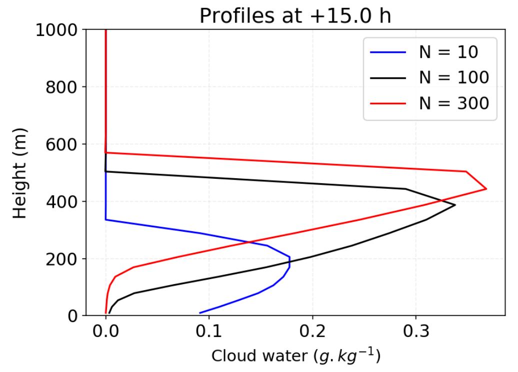
- $d = 0.43, \quad \alpha = 1 \Rightarrow \nu \sim 7$
- $d = 0.33, \quad \alpha = 3 \Rightarrow \nu \sim 1.22$



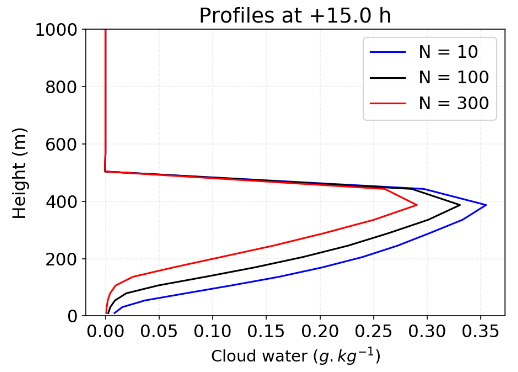
Appendix: sensitivity of the radiation and microphysics schemes

FIRE case: change N_0 either in the microphysics scheme or in the radiation scheme

microphysics



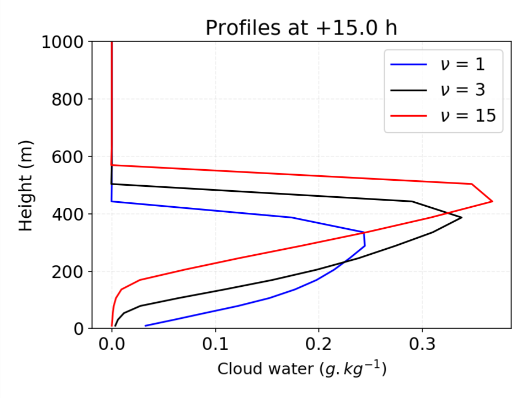
radiation



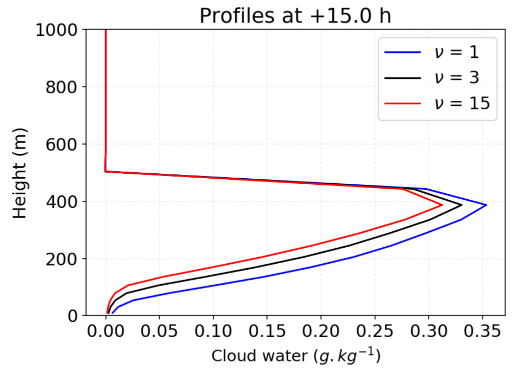
Appendix: sensitivity of the radiation and microphysics schemes

FIRE case: change ν either in the microphysics scheme or in the radiation scheme

microphysics



radiation



ν in the radiation scheme

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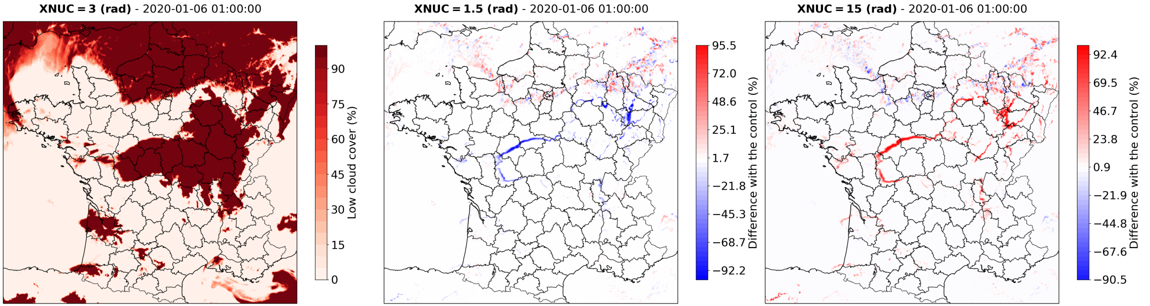

low cloud cover