Improving heavy rainfall forecasts by assimilating surface precipitation in the convective scale model AROME: A case study of the Mediterranean event of November 4, 2017

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Abstract
The ability of precipitation assimilation is assessed in a convective scale model in order to improve the precipitation forecast for a Mediterranean heavy rain event that took place on November 4, 2017. The proposed assimilation method is based on a two-step approach. First, one-dimensional variational (1D-Var) assimilation is applied on hourly accumulated precipitation to retrieve temperature and specific humidity profiles. These retrieved profiles are then combined in relative humidity profiles before being assimilated into the AROME (Application of Research to Operational at MEsoscale) 3D-Var system. Three experiments are run for this case study. The results show that precipitation assimilation has a positive impact on both moisture analysis and the forecast of dynamic fields. A comparison of 24 hr-accumulated precipitation forecasts with precipitation analysis from radar and gauge data (ANTILOPE) demonstrates the ability of rain assimilation to improve convective precipitation forecasts. A statistical evaluation against rain gauges indicates better scores due to the additional moisture information given by the precipitation assimilation.

KEYWORDS
1D-Var retrieval, data assimilation, radar-gauge precipitation, West Mediterranean event

1 | INTRODUCTION
Precipitation is of great importance in weather forecasting. It has a direct and significant impact on different domains, such as human safety, social and economic activities, and other sectors such as hydrology and agriculture. Improving the quality of the precipitation forecast, at short and medium ranges, is the goal of several researches in numerical weather prediction (NWP). One key component of an accurate precipitation forecast by an NWP model is its initial conditions. Data assimilation of meteorological observations, particularly those providing information about atmospheric moisture, bring substantial improvement to the precipitation forecast, as shown by Ducrocq et al. (2002). The NWP models nevertheless still face challenges when it comes to their ability to predict extreme precipitation events with accurate location and intensity. Indeed, such events occur in the western part of the Mediterranean Sea during the autumnal season. Indeed, from September to November, this region is regularly subjected to convective storms associated with heavy rain, strong winds and significant electrical activity (Miniscloux, 2001;
Boudevillain et al., 2009). The topography of the western coasts of the Mediterranean Sea is an additional element that increases the severity of the phenomenon. These events can generate devastating flash floods and cause not only material damage but also loss of life (Delrieu et al., 2005).

Much research on this topic (Ducrocq et al., 2008; Nuissier et al., 2008) has allowed a better understanding and simulation of such events, especially within the HyMeX (HYdrological cycle in the Mediterranean EXperiment) project (www.hymex.org). The use of convective-scale NWP models also has an important added value, especially with the assimilation of high-resolution observations such as radar data. In fact, the experimental assimilation of radar reflectivity generally revealed a good ability to improve precipitation forecasts (Caumont et al., 2010; Wang et al., 2013). The operational implementation of radar reflectivity assimilation in convective-scale models also provided significant enhancement of forecast quality (Montmerle and Faccani, 2009; Wattrelot et al., 2014). Another approach for the assimilation of observations from radar systems focuses on precipitation. Indeed, methods based on nudging (Macpherson, 2001; Stephan et al., 2008), variational (Marécal and Mahfouf, 2000) or ensemble assimilation (Lien et al., 2013) were developed in order to deal with precipitation data in both global (Lopez, 2011) and regional (Koizumi et al., 2005; Ban et al., 2017) NWP models. It should be mentioned, however, that in the case of precipitation, the observation operator involves nonlinear moist processes such as condensation and convection, which leads to difficulties when it comes to the variational assimilation framework. In order to address this issue, linearized physical parametrizations were developed for assimilation purposes (Mahfouf, 1999; Tompkins and Janisková, 2004; Lopez and Moreau, 2005). In this framework, linearized physics are used by one-dimensional variational (1D-Var) assimilation of precipitation observation. The initial phase provides retrieved temperature and humidity profiles which produce precipitation rates consistent with observations and model first guess (FG) (short-term forecast). The following phase consists of assimilating the retrieved profiles in a 3/4D-Var assimilation system. This technique was used, for instance, by Lopez and Bauer (2007) in order to assimilate National Centers for Environmental Prediction (NCEP) Stage-IV radar precipitation in the European Centre for Medium Range Weather Forecasts (ECMWF) global model. Their study indicates improvement in precipitation scores, which increase in cases of data-sparse areas.

In the present paper, a similar method to that used by Lopez and Bauer (2007) for the ECMWF global model, is applied to a limited-area higher resolution model. Indeed, the two-step approach (1D-Var + 3D-Var) is used to assimilate hourly precipitation analysis from French radars and rain gauges in the convective-scale model AROME (Application of Research to Operational at MEsoscale).

The main goal is to improve precipitation forecasts for a Mediterranean event. The case of heavy precipitation that occurred on November 4, 2017, was, therefore, investigated. AROME simulations were run and forecast verifications performed in order to assess the impact of precipitation assimilation on the quality of the precipitation forecast.

The paper is structured as follows. An overview of the meteorological situation of November 4, 2017, is outlined in Section 2. The 1D-Var + 3D-Var methodology and data are described in Section 3. Section 4 provides the assessment of AROME experiments’ ability to produce accurate precipitation forecasts for the case study. Conclusions are made in the final section.

2 | CASE OVERVIEW

Convective and stormy systems frequently affect southern France during the autumn (Richard, 2002). In fact, when the warm and humid air coming from the Mediterranean Sea is lifted above the Cevennes Mountains or above cold air coming from Iceland, it generates violent and sometimes stationary storms. Such situations lead to intense precipitation (> 150 mm in 24 hr), usually causing flash floods with much damage (Delrieu et al., 2005).

A typical stormy episode affected the French Mediterranean region between November 3 and 5, 2017. As shown in Figure 1b by Anasyg-Presyg (Santurette and Joly, 2002), the surface meteorological conditions in southern France were characterized by pressures varying between 1010 and 1015 hPa. At altitude, a jet stream was extended from the north of Morocco to the Gulf of Lion. At the left exit of this jet, heavy convective activity occurred over the Cevennes region inducing severe thunderstorms (Figure 1a).

The time evolution of this event was characterized by a first episode of heavy rain over the Cevennes Mountains from 0000 to 1700 UTC on November 4, 2017. After 1700 UTC, a stationary convection occurred over the plain to the north of Montpellier causing intense rainfall. Precipitation amounts frequently exceeded 100 mm, especially across the Ardèche, Gard and Lozère departments (Table 1).

3 | 1D-VAR + 3D-VAR ASSIMILATION OF THE RADAR-GAUGE RAIN ANALYSIS

3.1 | The AROME model and its 3D-Var data-assimilation system

The AROME model (Seity et al., 2011) is a non-hydrostatic model based on the Euler Equations system
The numerical resolution uses a two time-level scheme based on semi-implicit and semi-Lagrangian discretization. AROME is a spectral model, the variables of which are represented by a double Fourier decomposition. The vertical coordinate is a hybrid pressure terrain-following coordinate (Laprise, 1992). Representation of the turbulence in the planetary boundary layer is based on a prognostic Turbulent Kinetic Energy (TKE) equation (Cuxart et al., 2000) combined with a diagnostic mixing length (Bougeault and Lacarrère, 1989). Radiation parametrizations are those used at the ECMWF. As a convective-scale model, the deep convection is explicitly resolved by the model’s dynamics, whilst the shallow convection is based on the scheme of Pergaud et al. (2009). AROME covers a large part of occidental Europe (Figure 2a) with a horizontal resolution of 1.3 km and 90 vertical levels (Brousseau et al., 2016). The lateral boundary conditions are provided by hourly forecasts from the global model ARPEGE (Action de Recherche Petite Echelle Grande Echelle) (Courtier et al., 1991).

An incremental 3D-Var assimilation system is used to produce the analysis state (Seity et al., 2011). This is mainly based on the minimization of a cost function $J$ which measures the distance between the observations and the background, as expressed by Equation (1):

$$J(x) = \frac{1}{2}(x-x_b)^TB^{-1}(x-x_b) + \frac{1}{2}(y_o-H(x_b))^TS^{-1}(y_o-H(x_b))$$  

where $x$ is the control variable constituted of temperature, specific content of water vapour, surface pressure and the two components of the horizontal wind at model grid; $x_b$ is the background vector resulting from a previous short-range model forecast; and $S$ and $B$ are observation and model error covariance matrices, respectively.

The $B$ matrix is computed from an ensemble of perturbed assimilation cycles (Brousseau et al., 2011). The period of the data-assimilation cycle was reduced from 3 to 1 hr in order to improve the use of observations with a high spatial and temporal resolution. Tuning was therefore applied to the background-error covariance according to the 1 hr cycle period (Brousseau et al., 2016).
The considered observations are conventional data (radiosondes, wind profilers, ships and buoys reports, aircraft and automatic land station), satellite data (AMSU-A, MHS, SSMI/S, ATMS, IASI, ASCAT, SEVIRI), Global Navigation Satellite System-Zenith Total Delay data (GNSS-ZTD) from the European operational GNSS network) and radar data over France (reflectivity and radial velocity).

### 3.2 ANTILOPE: the French precipitation analysis

The precipitation data provided by ANTILOPE analysis (Champeaux et al., 2011) is a quantitative precipitation estimation combining data from the ARAMIS (Application RAdar la Météorologie Infra Synoptique) radar network (Parent du Châtelet, 2003) and around 1,200 rain gauges. The radar–gauge merging is based on a scale-separation approach. Indeed, a kriging is applied to the rain gauges to produce large-scale (stratiform) precipitation. Convective precipitation usually occurs at the small scale and is hardly ever caught by the gauge network. Accordingly, the convective cells are first detected on radar images and precipitation amounts are then corrected using the rain gauges located under these cells. ANTILOPE hourly precipitation amounts are available at near-real time ($H + 20$ min) with a spatial resolution of 1 km. For assimilation purposes, 30 observations were selected over the study area (Figure 2b) and 15 others across the rest of France.

### 3.3 The 1D-Var retrieval

For a given rain observation $R_o$, the 1D-Var retrieval looks for the optimal state of the model $x$ that minimizes the distance between the observation and model rain. The 1D-Var takes into account not only the background constraint $x_b$ provided by an earlier short-range model forecast but also the observations and model errors. Equation 2 expresses the cost function:

$$J(x) = \frac{1}{2}(x-x_b)^T B^{-1}(x-x_b) + \frac{1}{2} \left[ \frac{H_{1D}(x) - R_o}{\sigma_o} \right]^2,$$

where the state vector $x$ consists of temperature ($T$) and specific humidity ($q$) profiles as well as the surface pressure ($P_s$).

In order to avoid the non-normal distributions problem usually encountered when assimilating precipitation (Errico et al., 2000), a change of variable is performed in order to assimilate the decimal logarithm of precipitation.

The model equivalent at the observation point is calculated by the observation operator $H_{1D}$. Regarding precipitation, the observation operator consists of both a large-scale condensation scheme (Tompkins and Janisková, 2004) and a convection scheme (Lopez and Moreau, 2005). To feed the physical parameterizations called by the $H_{1D}$, additional fields are needed. In fact, the temperature and specific humidity tendencies, surface temperature, sensible and latent heat fluxes on the surface and wind stress are all extracted from the AROME background.
As seen by Lopez and Bauer (2007), only points where the background hourly precipitation is \( \geq 0.1 \) mm are assimilated because there is no sensitivity of the 1D-Var to a “no rain” background. This threshold is also applied to observations in order to avoid a dry bias in the analysis increments.

The standard deviation of observation error \( (\sigma_o) \) applied to precipitation is equal to 30% of the observed value with a minimum of 0.05 mm. In addition to the convergence control of the cost function during the 1D-Var minimization, thresholds \( \pm 2\sigma_o \) are applied to the analysis departure (observation minus analysis).

The analysed temperature and humidity profiles are used to calculate relative humidity (RH) profiles. The computation is only performed for precipitating levels (usually from the surface to 600 hPa). These profiles are then assimilated into the AROME 3D-Var as dropsonde data.

### 3.4 Experimental design

A schematic description of the 1D-Var + 3D-Var approach is shown in Figure 3. First, the 1D-Var is called to retrieve temperature and specific humidity profiles from the ANTILOPE rain observations. The analysed profiles are then converted to RH profiles. Second, the RH pseudo-profiles are assimilated into the AROME 3D-Var system.

To assess the impact of the pseudo-profiles in the AROME analysis and the subsequent forecasts, especially that of precipitation, three experiments were performed. Table 2 summarizes the data assimilated by these experiments. In the first experiment (“REF”), the data set operationally used in the AROME, excluding radar reflectivity, was assimilated (conventional, satellite observations and radar wind). In the second experiment “RAD_Z”, in addition to the observations involved in REF, radar reflectivity was assimilated using the 1D Bayesian method (Wattrelot et al., 2014). 1D-Var pseudo-observations were assimilated into the third experiment (“RAD_RR”) together with REF observations.

For each experiment, a 1 hr rapid update cycle (Brousseau et al., 2016) has been running since 1500 UTC on November 3, 2017. The cycling allows a progressive adjustment to be made between observations and model variables, during the forecasting steps of the assimilation cycle, in order to provide “warm start” initial conditions at 0000 UTC on November 4 (9 hr later). These initial conditions were then used to run forecast experiments up to a 24 hr range to be assessed in the following.

### 4 RESULTS

#### 4.1 Assessment of the 1D-Var retrieval

A first examination of the 1D-Var step was performed before the assimilation of the pseudo-observations of the RH profiles in the AROME 3D-Var system. Indeed, 1D-Var assimilation was run for 20 hr over November 3 and 4, 2017. As in Janisková (2015), the results were used to calculate the bias and the standard deviation (stdv) of first guess (FG) and analysis (AN) absolute departures \( (|\text{observation} - \text{FG}| \text{ and } |\text{observation} - \text{AN}|) \). The comparison was also performed by calculating the mean difference between the AN and FG absolute departures \( (\text{DIFF} = |\text{observation} - \text{AN} - |\text{observation} - \text{FG}|) \) and the difference in root mean square (rms) values \( (\text{RMSD} = \text{rms(}\text{observation} - \text{AN} - \text{rms(}\text{observation} - \text{FG})\text{)}) \)). These statistics include 1,129 assimilated observations during the case study; they are summarized in Table 3. The bias and stdv are reduced by > 70% and 50%, respectively. The rms of AN is also less than the rms of FG. Therefore, the 1D-Var analysis fits the observations better than the FG.

![Figure 3](image-url)

**TABLE 2** Summary of the assimilation experiments with the assimilated observation systems

| Experiment | Observations assimilated |
|------------|--------------------------|
| REF        | Conventional (radiosondes, wind profilers, ships and buoys reports, aircraft, automatic land station), SATOB wind, ATMS, SEVIRI, GNSS-ZTD and radar radial velocity |
| RAD_Z      | REF + radar reflectivity  |
| RAD_RR     | REF + radar rain          |
4.2 | Impact on the AROME fields

4.2.1 | Initial conditions

The quality of each forecast experiment depends on the behaviour of its analysis. In view of this fact, a comparison between the three experiments analysis and moisture-sensitive channels (SEVIRI 7.3 μm and ATMS 183 ± 7, 4.5, 3, 1.8 and 1 GHz) was performed (Figure 4). The model fields from each experiment were used as inputs for the radiative transfer model RTTOV (https://www.nwpsaf.eu/site/software/rttov/) so as to produce simulated brightness temperatures that are compared with satellite observations. For the SEVIRI channel, the RAD_Z experiment has a neutral impact regarding that of the REF, whereas the RAD_RR experiment reduces the root mean square error (RMSE) of the analysis departure. For the ATMS sensor, the RAD_Z shows good performance for channels 19 and 22 in contrast to channels 20 and 21. The RAD_RR analysis showed the best performance and the RMSE is reduced for almost all ATMS channels, except for channel 20. For the case study, therefore, the assimilation of RH profiles, retrieved from radar and rain gauge precipitation, has a positive impact on the humidity field, according to moisture-sensitive satellite channels assimilated into the AROME 3D-Var.

4.2.2 | Impact on model dynamics and precipitation forecasts

Dynamics

The differences identified in the analysis of the three experiments led to changes in the dynamic structure of the simulated atmosphere for each experiment. Indeed, an examination of the AROME 1.5 PVU (potential vorticity unit) geopotential altitude was performed against METEOSAT imagery from sensor SEVIRI, water vapour channel 7.3 μm at 1700 UTC on November 4, 2017 (Figure 5). A dark area in the southeast of France can be seen in the satellite imagery. This signal indicates a dry area due to an intrusion of stratospheric air. The three experiments simulated this tropopause drop over the concerned area, but this drop was deeper in the experiment RAD_RR with lower tropopause.

At 600 hPa, an area of warm and wet air, expressed by pseudo-adiabatic potential temperatures (PAPTs) between 13 and 15°C, was detected by the three experiments eastward of the tropopause drop (the circle in Figure 6). However, the RAD_RR simulated a larger area with higher PAPTs, which was normally favourable to convective activity. The comparison of the three experiments was extended to the vertical velocity field across the same area. Indeed, negative vertical velocities at 600 hPa were simulated by the REF, indicating the lifting of the air mass over the area of interest. This lifting was slightly strengthened in the RAD_Z experiment, but clearly intensified in the RAD_RR with values around \(-6\) Pas\(^{-1}\).

To summarize, for the case of November 4, 2017, the assimilation of the ANTILOPE precipitation analysis led to a more pronounced drop of the dynamic tropopause accompanied by a strengthened upward motion of warm and wet air at mid-level. This configuration showed that the convective activity was more intense in the RAD_RR when regarding the two other experiments. Heavier rain could, therefore, be simulated by the RAD_RR across the area of interest.

Impact on precipitation forecasts

The assimilation of radar reflectivity (RAD_Z) as well as the assimilation of ANTILOPE precipitation analysis...
RAD_RR brought substantial modification to the atmosphere dynamics simulated by the AROME model, as shown above. These modifications impacted the precipitation forecast patterns. The examination of 24 hr-accumulated precipitation simulated by the three experiments against the ANTILOPE was performed on November 4, 2017 (Figure 7). The ANTILOPE precipitation analysis (Figure 7a) showed a very intense rainfall system over the limit between the Ardèche, Gard, Lozère and Aveyron departments. Heavy rain was also present over the plain of Gard and Hérault. Local precipitation > 200 mm to the north of Montpellier and over the Cevennes. The experiment REF (Figure 7b) reproduced the northern part of the system, but the precipitation band was finer than that observed. The southern part (white ellipse) was clearly missed. The RAD_Z experiment (Figure 7c) extended the system in the north of Montpellier (Figure 7e), which was more consistent with the ANTILOPE precipitation analysis. There were also few precipitation cells with intensities between 50 and 100 mm over the limits between Hérault and Aveyron, but this left branch of the system is still strongly underestimated. The RAD_RR experiment (Figure 7d) was the closest to the ANTILOPE precipitation analysis. In fact, it reproduced the system extension to the south as the RAD_Z. Moreover, the left branch (Figure 7f) was well structured with higher precipitation intensities than the other experiments.

**Statistical evaluation**

An objective comparison of 24 hr-accumulated precipitation amounts produced by the three simulations with rain gauges was performed over the study area. A contingency table was calculated for the 50 mm threshold (33% of the observed precipitation was above this value). The results are summarized in Figure 8 for six categorical scores (Jolliffe and Stephenson, 2003; Wilks, 2006): forecast accuracy (ACC), frequency bias (FBI), probability of detection (POD), false alarm rate (FAR), equitable threat score (ETS) and Heidke skill score (HSS). The RAD_Z experiment slightly improved the ACC score when regarding the REF score. The RAD_RR had the best ACC score. The FBI indicated an underestimation of the precipitation amounts with a superiority of the RAD_RR. In addition, the RAD_RR had the best POD rate with a quasi-neutral impact on the FAR. Both the ETS and HSS were enhanced in the case of the RAD_Z experiment and even better in the case of the RAD_RR.
To assess the impact of precipitation assimilation on the overall precipitation forecast, the categorical scores were also calculated for the thresholds of 5 and 10 mm. The results (not shown) revealed a neutral to slightly positive impact for the RAD_RR when regarding the other experiments.

The statistical evaluation was performed for other cases involving either Mediterranean events (maximum 24 hr precipitation amounts around 200 mm) or Atlantic perturbations (maximum 24 hr precipitation amounts around 50 mm). The overall results for the 24 hr precipitation forecasts showed a neutral to slightly negative impact on precipitation amounts < 10 mm and a positive impact on amounts > 10 mm.

5 | CONCLUSIONS

In the present study, the impact of precipitation assimilation on the AROME forecasts was studied in the case of a heavy rainfall event. Several AROME experiments were performed in order to investigate a Mediterranean event that took place on November 4, 2017. The precipitation amounts were assimilated using a one-dimensional variational (1D-Var) + 3D-Var approach. First, pseudo-profiles of relative humidity (RH) were retrieved from an hourly accumulated surface precipitation analysis named ANTILOPE using a 1D-Var assimilation. The pseudo-profiles were then assimilated into an AROME 3D-Var assimilation system. The examination of moisture...
analysis showed a positive impact of the proposed method. In addition, the forecast of dynamic fields was more favourable for the production of strong convection and heavy precipitation, which led to precipitation forecasts in better agreement with the ANTILOPE precipitation analysis. The statistical evaluation against rain gauges showed that the additional rain observations had produced precipitation forecasts with improved skills, something which supports the previous results. The proposed method was applied to other rain events. It was found that the assimilation of surface precipitation did not have a significant impact on the prediction of 24 hr precipitation amounts < 10 mm, whilst the forecast of large amounts was substantially improved.

These findings should be confirmed by a continuous cycling over longer periods and several seasons. There is a need, however, for additional quality controls during the 1D-Var step. Indeed, Janisková (2015) demonstrated

**FIGURE 7** Twenty-four hr-accumulated precipitation analysed by ANTILOPE (a) and simulated by AROME on November 4, 2017: (b) REF, (c) RAD_Z and (d) RAD_RR; the differences are against REF for (e) RAD_Z and (f) RAD_RR

**FIGURE 8** Twenty-four hr-accumulated precipitation scores (for a threshold of 50 mm) for the three experiments against rain gauges over the study area on November 4, 2017
a noticeable impact of improved quality controls in the case of a 1D-Var + 4D-Var assimilation of cloud information from space-borne radar and lidar. Therefore, sensitivity studies on bias correction and quality control should be performed for the enhancement of the 1D-Var retrieval behaviours. The observation errors is another component that has to be investigated, especially regarding the representativeness errors that are closely linked to the thinning of high-density observations at a convective scale (Wattrelot et al., 2016; Gustafsson et al., 2018).

The assimilation of the radar reflectivity in the AROME (RAD_{Z}) in an operational framework was associated with stringent controls to avoid humidity biases that can be introduced by additional moist information. Consequently, the proposed method should be tested using similar constraints to assess its robustness.

In the case of retrieving pseudo-profiles from surface observations (precipitation), questions may arise concerning the vertical distribution of the new information. An alternative approach could be to assimilate vertically integrated variables such as total column water vapour (TCWV) instead of RH pseudo-profiles (Lopez and Bauer, 2007). An AROME pre-operational suite involving the 1D-Var + 3D-Var assimilation of surface precipitation shall be set up to provide a realistic framework for the better assessment of the strengths and weaknesses of the proposed method.

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