Impact of hydrometeor initialisation on short-term convective-scale Numerical Weather Prediction

Mayeul Destouches* (mayeul.destouches@umr-cnrm.fr)
PhD supervisors: Thibaut Montmerle* and Yann Michel*
(*) CNRM, Université de Toulouse, Météo-France, CNRS, Toulouse, France

To improve cloud and precipitation forecasts in AROME-France, we add hydrometeor species in the control variable of the AROME 3DEnVar scheme. Even without hydrometeor observation, hydrometeor increments are produced through cross-covariances of the **B** matrix. A 3-month cycling experiment in near-operational conditions reveals increase in forecast skill, up to the third hour in non-cycling mode.

Context

Hydrometeor variables (cloud water, ice crystals, rain, snow, graupel) are added to the current control variable (T, P_s, q_v, u, v) of the AROME 3DEnVar data assimilation system. No sensibility to hydrometeor is added in observation operators, but the **B** matrix of forecast error covariances is extended to hydrometeor variables. The modification is straightforward in our pure 3DEnVar where the **B** matrix is directly sampled from the AROME Ensemble Data Assimilation system.

The forecast-analysis system: AROME-France[1,2]

	Operational		Experimental
horizontal resolution	1.3km	→	3.2km
analysis cycle	1hour	→	3hours
assimilation	3DVar	→	3DEnVar

ICE3 microphysic scheme
Conventional observations, radar data (Z and DOW)
MW and IR radiances from polar and geostationary satellites (clear-sky)[1]

The data assimilation scheme: AROME 3DEnVar[3]

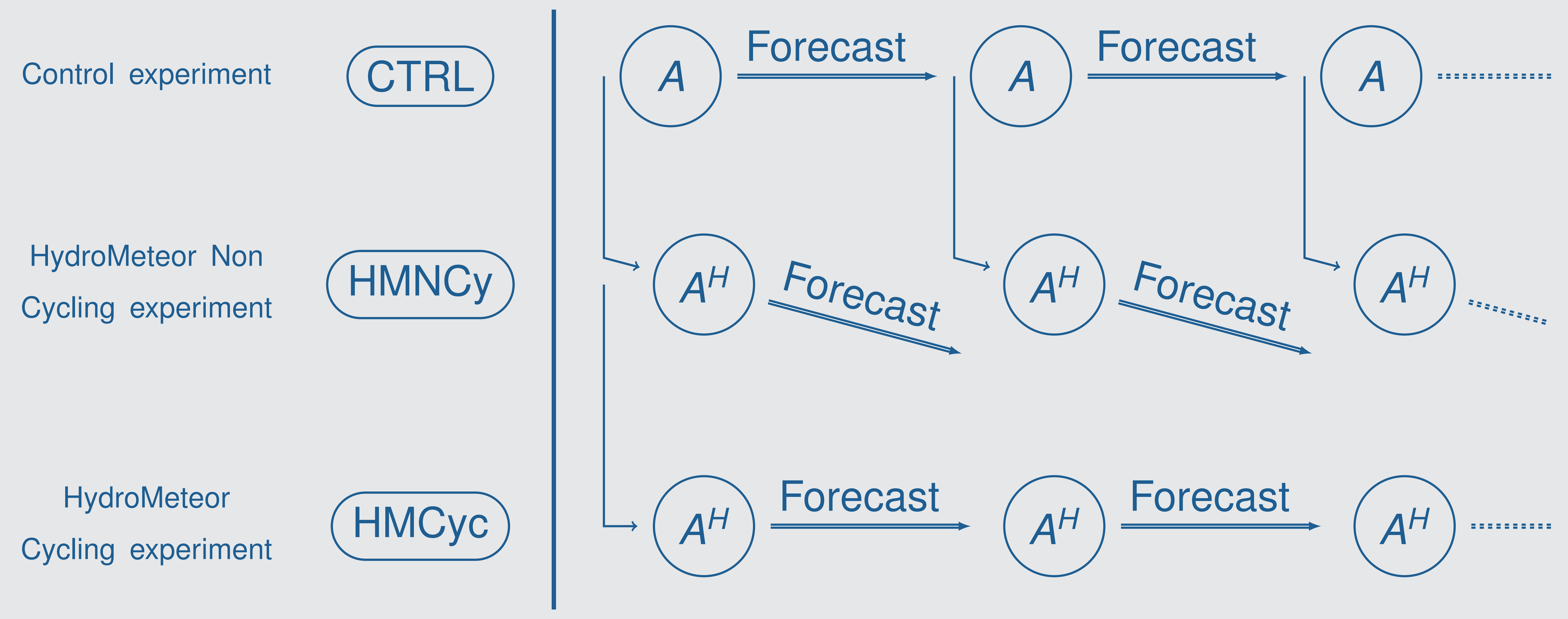
Ensemble Data Assimilation system
50 members every 3 hours, $\Delta x = 3.2$km

Sampled background error covariances **B**
every 3 hours; localisation: 150km / 0.4 log(hPa)

AROME 3DEnVar
deterministic, $\Delta x = 3.2$km

with hydrometeor fields
↓
with hydrometeor errors and cross-covariances
↓
with hydrometeor increments

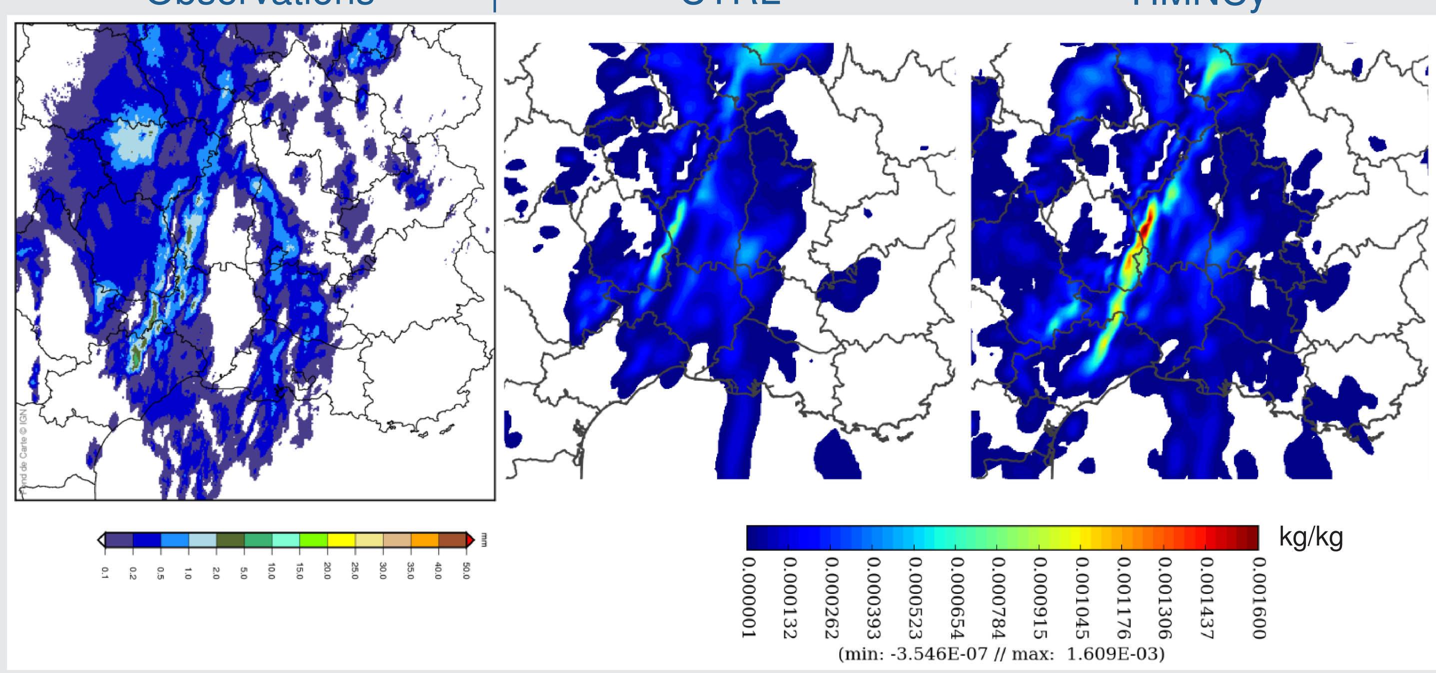
Experiments



$A^{(H)}$: Analysis (with hydrometeor variables)   Test period: 13 May - 15 August 2018 (3 months)

Impact on hydrometeor increments

Hourly rainfall Observations | rain@800hPa, first time step CTRL | HMNCy

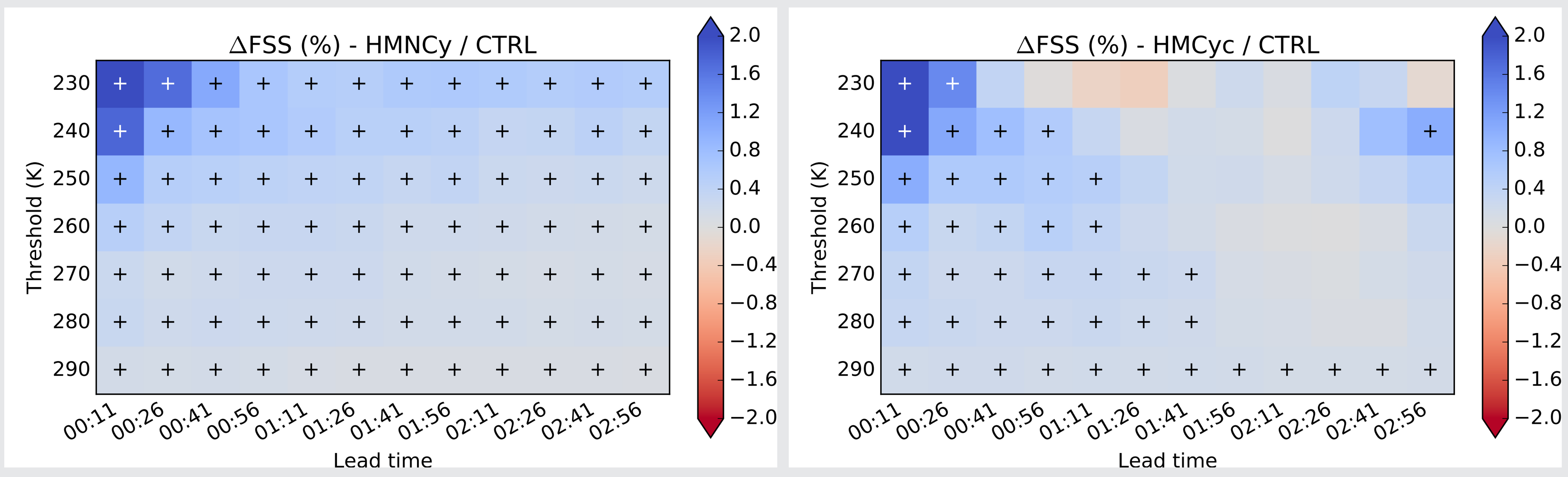


Relative humidity profiles retrieved from radar allow to generate additional hydrometeor through the cross-covariances in **B**, extending the rain line to the south.

Quantitative verification

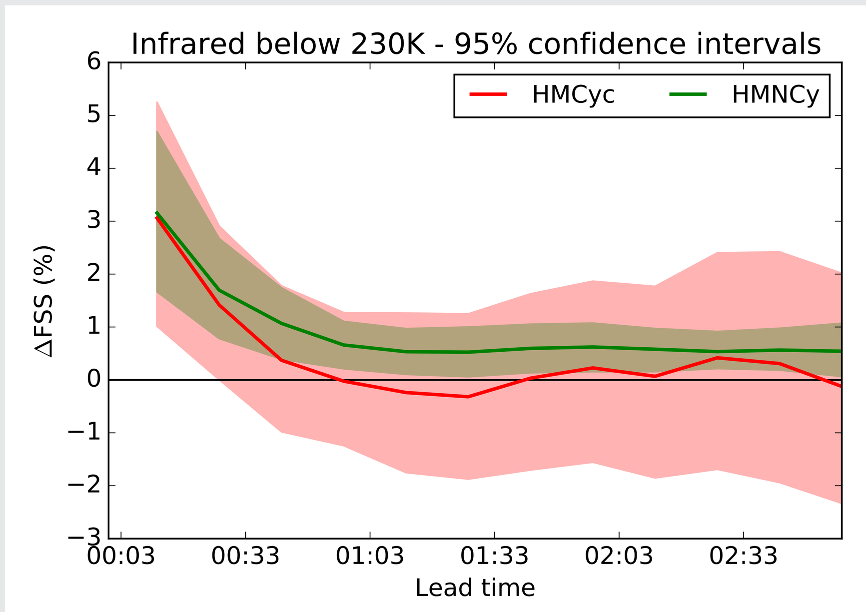
- Fractions Skill Score[4] (FSS) / Contingency tables with error compensation[5]
- Tolerance to spatial displacement: 52km / 41km neighborhoods
- All scores relative to CTRL experiment
- 95% Confidence intervals: bootstrap procedure[6] per each base hour

Against infrared satellite observations (SEVIRI, 10.8μm: clouds)



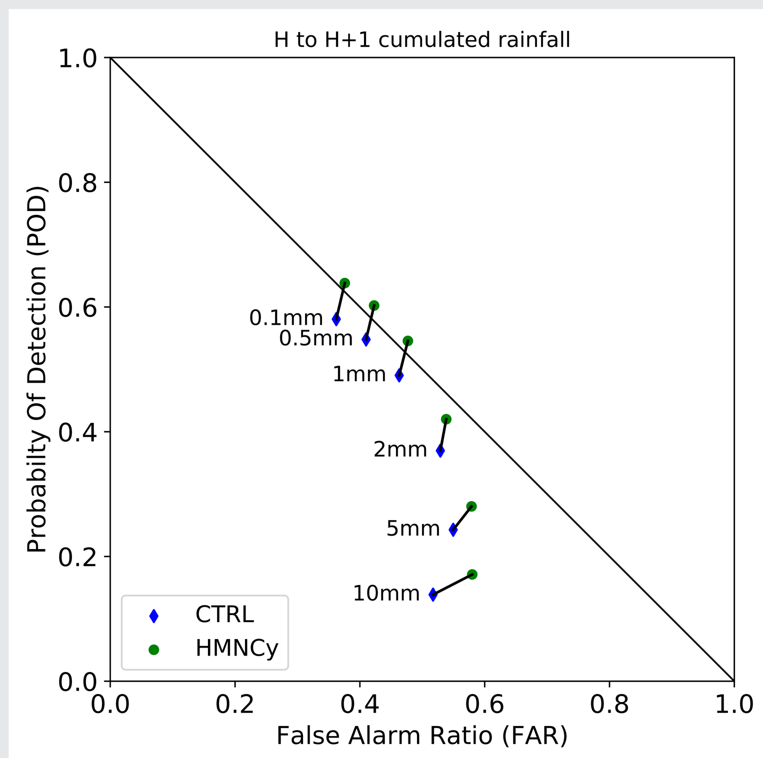
Forecast skill is significantly increased across all thresholds and all lead times from 0 to 3h. This improvement is less marked in cycling mode, especially for high clouds (low brightness temperatures).

Cycling *vs* Non-Cycling



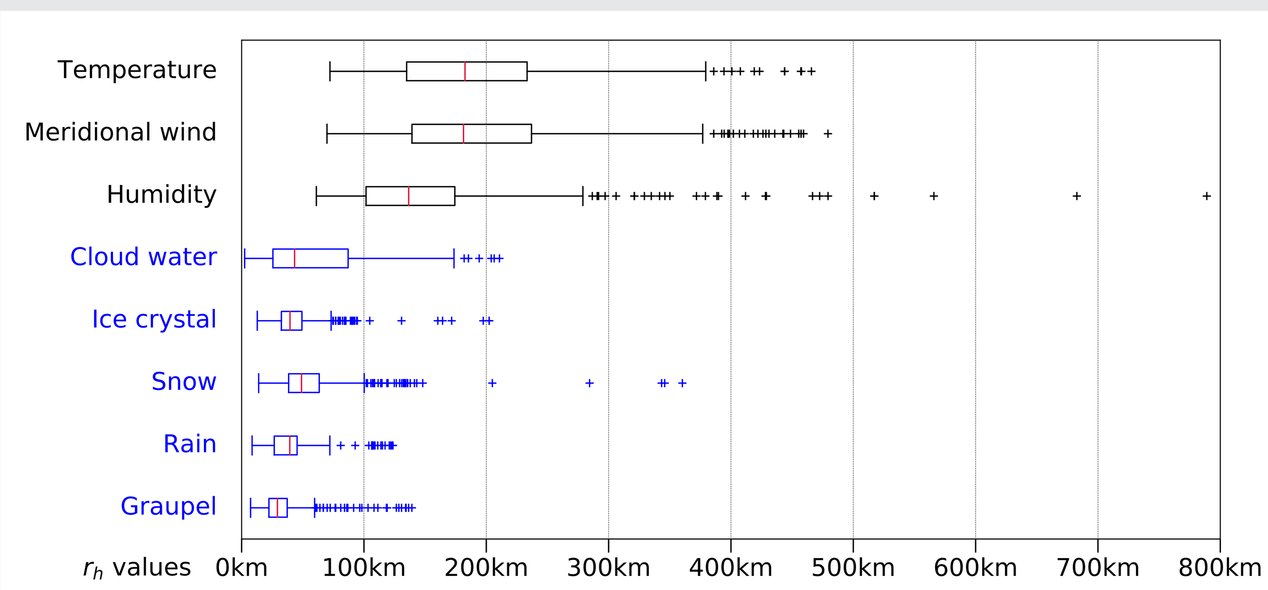
The improvement in forecast skill is more variable from day to day in the cycling experiment. Compared to non-cycling experiment, this larger variability translates into greater uncertainty on the global skill over the period.

Against cumulated precipitations from rain gauges and radars



Precipitation forecast is improved in the non-cycling experiment. Yet, too much false detections happen for large precipitation thresholds.

Perspectives



Comparison of optimal horizontal localisation lengths for several variables. For 50 member ensembles (AROME EDA) from 8 different meteorological situations, from surface level to 190hPa.

- Recent studies based on the optimal localisation diagnosis method[7] showed that shorter horizontal localisation lengths should be used for localisation of hydrometeor error covariances. New experiments will be performed with a more refined localisation scheme accounting for this hydrometeor specificity.
- Forecast and scores will be extended to see if the impact lasts after hour 3.
- Work is ongoing to study the impact of adding hydrometeor variables in **B** on initial balances between prognostic variables.

1 Brousseau *et al.*, 2016. *Improvement of the forecast of convective activity from the AROME-France system*, QJRMS. doi:10.1002/qj.2822
2 Seity *et al.*, 2011. *The AROME-France convective-scale operational model*, MWR. doi:10.1175/2010mwr3425.1
3 Montmerle *et al.*, 2018. *A 3D ensemble data assimilation scheme for the limited-area AROME model: Formulation and preliminary results*, QJRMS. doi:10.1002/qj.3334
4 Roberts and Lean, 2008. *Scale-selective verification of rainfall accumulations from high-resolution forecasts of convective events*, MWR. doi:10.1175/2007mwr2123.1
5 Stein and Stoop, 2018. *Neighborhood-based contingency tables including errors compensation*, MWR. doi:10.1175/mwr-d-17-0288.1
6 Gilleland *et al.*, 2018. *Testing the tests: What are the impacts of incorrect assumptions when applying confidence intervals or hypothesis tests to compare competing forecasts?*, MWR. doi:10.1175/mwr-d-17-0295.1
7 Ménétrier *et al.*, 2015. *Linear filtering of sample covariances for ensemble-based data assimilation. Part II: Application to a convective-scale NWP model*, MWR. doi:10.1175/mwr-d-14-00156.1