New possibilities with AROME 3DEnVar: assimilation of MTG/LI Flash Extend Accumulation (FEA) and direct assimilation of ground-based radar reflectivity

ISDA 2023, Bologne

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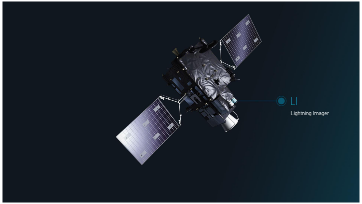
Outline

Ajaccio radar (© DSO/CMR)



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AROME 3DEnVar data assimilation system

Assimilation of ground-based radar reflectivity
- Reflectivity observation operator
- Single observation example
- Performances

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- Observation operator
- Case situation

Issues with hydrometeors in control variable

Conclusion and perspectives

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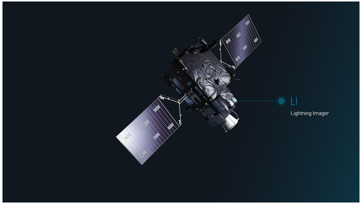

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Context

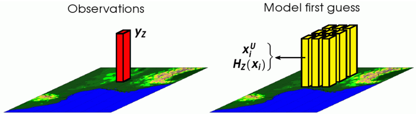
AROME 3D-Var configuration

AROME is Météo-France convective-scale NWP model:

- 1.3km resolution, 90 vertical levels [Seity et al., 2011]
- 3D-Var hourly cycle [Brousseau et al., 2016]
- Control variables: ζ, η, T, P_s, q [Brousseau et al., 2011]
- Assimilated observations:
  - satellite IR and MW radiances and winds (GEO and LEO)
  - airplanes (AIREP, AMDAR, MODE-S)
  - conventional observations (SYNOP, TEMP, buoys)
  - GNSS (ground and satellite)
  - ground based radar (Doppler winds and reflectivity)

Observations linked to hydrometeors contents

Observation operators link hydrometeors contents to observed quantity, for instance radar reflectivity [Caumont et al., 2006].
Bayesian inversion is used to assimilate pseudo-observations of humidity [Wattrelot et al., 2014]



$$\boldsymbol{y}_{\mathbf{po}}^{\boldsymbol{U}} = \sum_{\substack{i\,\in\\ \text{neighbours}}} \boldsymbol{x}_i^{\boldsymbol{U}} \frac{\exp\left(-\frac{1}{2}\|\boldsymbol{y_Z} - \boldsymbol{H_Z}(\boldsymbol{x}_i)\|^2\right)}{\sum_{\substack{j\,\in\\ \text{neighbours}}} \exp\left(-\frac{1}{2}\|\boldsymbol{y_Z} - \boldsymbol{H_Z}(\boldsymbol{x}_j)\|^2\right)}$$

$\boldsymbol{y}_{\mathbf{po}}^{\boldsymbol{U}}$: column of pseudo-observed relative humidity,
$\boldsymbol{y_Z}$: column of observed reflectivities,
$\boldsymbol{x}_i^{\boldsymbol{U}}$: column of relative humidity,
$\boldsymbol{H_Z}(\boldsymbol{x}_i)$: column of simulated reflectivities.

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Observations linked to hydrometeors contents

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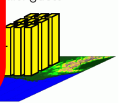
ate

Is it possible to assimilate observations only linked to hydrometeors contents?

Yes!
In a 3DEnVar assimilation system with hydrometeors in the control variable.

first guess



$$y^U_{po} = \sum_{i \in \text{neighbours}} x^U_i \frac{\exp\left(-\frac{1}{2}\|y_Z - H_Z(x_i)\|^2\right)}{\sum_{j \in \text{neighbours}} \exp\left(-\frac{1}{2}\|y_Z - H_Z(x_j)\|^2\right)}$$

y^U_{po}: column of pseudo-observed relative humidity,
y_Z: column of observed reflectivities,
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$H_Z(x_i)$: column of simulated reflectivities.

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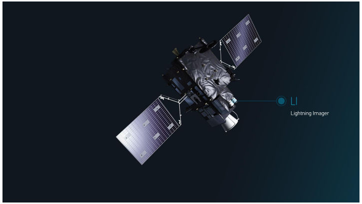

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AROME 3DEnVar data assimilation system

AROME 3DEnVar configuration

Current Météo-France e-suite [Brousseau et al., 2023]:

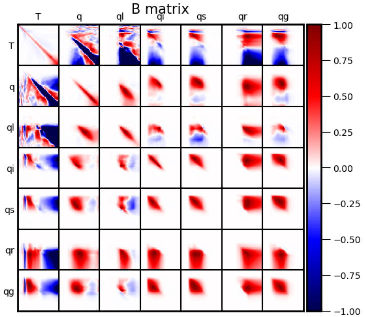
- Same AROME model configuration as operational suite, except assimilation system
- Background error covariances from EDA (50 members, 3.2km, 90 vertical levels)
- Tuning of horizontal and vertical localization

Pure EnVar solution allows to extend the control variable to hydrometeors in OOPS framework.

See L. Berre presentation, today 17h: A 3DEnVar scheme for the operational convective scale NWP system AROME-France.

Hydrometeors in the control variable

Control variable has been extended to AROME prognostic hydrometeors contents (rain, snow, graupel, cloud water, ice water) directly available from EDA [Destouches et al., 2023].



AROME 3DEnVar data assimilation system

AROME 3DEnVar configuration

Current Météo-France e-suite [Brousseau et al., 2023]:

- Same AROME model configuration as operational suite, except assimilation system
- Backgroun
- members,
- Tuning of h

Operators linking observed quantities to hydrometeors contents can now be used to modify background fields during the assimilation process.

Pure EnVar solution allows to extend the control variable to hydrometeors in OOPS framework.

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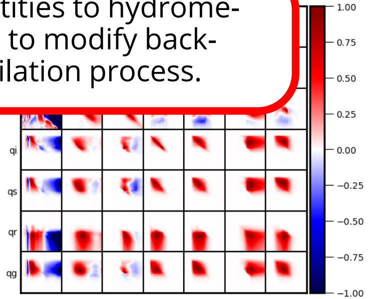

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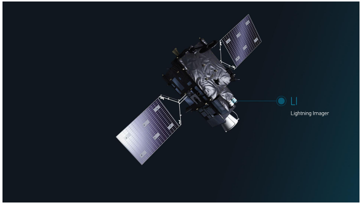

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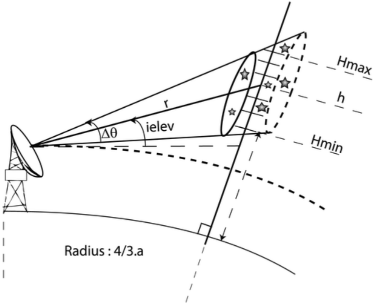
Assimilation of ground-based radar reflectivity

Reflectivity observation operator

From hydrometeors to reflectivity

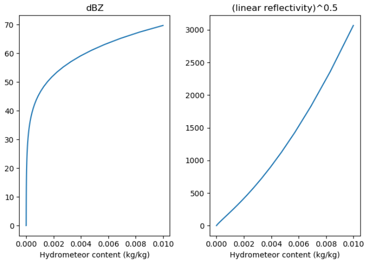
Tangent Linear and Adjoint versions of the observation operator are developed. We can use it in the 3DEnVar minimization scheme.



Reflectivity radar operator [Wattrelot et al., 2014]

Unit change

In order to have a "more linear" observation operator, we chose to change the studied quantity from *dBZ* to $\sqrt{\textit{linear reflectivity}}$

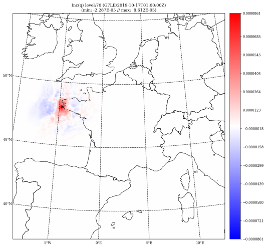


Assimilation of ground-based radar reflectivity

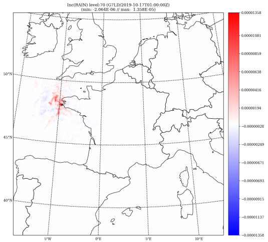
Single observation example

Assimilation of relative humidity

Increment of specific humidity



Assimilation of reflectivity



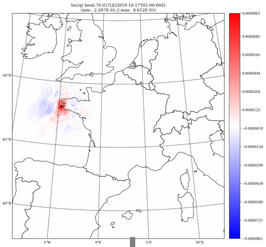
Increment of rain content

Assimilation of ground-based radar reflectivity

Single observation example

Assimilation of relative humidity

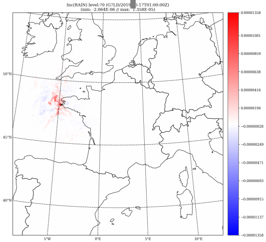
Increment of specific humidity



Cross covariances

Assimilation of reflectivity

Cross covariances

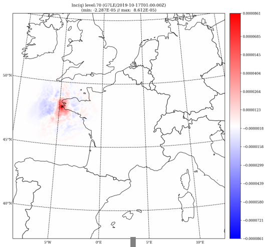


Increment of rain content

Assimilation of ground-based radar reflectivity
Single observation example

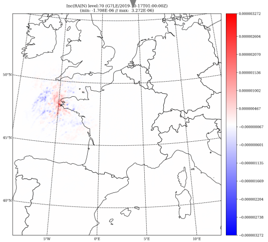
Assimilation of relative humidity

Increment of specific humidity



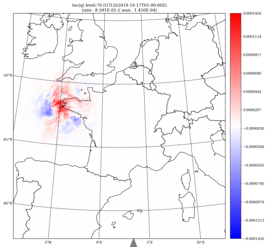
Cross covariances

Increment of rain content



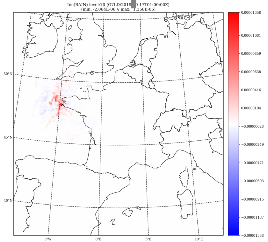
Assimilation of reflectivity

Increment of specific humidity



Cross covariances

Increment of rain content



Assimilation of ground-based radar reflectivity

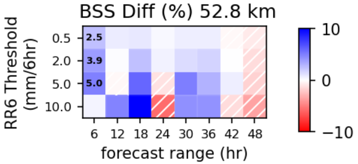
Performances

Framework of the experiments

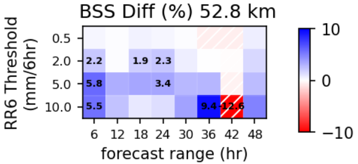
- 2 months (September-October 2022)
- AROME-France 3DEnVar configuration with hydrometeors in the control variable
- three experiments:
  - REF = no radar assimilation
  - REF+HU = assimilation of radar Doppler winds and radar reflectivity using Bayesian inversion
  - REF+Z = assimilation of radar Doppler winds and radar reflectivity directly
- Scores:
  - Brier Skill Scores (BSS) with 52.8km neighboring
  - 6-hour accumulation rain from forecast range 6 to 48.
  - various thresholds (0.5, 2.0, 5.0 and 10mm/6h)

Direct assimilation (REF+Z) gives better results than Bayesian inversion (REF+HU) for high thresholds (10 mm/6h).

Comparison between REF and REF+HU



Comparison between REF and REF+Z



Blue = REF+HU or REF+Z better than REF. Differences are statistically significant (bootstrap test) when numbers are written.

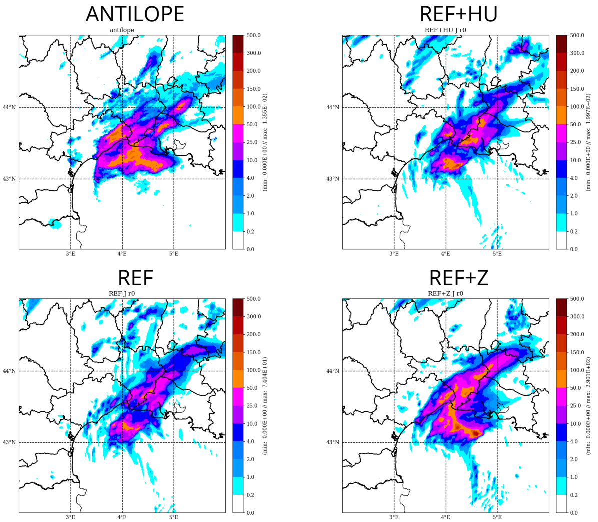
Assimilation of ground-based radar reflectivity
Performances

Case study

Heavy rain over south of France between 0h UTC and 12h UTC, September 7th 2022.

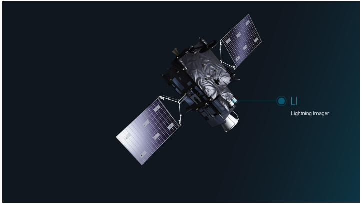
- observation = ANTILOPE rain accumulation (radar-rain gauges product)
- forecast base hour 2022/09/07 0h UTC.
- comparison between 3 experiments:
  - REF = no radar assimilation
  - REF+HU = assimilation of radar Doppler winds and radar reflectivity using Bayesian inversion
  - REF+Z = assimilation of radar Doppler winds and radar reflectivity directly

Better geographic description of the high precipitation area in REF+Z experiment.



Outline

Ajaccio radar (© DSO/CMR)



MTG-LI (© EUMETSAT)

Regression model

Comparison of proxies:

- dynamical proxies (vertical velocity, updraft volume,...)
- microphysical proxies (IWP, graupel mass,...)

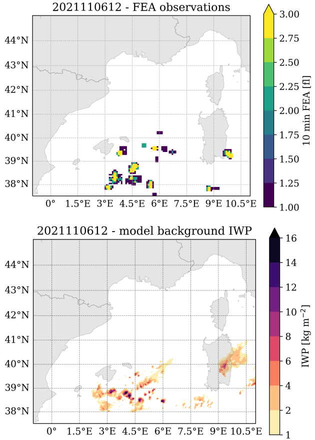
Regression model tested:

- regression (linear or polynomial)
- linear support vector regressor
- multi-layer perceptron
- random forest regressor

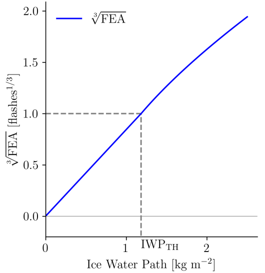
[Combarnous et al., 2022]

Observation operator in AROME

Best compromise is Ice Water Path (IWP) in a third order polynomial regression (change of unit to improve linearization).



$$IWP = \sum_{T < -10\ \mathrm{deg}} \rho \times (q_s + q_g) \times \Delta z$$



Assimilation of MTG/LI FEA
Case situation

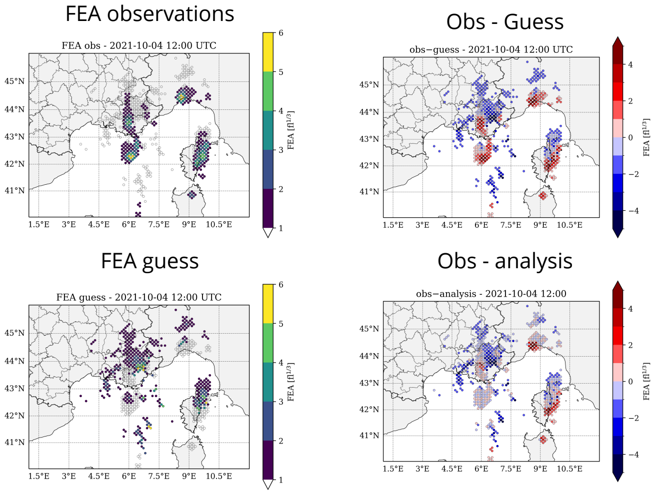
Meteorological situation

Heavy rain over south of France, October 4th 2021.
Forecast base hour: 2023/10/04 12h UTC.

Experiments

Two configurations are considered:

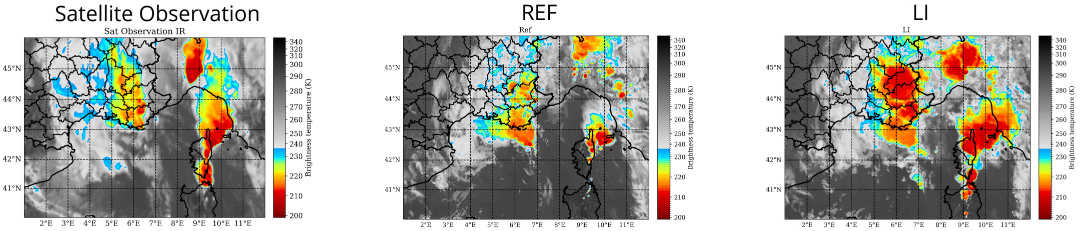
- Ref = 3DEnVar assimilation with hydrometeors in control variable, observations from operational Météo-France AROME suite (SYNOP, satellite, ground-based radars,....).
- LI = Ref + assimilation of LI observations (MTG/LI observations simulated from Météorage ground-based lightning detection network (following [Erdmann et al., 2022])



see [Combarnous et al., 2023]

Assimilation of MTG/LI FEA
Case situation

Comparisons of brightness temperature at 10.8 μm from forecast 1h.



Assimilation of lightning observations allows to better describe low brightness temperature (indicator of convection areas) at short range forecasts.
Waiting for MTG/LI data to work on observation errors, thinning,... in order to improve longer range forecasts quality.

see [Combarnous et al., 2023]

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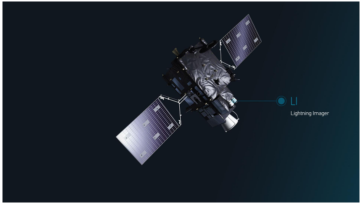

MTG-LI (© EUMETSAT)

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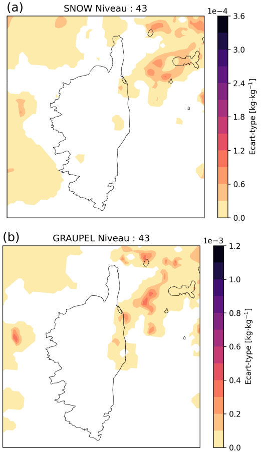


Background covariances estimation (level 43)

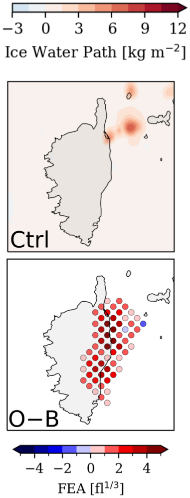
Zero-gradient issue in the background covariances: example of LI assimilation

LI observation operator links IWP (column of snow+graupel) to lightnings.
Background covariances depend on snow and graupel contents in the EDA fields.

Problem: snow and graupel fields in EDA are near 0.
$\Rightarrow$ IWP increment is near 0, assimilation of LI observation is not efficient

Some ideas:

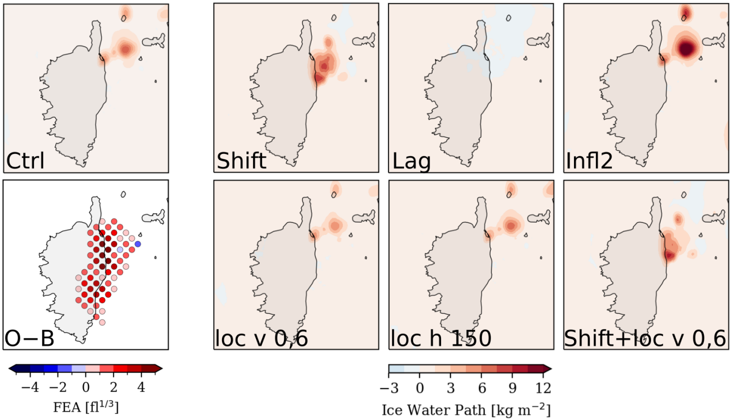
- lagged ensemble: use of EDA forecasts of different length, valid at the correct time [Lorenc, 2017]
- shifted ensemble: use of EDA forecasts valid at different times [Lorenc, 2017]
- modify localization lengths (horizontal and/or vertical)
- use scale-dependent localization (SDL) [Caron et al., 2019]



Issues with hydrometeors in control variable

Shifted-ensemble seems to have the biggest impact on this specific case. But it is not totally satisfying.

Still work to do to solve this zero-gradient issue in 3DEnVar with hydrometeors in the control variable.



IWP analysis increments examples. 2021/10/04 10h UTC.

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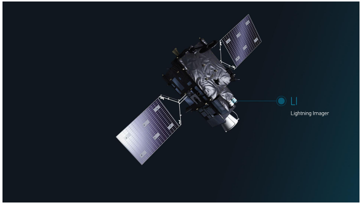

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Conclusion and perspectives

Conclusion

Adding hydrometeors in the control variable allows to assimilate directly ground-based radar reflectivity and lightning observations.

Results for ground-based reflectivity are comparable to indirect solution (1D+3DEnVar with Bayesian inversion) and even better for high precipitation thresholds.
Results for lightning observations are encouraging. We are waiting for MTG/LI data to tune error observations and thinning.

Perspectives

3DEnVar assimilation system with hydrometeors in the control variable gives more flexibility in the use of observation, especially with observations directly linked to hydrometeors contents.

There are still work to do, in particular with the zero-gradient issue. Some ideas have been tested on one case but need to be studied more precisely. SDL has to be tested.

Thank you for your attention.

References I

Brousseau, P., Berre, L., Bouttier, F., and Desroziers, G. (2011).
Background-error covariances for a convective-scale data-assimilation system: Arome–france 3d-var.
Quarterly Journal of the Royal Meteorological Society, 137(655):409–422.

Brousseau, P., Seity, Y., Ricard, D., and Léger, J. (2016).
Improvement of the forecast of convective activity from the arome-france system: Improvement of the forecast of convective activity from the arome-france system.
Quarterly Journal of the Royal Meteorological Society, 142.

Brousseau, P., Vogt, V., Arbogast, E., and Martet, M. (2023).
Configuration and evaluation of a 3denvar data assimilation scheme for the météo-france operational convective model arome-france.
to be submitted.

Caron, J.-F., Michel, Y., Montmerle, T., and Arbogast, É. (2019).
Improving background error covariances in a 3d ensemble–variational data assimilation system for regional nwp.
Monthly Weather Review, 147(1):135–151.

Caumont, O., Ducrocq, V., Delrieu, G., Gosset, M., Pinty, J.-P., Du Chatelet, J. P., Andrieu, H., Lemaître, Y., and Scialom, G. (2006).
A radar simulator for high-resolution nonhydrostatic models.
Journal of Atmospheric and Oceanic Technology, 23(8):1049–1067.

References II

Combarnous, P., Erdmann, F., Caumont, O., Defer, É., and Martet, M. (2022).
A satellite lightning observation operator for storm-scale numerical weather prediction.
Natural Hazards and Earth System Sciences, 22(9):2943–2962.

Combarnous, P., Martet, M., Caumont, O., and Defer, É. (2023).
Assimilation of satellite lightning data in a storm-scale numerical weather prediction system using a 3d-envar data assimilation scheme.
Monthly Weather Review.
submitted.

Destouches, M., Montmerle, T., Michel, Y., and Caron, J.-F. (2023).
Impact of hydrometeor control variables in a convective-scale 3denvar data assimilation scheme.
Quarterly Journal of the Royal Meteorological Society.

Erdmann, F., Caumont, O., and Defer, E. (2022).
A geostationary lightning pseudo-observation generator utilizing low-frequency ground-based lightning observations.
Journal of Atmospheric and Oceanic Technology, 39(1):3–30.

Lorenc, A. C. (2017).
Improving ensemble covariances in hybrid variational data assimilation without increasing ensemble size.
Quarterly Journal of the Royal Meteorological Society, 143(703):1062–1072.

References III

Seity, Y., Brousseau, P., Malardel, S., Hello, G., Bénard, P., Bouttier, F., Lac, C., and Masson, V. (2011).
The arome-france convective-scale operational model.
Monthly Weather Review, 139(3):976–991.

Wattrelot, E., Caumont, O., and Mahfouf, J.-F. (2014).
Operational implementation of the 1d+ 3d-var assimilation method of radar reflectivity data in the arome model.
Monthly Weather Review, 142(5):1852–1873.