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High-Resolution Data Assimilation for Two Maritime Extreme Weather Events: A comparison between 3DVar and EnKF.

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Abstract

Populated coastal regions in the Mediterranean are known to be severely affected by extreme weather events. Generally, they are initiated over maritime regions, where a lack of in-situ observations is present, hampering the initial conditions estimations and hence, the forecast accuracy. To face this problem, Data Assimilation (DA) is used to improve the estimation of the initial conditions and their respective forecasts. Although comparisons between different DA methods have been performed at global scales, few studies are performed at high-resolution, focusing on extreme weather events triggered over the sea and enhanced by complex topographic regions. In this study, we investigate the role of assimilating different types of conventional and remote-sensing observations using the variational 3DVar and the ensemble-based EnKF, which are of the most common DA schemes used globally at National Weather Centers. To this aim, two different events are chosen because of both the different areas of occurrence and the triggering mechanisms. Both the 3DVar and the EnKF are used at convection permitting scales to improve the predictability of these two high-impact coastal extreme weather episodes, which were poorly predicted by numerical weather prediction models: (a) the heavy precipitation event IOP13 and (b) the intense Mediterranean Tropical-like cyclone Qendresa. Results show that the EnKF and 3DVar perform similarly for the IOP13 event for most of the verification metrics, although looking at the ROC and AUC scores, the EnKF clearly outperforms the 3DVar. However, the ensemble mean of the EnKF is in general worse than the 3DVar for Qendresa, although some of the ensemble members of the EnKF individually outperforms the 3DVar allowing for gaining information on the physics of the event and hence the benefits of using an ensemble-based DA scheme.

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1. Introduction

The Mediterranean basin is recognized as one of the geographical regions most frequently affected by high impact weather events in the world (Petterssen, 1956). The Mediterranean region has a natural disposition for these events because of its singular orographic features, which include having a relatively warm sea surrounded by complex terrain. This geographical configuration forces the warm and moist airflow to lift, favoring condensation and triggering convection. Hazardous weather events in this region, such as heavy precipitation (e.g., flash floods, snowstorms), cyclogenesis or windstorms (e.g., squall lines, tornadic thunderstorms), produce huge economic, injury and human losses in populated coastal regions (e.g., Romero et al., 1998b; Llasat and Sempere-Torres, 2001; Llasat et al., 2010; Jansa et al., 2014; Flaounas et al., 2016; Pakalidou and Karacosta, 2018; Amengual et al., 2021). Since 1900, more than 500 billion Euros associated with total damages to the property and over 1.3 million fatalities related to hydrometeorological disasters has been registered for the EM-DAT international disaster database[1]. These effects underscore the critical need for accurate and rapid high-resolution weather forecasting systems, aimed at extending the lead time for severe weather warnings, thereby enabling the implementation of effective mitigation strategies to reduce fatalities and economic losses. However, while the accuracy of weather forecasting has significantly improved in recent years, with better representation of physical processes and dynamics, accurate prediction of high impact weather events in terms of their location, timing, and intensity remains a major challenge for the scientific community (Stensrud et al., 2009; Mass et al., 2002; Bryan and Rotunno, 2005; Yano et al., 2018; Torcasio et al., 2021). For this reason, improving the forecast of high-impact weather events becomes an imperative goal.

Deficiencies in the accurate prediction of the location (spatial and temporal), intensity and phenomenology of extreme weather events are tightly related to the accuracy of the initial conditions of the system (Wu et al., 2013). The initial conditions of the hazardous weather events affecting coastal populated regions, are typically poorly estimated, mainly because these weather systems originate over the sea, where there is a lack of *in-situ* observations. Enhanced representations of the initial conditions are typically achieved by blending information from observations into numerical models through sophisticated *Data Assimilation* (DA) techniques (Kalnay, 2003), which accounts not only for the nominal values of the observations and the model, but also accounts for their respective error statistics. DA has been widely used and applied for global numerical weather prediction (NWP) problems (e.g., Eliasen, 1954; Lorenc, 1981; Le Dimet and Talagrand, 1986; Rabier et al., 2000, Whitaker et al., 2008, Carrassi et al., 2018; Albergel, et al., 2020, among others). However, less attention has been paid to convective-scale NWP problems, especially those associated with small scale convective phenomena initiated over regions with sparse observational data coverage, such as the extreme weather events affecting coastal regions in the Mediterranean basin (Carrió et al., 2016; Amengual et al., 2017; Mazzarella et al., 2021). To improve forecasts of such extreme weather events, accurate high resolution numerical weather models which solve convective scale processes are required, as well as dense observations at high spatial and temporal resolution. These will provide accurate information regarding the convective systems themselves or their environmental conditions. One of the most important sources of convective scale information are ground weather radars that provide three-dimensional data related to the storms at high spatial (order of hundreds of meters) and temporal (order of few minutes) resolution. In addition, weather radars provide thermodynamic and dynamic information of thunderstorms, which are crucial to understand and forecast convective structures. Due to the high spatio-temporal variability of convective structures, a rapid update cycle of the initial state (i.e.,

[1] https://www.emdat.be/

analysis) using weather radar observations is required to reduce errors and keep physical balances in the initial conditions. Several studies have shown the positive impact in forecasting severe weather events by assimilating weather radar information (e.g., Xiao and Sun, 2007; Lee et al., 2010; Wheatley et al., 2012; Yussouf et al., 2015; Carrió et al., 2019; Mazzarella et al., 2021).

During the last decades, different DA algorithms have been developed with the aim of improving weather forecasts making use of all available observations in the best possible way. In this context, most of the developed DA methods are based on exploiting Bayes' Theorem (Lorenc, 1986) and making use of different types of approximations. Generally, DA algorithms can be classified into the following three Bayesian-based families: (a) Variational DA (e.g., 3DVar (Barker et al., 2004) or 4DVar (Huang et al., 2009)); (b) Ensemble-based DA, which are based on the *Ensemble Kalman Filter* (EnKF; Evensen, 1994) and (c) Monte-Carlo DA methods. Variational DA minimizes a cost function to obtain the analysis (i.e., the best estimation of the initial conditions). More specifically, variational DA methods provide a (quasi) optimal analysis based on an imperfect forecast (*prior* state or *background*), a set of imperfect observations and their respective error statistics that are prescribed and assumed to be Gaussian, for simplicity. In addition, variational DA algorithms require a linearized and adjoint version of the numerical model, which can be very difficult to develop and maintain. This often involves the use of automatic differentiation tools or complex manual derivation, both of which are error-prone and time-consuming. On the other hand, the ensemble-based DA algorithms do not require the use of linearized or adjoint versions of the model, and they do not use prescribed error statistics. Instead, they compute the error statistics from an ensemble of forecasts, with the main property that these errors are evolving in time as the system evolves. The Monte-Carlo DA method allows the assimilation of observations described with non-Gaussian errors. Particle filters (PF; Van Leewen, 2009; Poterjoy, 2016) are a clear example of Monte-Carlo DA algorithm. However, PFs are not well-suited for large multidimensional systems, such as the atmosphere, although a lot of improvements have been achieved recently. In the present study, we will focus on the most widely used DA schemes typically used in major operational weather centers, which are the variational and ensemble-based DA schemes, leaving the Monte-Carlo methods for future work.

Although variational DA schemes have been used in numerical weather prediction for many years (Courtier et al., 1994; Park and Zupanski, 2003; Rawlins et al., 2007), allowing the assimilation of a wide range of different observations, they present a well-known limitation. This limitation is related to the use of a climatological background error covariance matrix to characterize the error statistics, which is kept constant along the assimilation window, where the different observations are distributed at different times. This weakness is specifically linked to the 3DVar method, which typically uses the National Meteorological Center (NMC) method (Parrish and Derber, 1992) to generate those static background error covariances using forecast differences over a period of time reasonably close to the event. The error statistics derived from such DA schemes are static, isotropic and nearly homogenous, misrepresenting the true error statistics in space and time, which are inherently flow-dependent, resulting in less accurate analysis. On the other hand, the EnKF DA scheme is designed to provide flow-dependent background error covariances. Some studies have shown the potential of the EnKF spreading information from the observations flow-dependently in comparison with the 3DVar (Yang et al., 2009; Gao et al., 2018). On the other hand, 3DVar techniques require less computational resources and there is no need to build an ensemble compared to EnKF or even simulate the model trajectory as in 4DVar. Therefore, the assimilation with 3DVar takes only a few tens of minutes, making this technique particularly suitable for operational purposes.

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To solve convective scale (i.e., grid spacing of a few kilometers) physical processes associated with extreme weather phenomena, high-resolution numerical simulations are required. Performing computational expensive high-resolution simulations presents a significant challenge as it constrains the feasible number of ensemble members that can be used in EnKF DA schemes, and thus it could hamper significantly the estimation of the background error covariance matrix. In this context, which DA method is more suitable? The 3DVar using an *ad hoc* background error covariance matrix or the low-rank background error covariance matrix obtained from the EnKF?

Recently, a few DA studies at convective scale mainly focused just on the mature stage of the weather event have been carried out (e.g., Wheatley et al., 2015; Jones et al., 2016; Yussouf et al., 2020). However, investigating the mature stage means that the weather system is already developed and probably affecting the population. In such situations, the value of improving the atmospheric condition estimation using DA is very limited in terms of lead time, because there is no time left for warning the population and to take actions to reduce socio-economic impacts. In this context, very limited work has been done to assess the impact of DA in pre-convective systems to significantly improve the lead time, allowing warning systems to act as soon as possible. Here, we also investigate the role of the 3DVar and EnKF DA methods in improving pre-convective environment conditions of extreme weather events and how such improved pre-convective conditions could lead to a forecast improvement with significant time in advance to warn the population to take actions.

The following study aims at:

(a) Assessing the impact of high-resolution 3DVar in comparison with a high-resolution EnKF system to predict small-scale extreme weather events initiated over different areas and with lack of *in-situ* observations.

(b) Investigate the potential of using 3DVar and EnKF to enhance the accuracy of atmospheric conditions in the pre-convective environment, hours before the mature stage of convective systems are reached, thereby improving early prediction and warning capabilities for extreme weather events.

(c) Quantify the impact of assimilating *in-situ* conventional observations in comparison to assimilating high spatial and temporal resolution data from remote sensing instruments.

(d) Provide a quantitative assessment between the different DA schemes by means of using several statistical verification methods.

It is important to emphasize that this study is not aimed to draw any statistically significant conclusion. Instead, we are interested in comparing the performance of EnKF and 3DVar in two distinct extreme weather events, each with its unique set of conditions and constraints. A heavy rainfall episode affecting coastal regions of Italy during October 2012 (IOP13; Pichelli et al., 2017) and a low-predictable Mediterranean Tropical-like cyclone (medicane) affecting Sicily, known as Qendresa (Pytharoulis et al., 2017; Pytharoulis, 2018; Cioni et al., 2018; Di Muzio et al., 2019), are used for this study.

This paper is organized as follows. Section 2 briefly describes the meteorological characteristics of the two events used for comparing the impact of 3DVar and EnKF. In Section 3 the observation dataset that will be assimilated by the different DA methods will be presented.

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Section 4 briefly explains the main characteristics of the two DA algorithms that will be used in this study. Then, the numerical model configuration and the design of the different experiments for the two different case studies will be described in Section 5 and 6, respectively. Section 7 describes the verification methods used in this study. Results of the different numerical experiments for both meteorological situations are summarized in Section 8. Finally, conclusions are presented in Section 9.

2. Brief Description of Case Studies

Two different extreme weather systems, occurring in the Mediterranean region and affecting populated coastal regions, are considered in this study. The first extreme weather event was associated with heavy rainfall affecting central and northern Italy during October 2012 (IOP13), while the second extreme weather event was associated with the Qendresa medicane affecting southern Sicily, Lampedusa, Pantelleria and Malta islands during November 2014. Both systems were poorly forecasted, and for this reason they are perfect candidates for this intercomparison study.

2.1. The IOP13 Heavy Precipitation Episode

The *IOP13* occurred during the *First Special Observation Period* (SOP1) of the international project *Hydrological cycle in the Mediterranean Experiment* (HyMeX; Drobinski et al., 2014), that was mainly designed to better understand heavy rainfall and flash flooding episodes occurring in the Mediterranean region. The heavy precipitation IOP13 event took place between 14 and 16 October 2012, and it was characterized by a frontal precipitation system associated with a deep upper-level trough extending from northern France towards northern Spain (Fig. 1). It initially affected southern France coastal areas, and afterward it also affected the northern and central parts of Italy. During 15 October, the Italian rain gauge network registered 24-hour accumulated precipitation with peaks reaching 60 mm in central Italy, 160 mm in northeastern Italy and 120 mm in Liguria and Tuscany. During the night of 14 October, a cold front affected the Western Mediterranean region and during 15 October the system rapidly moved from France to Italy, advecting low-level moisture towards the western coast of Italy and Corsica, destabilizing the atmosphere and favoring deep moist convective activity. More details on the synoptic situation and observational data collected during IOP13 can be found in Ferretti et al., 2014.

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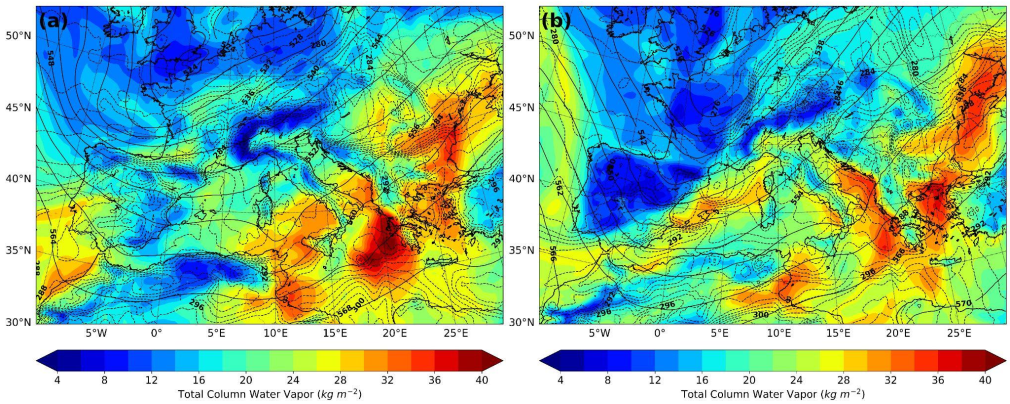

Figure 1. IOP13 ERA5 analyses: 500 hPa geopotential (solid black lines), 925 hPa temperature (dashed grey lines) and total column of water vapor (color shaded areas) at (a) 12 UTC 14 October and (b) 00 UTC 15 October 2012.

2.2. The Qendresa Tropical-Like Cyclone Episode

Among the wide spectrum of maritime extreme weather events, tropical-like Mediterranean cyclones, a.k.a. medicanes (Emmanuel, 2005), draw particular attention to the community mainly because they share similar morphological characteristics with tropical cyclones. Given their tendency to impact densely populated and economically critical areas around the Mediterranean basin, enhancing the accuracy and reliability of medicanes forecasts has become an urgent priority. Here, we focus on the 7 October 2014 medicane (Qendresa; Cioni et al., 2018) that affected the islands of Lampedusa, Pantelleria, Malta and the eastern coast of Sicily. This event was recognized by the community for its limited predictability (Carrió et al., 2017), making it a compelling case study for investigating the performance of the 3DVar and EnKF DA methods. *In-situ* observations located in Malta's airport registered gust wind values exceeding 42.7 m s^{-1} and a sudden and deep pressure drop greater than 20 hPa in 6 hours. Satellite imagery during its mature phase showed a well-defined cloud-free eye surrounded by axisymmetric convective activity, which resembles the morphological properties of classic tropical cyclones.

A deep upper-level trough associated with a cyclonic flow at mid-levels characterized the synoptic situation in the Western Mediterranean from 5 to 8 November 2014. The upper-level trough was associated with an intense PV streamer extending from Northern Europe to Southern Algeria, and the cyclonic flow at mid-levels was dominated by a strong ridge over the Atlantic and a deep trough moving along Western Europe. Late on 7 November, the upper-level trough became negatively tilted, evolving into a deep upper-level cut-off low and the PV streamer disconnected from the northern nucleus (Fig. 2). A small well-defined spiral-to-circular cloud shape formed just south of Sicily and evolved east-northeastward, reaching its maximum intensity over Malta, at midday. Finally, the cyclonic system dissipated as it crossed the Catania (eastern) coast of Sicily. More details on the synoptic situation and observational data collected during this event can be found in Carrió et al., 2017.

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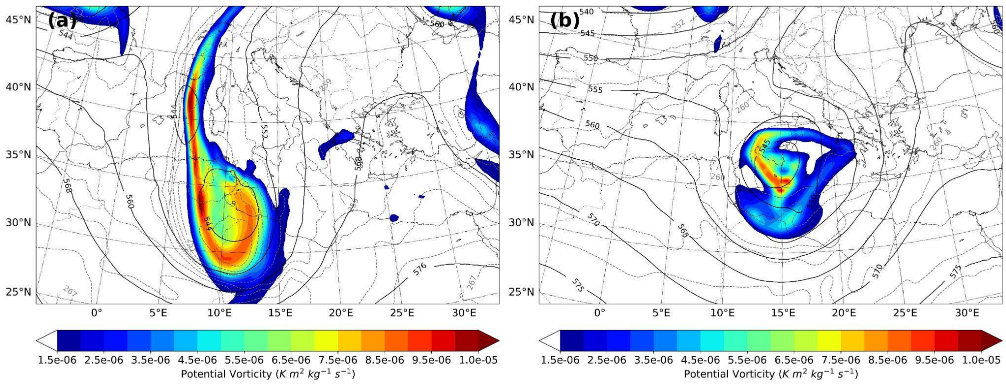

Figure 2. Qendresa ERA5 analyses: 500 hPa geopotential (solid black lines), 500 hPa temperature (dashed grey lines) and 300 hPa Potential Vorticity (color shaded areas) at (a) 00 UTC 7 November and (b) 00 UTC 8 November 2014.

3. Observations Description

In this study, different sources of remote-sensing and *in-situ* observations were available for the two case studies. Specifically, the following three types of observations were assimilated: (a) *in-situ* conventional data, (b) high temporal and spatial reflectivity data from two Doppler Weather Radars and (c) 3D wind speed and direction data derived from satellites.

3.1. IOP13 Observations

For the IOP13, *in-situ* conventional data and remote sensing observations from two Doppler Weather Radars were available. Moreover, conventional data were obtained from the NOAA's *Meteorological Assimilation Data Ingest System* (MADIS), which has the main advantage of providing high-level quality-controlled data[2] worldwide. In particular, pressure, temperature, humidity and horizontal wind speed and direction from *in-situ* instruments such as METARs, maritime buoys, rawinsondes and aircrafts (Fig. 3a). In addition to these conventional observations, reflectivity data from two Météo-France polarimetric S-band Doppler Weather Radars, were also available on the Gulf of Genoa. One located in Corsica Island (9.496ºE, 42.129ºN) at 63 m ASL, known as Aleria, and the other located in southern France (4.502ºE, 43.806ºN) at 76 m ASL, known as Nimes (Fig. 3a). These two radars, strategically positioned, ensure a good spatial coverage over the Ligurian Sea, the area where initiation and intensification of deep convection occurred, and provide key information about the 3D structure of the convective systems at high spatial and temporal resolution. The two radars perform 5 and 9 elevation scans every 5 minutes, respectively, and their data are available at the HyMeX's official website (see https://www.hymex.org). Specifically, Aleria radar provides data at 5 elevation angles: 0.57º, 0.96º, 1.36º, 3.16º and 4.57º with a mean frequency of 2.8 GHz. In comparison, Nimes radar provides data at 9 elevation angles: 0.58º, 1.17º, 1.78º, 2.38º, 3.49º, 4.99º, 6.5º, 7.99º and 89.97º, also at the same frequency. It is worth mentioning that Aleria and Nimes radar reflectivity data are provided by the Météo-France operational radar network and undergo rigorous data quality control. This ensures that common radar error sources, such as signal attenuation, ground clutter or beam blocking, are meticulously identified

[2] See https://madis.ncep.noaa.gov/madis_qc.shtml for further details on the Quality Control techniques used.

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and corrected. Radial velocity from Aleria and Nimes Doppler radars was also available, but because of the low reliability of the data (not quality controlled properly) it was not used in this study.

Hence, the following observations were assimilated for this event:

- Conventional *in-situ* data were hourly assimilated over the entire numerical domain considered (Fig. 3a).
- Reflectivity data from two weather radar from Météo-France were assimilated every 15 minutes (Fig. 3a).

The high spatial resolution of the reflectivity data poses significant challenges for their direct assimilation, potentially leading to detrimental analysis related with signal aliasing and the violation of the uncorrelated observational error assumptions followed in the derivation of the 3DVar and EnKF analysis equations. To mitigate the adverse effects associated with these issues, the *Cressman Objective Analysis* technique (Cressman, 1959) was used to interpolate raw radar observations to a regularly spaced 6 km horizontal grid, as suggested by previous work (i.e., Wheatley et al., 2015; Yussouf et al., 2015). It is important to note that reflectivity observations are typically obtained in polar coordinates, a prerequisite step before applying the Cressman interpolation involves converting them to a Cartesian coordinate system. We have performed several sensitivity tests using different grid space resolution (e.g., 3, 6, 9 km) and we found that using 6 km grid space produces the best analysis. To reduce spurious convective signals and remove excessive humidity the *null-echo* option, which allows assimilation of no precipitation echoes, has been adopted in 3DVAR experiment.

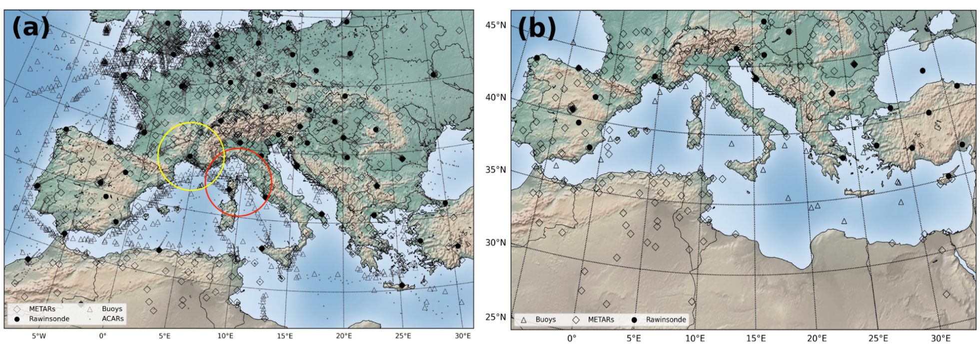

Figure 3. (a) IOP13 Episode: Spatial distribution of *in-situ* observations (gray and black markers) assimilated on the parent numerical domain during 24 h assimilation window from 00 UTC 14 October to 00 UTC 15 October 2012. Doppler Weather Radars located at Nimes and Aleria and their coverage range, depicted in yellow and red circles, respectively. (b) Qendresa Episode: Spatial distribution of *in-situ* observations hourly assimilated during 12 h assimilation window from 12 UTC 6 November to 00 UTC 7 November 2014.

3.2. Qendresa Observations

For the Qendresa episode, two different observational sources were available: (a) conventional *in-situ* observations and (b) satellite-derived observations. Conventional *in-situ* observations were obtained from MADIS database. However, only observations from buoys, METAR and rawinsonde were used for this case. It is essential to highlight that observation gaps persist

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across large areas of the region, particularly over the sea (Fig. 3b), where Qendresa initiated and evolved. As for the IOP13, we were interested in Doppler Weather Radars data to enhance the intensity and trajectory forecasts of Qendresa. Unfortunately, Doppler Weather Radars were not available in the neighborhood of the region where Qendresa initiated and evolved, but another source of observations, the so-called *Rapid-Scan Atmospheric Motion Vectors* (RSAMVs; Velden et al., 2017), which provides 3D wind information throughout the entire atmosphere (both speed and direction) at high spatial and temporal resolution (i.e., every 20-min), were available for this event over the sea. This satellite product is obtained using the *Spinning Enhanced Visible and Infrared Imager* (SEVIRI) instrument onboard the *Meteosat Second Generation* (MSG) satellite, which has a scanning frequency as low as 5 minutes. The final product is indeed obtained averaging 4 consecutive images.

Hence, the following observations were assimilated for this event:

- Conventional *in-situ* data from buoys, METAR and rawinsonde for the entire Mediterranean region were hourly assimilated.
- Wind speed and direction from the *Rapid-Scan Atmospheric Motion Vectors* for the entire atmosphere at high spatial and temporal resolution were assimilated every 20 minutes.

Recent studies have shown that upper-level dynamics played a key role in the genesis and the development of Qendresa (Carrió et al., 2017; Carrió, 2022), so the assimilation of RSAMVs is expected to significantly improve its predictability. Here, the infrared channel from RSAMVs (10.8 μm), which contains information throughout the entire atmosphere, was selected to be assimilated (Fig. 4). However, before assimilating RSAMVs, a quality control check to reject non-physical and outlier observations that could deteriorate the quality of the analysis and the successive forecast was applied. In addition, to minimize the effect of having spatial correlated observation errors associated to high density observations, the "*superobbing*" technique consisting in reducing the data density through spatially averaging the observations within a predefined prism is applied (i.e., Pu et al., (2008); Romine et al., (2013); Honda et al., (2018)). Based on the most accurate analysis obtained by multiple sensitivity experiments (not shown) for Qendresa, the RSAMVs data are thinned using a prism with horizontal dimensions of 128x128 km^2 and 25 hPa in the vertical dimension.

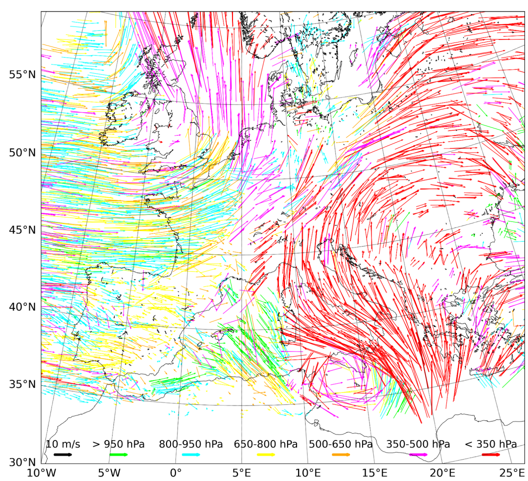

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Figure 4. Raw EUMETSAT's RSAMV observations depicted at different vertical levels by infrared channel 10.8 μm at 12 UTC on 7 November 2014 over the Mediterranean region. Wind information is only valid at the center of the wind vectors.

Observations from aircraft (i.e., ACARS) were not assimilated in this case because preliminary assimilation tests indicated a worsening of the results and led to a poorer estimation of the atmospheric state. Buoys, METAR and rawinsonde observations covering the entire Mediterranean region were hourly assimilated.

Finally, observational errors used for the assimilation of the observations associated with both IOP13 and Qendresa are motivated by Table 3 in Romine et al., (2013) with the following minor changes: METAR altimeter (1.5 hPa), marine altimeter (1.20 hPa), METAR and marine temperature (1.75 K) and RSAMV wind observations (1.4 m s^{-1}). These minor changes are found to provide better data assimilation analysis for the IOP13 and Qendresa extreme weather events in the Mediterranean region. The remaining of the observation errors are the same as the ones in Romine et al., (2013).

4. Data Assimilation Schemes

In the present study, two widely used data assimilation algorithms are used for improving the forecast of extreme weather events initiated and developed over poorly observed maritime regions and affecting densely populated coastal areas. We refer to the *Ensemble Adjustment Kalman Filter* and the variational *3DVar* data assimilation schemes, which are described below.

a) The Ensemble Adjustment Kalman Filter (EnKF)

The *Ensemble Adjustment Kalman Filter* (EAKF; Anderson 2001), which is implemented in the *Data Assimilation Testbed Research* (DART[3]), is used in this study as the former ensemble-based data assimilation technique. The EAKF provides an optimal estimation, in the least square error sense, of the true probability distribution of the state of the atmosphere by merging two main sources of information: (a) the available observations and (b) an ensemble of forecasts (a.k.a. *background*) valid at the analysis time. In particular, the EAKF assimilates the observations serially. This means that the analysis ensemble obtained by the EAKF after the assimilation of the first observation at a given time is then used as the *background* for the next observation at the same analysis time. This is done recursively until all the observations valid at the same analysis time are finally assimilated.

[3] http://www.image.ucar.edu/DAReS/DART/

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In particular, for each observation j from a set of p observations valid at the same analysis time, the EAKF can be summarized with the 4 main steps described below:

Step 1) Obtain the observed value y_j^o, and the associated observation error variance, R_{jj}

Step 2) Update the ensemble mean $\langle y_j^f \rangle$ and ensemble members y_j^f of the observed variable using:

$$\langle y_j^a \rangle = \langle y_j^f \rangle + \frac{H_j Z \left(H_j Z\right)^T}{H_j Z \left(H_j Z\right)^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right) = \langle y_j^f \rangle + \frac{H_j \mathbf{P}^f H_j^T}{H_j \mathbf{P}^f H_j^T + R_{jj}} \left(y_j^o - \langle y_j^f \rangle \right) \qquad \text{(Eq. 1)}$$

$$y_{ji}^a = y_{ji}^a + \sqrt{\left[1 - P^f \left(P^f + R_{jj}\right)^{-1}\right]} \left(y_{ji}^f - \langle y_j^f \rangle \right); \ \text{ for } i=1,\ldots,K \text{ and } P^f = H_j P^f H_j^T \qquad \text{(Eq. 2)}$$

where $y_{ji}^f = H_j\left(\mathbf{x}_i^f\right);\ \langle y_j^f \rangle = \frac{1}{K}\sum_{i=1}^{K} H_j\left(\mathbf{x}_i^f\right);\ H_j Z = \frac{1}{\sqrt{K-1}}\left[y_{j1}^f - \langle y_j^f \rangle, \ldots, y_{jK}^f - \langle y_j^f \rangle \right]$

Step 3) Find corresponding analysis ensemble for the observations and model variables using a linear regression step:

$$y_{ki}^a = y_{ki}^f + \frac{H_k Z \left(H_j Z\right)^T}{H_k Z \left(H_j Z\right)^T + R_{jj}} \left(y_{ji}^a - y_{ji}^f \right), \text{ for } k = 1,\ldots,p \text{ and } i = 1,\ldots,K \qquad \text{(Eq. 3)}$$

$$x_{\mu i}^a = x_{\mu i}^f + \frac{Z(\mu,:) \left(H_j Z\right)^T}{H_k Z \left(H_j Z\right)^T + R_{jj}} \left(y_{ji}^a - y_{ji}^f \right), \text{ for } \mu = 1,\ldots,n \text{ and } i = 1,\ldots,K \qquad \text{(Eq. 4)}$$

where n is the number of model variables.

Step 4) Let the analysis ensemble become the background ensemble for the next observation:

$$y_{ki}^f = y_{ki}^a, \quad \text{for } k = 1,\ldots,p \text{ and } i = 1,\ldots,K \qquad \text{(Eq. 5)}$$

$$x_{\mu i}^f = x_{\mu i}^a, \quad \text{for } \mu = 1,\ldots,n \text{ and } i = 1,\ldots,K \qquad \text{(Eq. 6)}$$

In the above equations, K is the number of ensemble members, p the number of observations, n is the number of model variables, H is the observation operator (non-linear) and Z the ensemble perturbations about the mean. The superscripts "*a*" and "*f*" stand for the analysis and forecast, respectively.

Ensemble covariances used in high-resolution simulations, such as the present study, where only a limited number of ensemble members is feasible, suffers from sampling error, resulting in the generation of spurious correlations that hamper the analysis (Hacker et al., 2007). The detrimental effects of these spurious correlations are mitigated by employing covariance localization functions that go to zero as the distance between the assimilated observation and the grid model point where the analysis occurs, increases (Houtekamer and Mitchell, 1998). In our case, a fifth-order piece-wise rational Gaussian localization function is used (Gaspari and

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Cohn, 1999). For this study, after several sensitivity simulations it was found that using a half-radius[4] of 230 km in the horizontal and a half-radius of 4 km in the vertical for the horizontal and vertical localizations, respectively, results in the best performance of the DA scheme.

The assimilation of each observation results in a reduction of the ensemble spread, attributed to using a reduced-moderate ensemble size (Anderson and Anderson, 1999). To address this issue and help to maintain the spread, an *adaptive inflation technique* (Anderson and Collins, 2007; Anderson et al., 2009) is applied to the prior ensemble before assimilating the observations. The adaptive inflation technique increases the spread of the ensemble without changing the mean. The inflation value has a probability density distribution described by a mean and a standard deviation. In this study, it was determined that initializing the mean value of inflation at 1.0 and using a standard deviation of 0.6, yields the best performance of the DA scheme.

b) Three-dimensional Variational Data Assimilation (3DVar)

The 3DVar technique, implemented in WRFDA (Barker et al., 2004), is adopted for the numerical simulations. The 3DVar aims to seek the best estimate of the initial conditions through the iterative minimization of a cost function:

$$J(\mathbf{x}) = \frac{1}{2}\left\{(\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \left[\mathbf{y}_o - \mathbf{H}(\mathbf{x})\right]^T \mathbf{R}^{-1}\left[\mathbf{y}_o - \mathbf{H}(\mathbf{x})\right]\right\} \qquad \text{(Eq.7)}$$

where **B** and **R** are the background and observation error matrices, respectively; **x** is the state vector; $\mathbf{y}_o$ is the observations, $\mathbf{x}_b$ is the first guess and H is the forward (non-linear) operator that converts data from model space to observation space.

The solution of the above cost function J consists in finding a state $\mathbf{x}_a$ (analysis), that minimizes the distance between the observations and the background field. However, in a model with 10^6 degrees of freedom, the direct solution is computationally expensive. To reduce the complexity and calculate $\mathbf{B}^{-1}$ more efficiently, a pre-conditioning is applied by transforming the control variables, respectively, pseudo relative humidity, temperature, u, v, and surface pressure, as $\mathbf{x} - \mathbf{x}_b = \mathbf{U}v$, where v is the control variable and **U** the transformation operator.

Regarding the assimilation of radar reflectivity, the observation operator from Sun and Crook (1997) is adopted:

$$Z = a + b\log_{10}(\rho q_r) \qquad \text{(Eq. 8)}$$

where Z is the reflectivity, q_r is the rainwater mixing ratio, ρ the air density whereas the coefficients a and b are equal to 43.1 and 17.5, respectively.

The background error covariance matrix **B** matrix plays a key role in the assimilation process by weighing and smoothing the information from observations and by ensuring a proper balance between the analysis fields. The *National Meteorological Center* method (NMC; Parrish and Derber, 1992) was used to model the B matrix. This method evaluates the

[4] The half-radius or cutoff term is defined here as 0.5 times the distance to where the impact of the observation assimilated go to zero. Multiplying the half-radius by 2 results in the maximum distance at which an observation can modify the model state.

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differences, over a period of two weeks, between two short-term forecasts valid at the same time but with different lead time, 12h and 24h, respectively, to generate the forecast error covariance matrix **B**. Recently, several works (Wang et al., 2013; Li et al., 2016; Shen et al., 2022; Ferrer Hernandez et al., 2022) show the benefit of using a slightly different approach for the **B** matrix (CV7) in assimilating radar reflectivity, besides in precipitation forecast accuracy. The CV7 differs from the others by using empirical orthogonal functions (EOFs) to represent the vertical covariance instead of a vertical recursive filter. Moreover, the control variables are in eigenvector space, and they are the following: u, v, temperature, pseudo relative humidity (RH_s), and surface pressure (P_s). Therefore, CV7 option has been used to generate the **B** matrix for both case studies. In this study, the weak penalty constraint (WPEC) option (Li et al., 2015) implemented in WRFDA has been activated to improve the balance between the wind and thermodynamic state variables, enforcing the quasi-gradient balance on the analysis field.

5. Model set-up

The mesoscale Advanced Research Weather Research and Forecasting Model (WRF; Skamarock et al., 2008) version 3.7 is used in this study. WRF solves a fully compressible and non-hydrostatic set of equations, using a η terrain-following hydrostatic-pressure vertical coordinate. The Arakawa C-grid staggering scheme and a third-order Runge-Kutta time-integration, to improve the precision of the numerical solutions, are used. Because IOP13 and Qendresa episodes took place in different locations and with different conditions, two different model configurations were used. For the IOP13 episode, a one-way nested model configuration with the parent domain centered over the Western Mediterranean Sea, covering Central Europe and North Africa, with a horizontal grid-resolution of 15 km (168x247) and a nested domain centered over Gulf of Genoa with a horizontal grid-resolution of 3 km (250x250) were used (Fig. 5a). Both domains were characterized to have 51 vertical model levels, from surface to 50 hPa, with higher density of levels in the lower part of the atmosphere than in the upper. For Qendresa, a two one-way nested model configuration is also used, but now the parent domain is centered over the Central Mediterranean Sea, covering most of the European region and the northern part of Africa (Fig. 5b), using a horizontal grid resolution of 15 km (245x245). The nested domain is centered over Sicily (Southern Italy) using a grid resolution of 3 km (253x253). Both numerical domains use a 51 terrain-following η levels up to 50 hPa, as in the IOP13 case.

For the EnKF DA experiments, initial and boundary conditions used to perform the simulations associated with IOP13 were obtained from the *European Center of Medium Range Weather Forecasts Global Ensemble Prediction System* (EPS-ECMWF), which stored meteorological fields using a horizontal and vertical spectral triangular truncation of T639L62 (i.e., ~32 km grid resolution in the horizontal). In particular, the EPS-ECMWF provides 51 different initial and boundary conditions from 50 perturbed ensemble members plus a control simulation. However, due to unfeasible computational resources required to run our numerical simulations at high grid resolution, here we will use an ensemble consisting of 36 members. This configuration is analogous to the one used at the internationally prestigious *National Oceanic and Atmospheric Administration - National Severe Storms Laboratory* (NOAA-NSSL) in Norman (Oklahoma, USA) to improve predictability of tornadoes. To obtain the desired 36-member ensemble, a *Principal Components Analysis* and *K-mean* clustering technique were used together to select the 36 ensemble members from the EPS-ECMWF showing more dispersion over the entire numerical domain (see Garcies and Homar, 2009 and Carrió et al., 2016 for more details using these techniques). To perform Qendresa DA simulations, the initial

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and boundary conditions were obtained following the same methodology explained above for the IOP13 case, i.e., using an ensemble of 36 members obtained from the EPS-ECMWF. On the other hand, the initial and boundary conditions for 3DVar simulations are provided by the *Integrated Forecast System* (IFS) global model from the ECMWF, with a spatial resolution of 0.1° x 0.1° and updated every 3 hours.

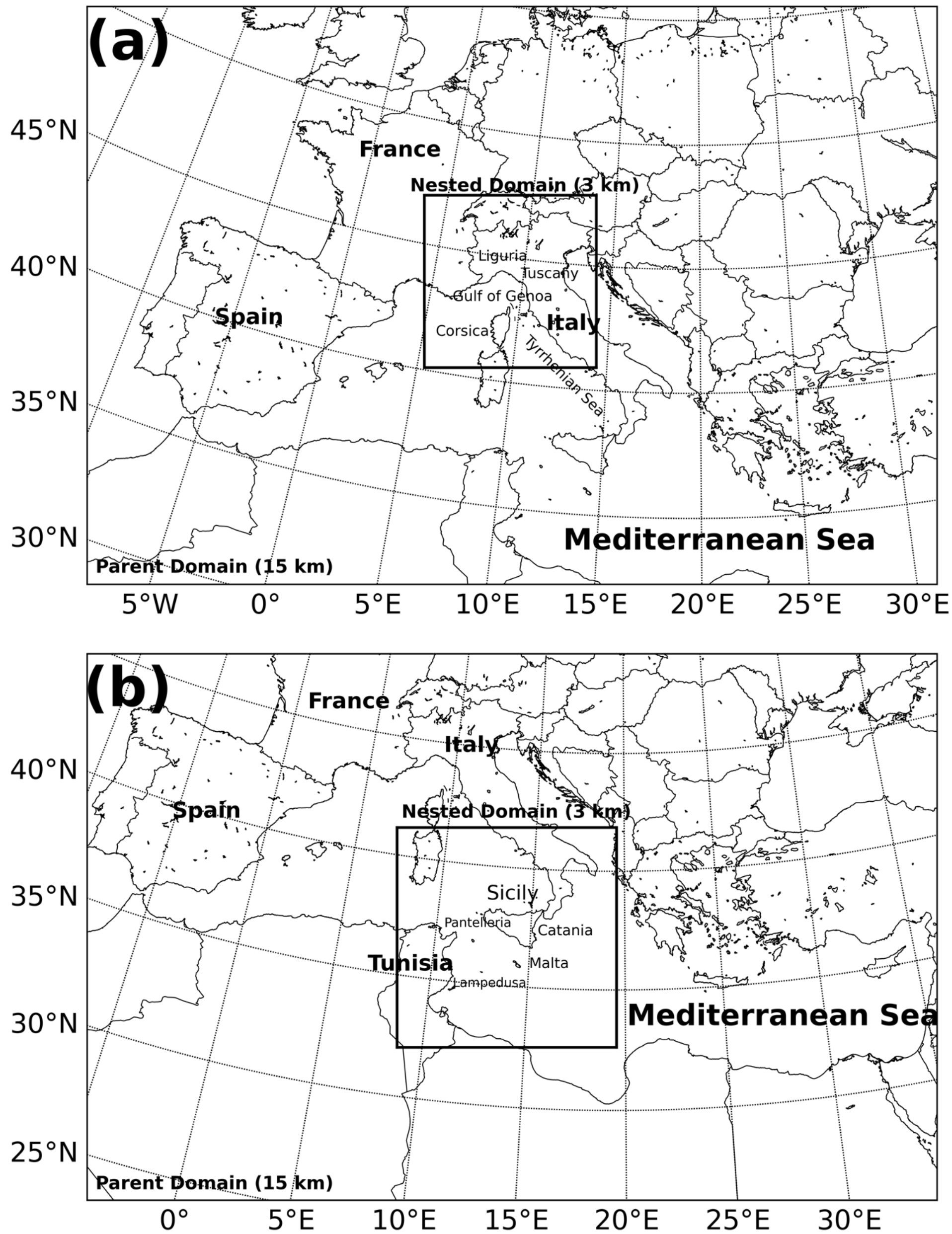

Figure 5. Mesoscale and storm-scale numerical domains used in this study for the (a) IOP13 and (b) Qendresa episodes, respectively.

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To estimate the uncertainties of WRF, which is a necessary information for the EnKF, a multiphysics ensemble is built for both the IOP13 and Qendresa event (e.g., Stensrud et al., (2000); Wheatley et al., (2012)), where each ensemble member gets a different set of parameterizations (see Table 1). In particular, the diversity in our ensemble consists of (a) two short- and long-wave radiation schemes [Dudhia (Dudhia, 1989) and RRTMG (Iacono et al., 2008)], (b) three cumulus parameterizations schemes [Kain-Fritsch (KF; Kain and Fritsch, 1993; Kain, 2004), Tiedtke (Tiedtke, 1989) and Grell-Freitas (GF; Grell and Freitas, 2013)] and (c) three planetary boundary layer schemes [Yonsei University (YSU; Hong et al., 2006), Mellor-Yamada-Janjic (MYJ; Janjic, 1990, 2001), and Mellor-Yamada-Nakanishi-Niino level 2.5 (MYNN2; Nakanishi and Niño, 2006, 2009)]. Two widely used physics parameterizations are adopted for the microphysical processes and land surface interactions, the New Thompson (Thompson et al., 2008) and Noah (Tewari et al., 2004) schemes, respectively. Note that the above-mentioned physical parameterizations are used for both the large-scale ensemble in the parent domain and the storm-scale ensemble in the nested domain, except for the cumulus parameterization that is only applied in the parent domain ensemble. On the other hand, for the WRF deterministic simulation using 3DVar, the microphysical processes are parametrized by using the New Thompson scheme, while a YSU scheme is adopted for PBL. Long- and short-wave radiation are considered through a RRTMG and Dudhia scheme, respectively; while Kain-Fritsch scheme is used for the convection, except for the inner domain where it is explicitly resolved.

Table 1: Multiphysics parameterizations used to generate the 36-member ensemble for the EnKF experiments in IOP13 and Qendresa episodes. PBL, SW and LW stand for planetary boundary layer, short-wave and long-wave, respectively.

Multiphysic Configuration											
Ens. Memb.	**MP**	**CU**	**PBL**	**Land Sfc**	**SW/LW Rad.**	**Ens. Memb.**	**MP**	**CU**	**PBL**	**Land Sfc**	**SW/LW Rad.**
1	New Thompson	KF	YSU	Noah	Dudhia	**19**	New Thompson	KF	YSU	Noah	Dudhia
2	New Thompson	KF	YSU	Noah	RRTMG	**20**	New Thompson	KF	YSU	Noah	RRTMG
3	New Thompson	KF	MYJ	Noah	Dudhia	**21**	New Thompson	KF	MYJ	Noah	Dudhia
4	New Thompson	KF	MYJ	Noah	RRTMG	**22**	New Thompson	KF	MYJ	Noah	RRTMG
5	New Thompson	KF	MYNN2	Noah	Dudhia	**23**	New Thompson	KF	MYNN2	Noah	Dudhia
6	New Thompson	KF	MYNN2	Noah	RRTMG	**24**	New Thompson	KF	MYNN2	Noah	RRTMG
7	New Thompson	GF	YSU	Noah	Dudhia	**25**	New Thompson	GF	YSU	Noah	Dudhia
8	New Thompson	GF	YSU	Noah	RRTMG	**26**	New Thompson	GF	YSU	Noah	RRTMG
9	New Thompson	GF	MYJ	Noah	Dudhia	**27**	New Thompson	GF	MYJ	Noah	Dudhia

10	New Thompson	GF	MYJ	Noah	RRTMG	**28**	New Thompson	GF	MYJ	Noah	RRTMG
11	New Thompson	GF	MYNN2	Noah	Dudhia	**29**	New Thompson	GF	MYNN2	Noah	Dudhia
12	New Thompson	GF	MYNN2	Noah	RRTMG	**30**	New Thompson	GF	MYNN2	Noah	RRTMG
13	New Thompson	Tiedke	YSU	Noah	Dudhia	**31**	New Thompson	Tiedke	YSU	Noah	Dudhia
14	New Thompson	Tiedke	YSU	Noah	RRTMG	**32**	New Thompson	Tiedke	YSU	Noah	RRTMG
15	New Thompson	Tiedke	MYJ	Noah	Dudhia	**33**	New Thompson	Tiedke	MYJ	Noah	Dudhia
16	New Thompson	Tiedke	MYJ	Noah	RRTMG	**34**	New Thompson	Tiedke	MYJ	Noah	RRTMG
17	New Thompson	Tiedke	MYNN2	Noah	Dudhia	**35**	New Thompson	Tiedke	MYNN2	Noah	Dudhia
18	New Thompson	Tiedke	MYNN2	Noah	RRTMG	**36**	New Thompson	Tiedke	MYNN2	Noah	RRTMG

6. Design of IOP13 and Qendresa Experiments

To quantitatively assess the benefits of assimilating different types of observations using the 3DVar and the EnKF DA schemes, a few numerical experiments are performed. A reference experiment without any data assimilation is carried out. Then, several numerical experiments using different types of observations for the assimilation are performed. Only conventional *in-situ* observations are assimilated using the 3DVar and the EnKF, for the first set of experiments. All available observations (i.e., conventional, radar based and satellite derived data) are assimilated using both 3DVar and EnKF, for the second type of experiments. The comparison between these numerical experiments will provide information on which DA scheme and observation is performing better for these weather events. The DA experiments mainly consist of two phases: the first one is related to the data assimilation procedure, where different types of observations are assimilated by the variational 3DVar and the ensemble-based EnKF DA schemes; the second phase is associated with the free model run initialized using the initial conditions obtained during the first phase. The total forecast time is 24 h and 36 h for IOP13 and Qendresa, respectively. For IOP13, a further simulation lasting 6-hour from 18 UTC 13 October to 00 UTC 14 October 2012 (Carrió et al., 2019) is performed (Fig. 6) to reduce spin-up problems related to the direct downscaling from global ECMWF analysis (32 km grid resolution) to the WRF parent domain used in our simulations (16 km grid resolution). This procedure improved the DA for IOP13, but it had a small impact for Qendresa.

Therefore, the following model simulations were performed:

- No Data Assimilation (NODA)
- Only conventional *in-situ* observations are assimilated using the 3DVar and the EnKF (SYN)
- All available observations (i.e., conventional, radar based and satellite derived data) are assimilated using both 3DVar and EnKF (CNTRL)

The comparison between SYN and CNTRL will allow for assessing the role of radar and/or satellite data, especially for the events originated in the area where observations are not available. Moreover, the assimilation of the radar and/or satellite will produce important information on the triggering phase of both events developing on the sea.

6.1. CNTRL Experiments

For IOP13, the CNTRL experiment is designed to assimilate both *in-situ* conventional and reflectivity observations from Aleria and Nimes Doppler weather radars. The assimilation of the reflectivity is expected to improve the forecast of this event by significantly improving the initial conditions over the sea, where convective activity initiated and evolved into deep convection affecting coastal populated areas of Italy. As briefly described in the previous section, this experiment consists of three stages: 1) the spin-up of the storm-scale domain is accounted for by running the WRF model during 6 hours from 18 UTC 13 October to 00 UTC 14 October 2021. Note that for the 3DVar experiment, the spin-up is accounted by just initializing WRF with the deterministic analysis from the IFS ECMWF. However, for the EnKF counterpart, the spin-up is accounted by initializing the 36-member ensemble at 18 UTC 13 October; 2) *in-situ* conventional observations were hourly assimilated during 24 hours from 00 UTC 14 October to 00 UTC 15 October, meanwhile reflectivity observations were assimilated using a Rapid-Update Assimilation Cycle every 15 minutes during a period of 6 hours, from 18 UTC 14 October to 00 UTC 15 October (Fig. 6b); and 3) a 24-h ensemble (deterministic) forecast until 00 UTC 16 October, using the recently obtained initial conditions, is performed by the EnKF (3DVar).

For the Qendresa episode, CNTRL experiment is designed to assimilate both *in-situ* conventional and RSAMV observations. The assimilation of RSAMV observations is expected to improve the representation of the atmospheric circulation at upper-levels, whereas the assimilation of surface conventional observations is expected to enhance the one at low-levels. The Qendresa CNTRL experiment consists of two main phases: 1) *in-situ* conventional and satellite derived RSAMV observations are hourly and 20-min assimilated, respectively, during a 12-h period from 12 UTC 6 November to 00 UTC 7 November 2014 to end up with the last analysis at the end of the assimilation window (i.e., 00 UTC 7 November); 2) a free 36-h ensemble (deterministic) forecast is performed by the EnKF (3DVar) from 00 UTC 7 November to 12 UTC 8 November 2014 (Fig. 6e).

6.2. SYN Experiments

For IOP13, the SYN experiment assesses the impact of *in-situ* conventional observations, which are crucial to characterize mesoscale atmospheric circulation. Analogous to the CNTRL, SYN follows the same three phases, but in the second phase only the hourly *in-situ* conventional observations from 00 UTC 14 October to 00 UTC 15 October 2012 are assimilated. The analysis obtained from the assimilation stage is used as initial conditions for running the free forecast for 24h, in the third phase (Fig. 6a).

Similarly, also for Qendresa, in the SYN experiment only *in-situ* conventional observations are hourly assimilated for 12 hours, from 12 UTC 6 November to 00 UTC 7 November 2014 (Fig. 6d).

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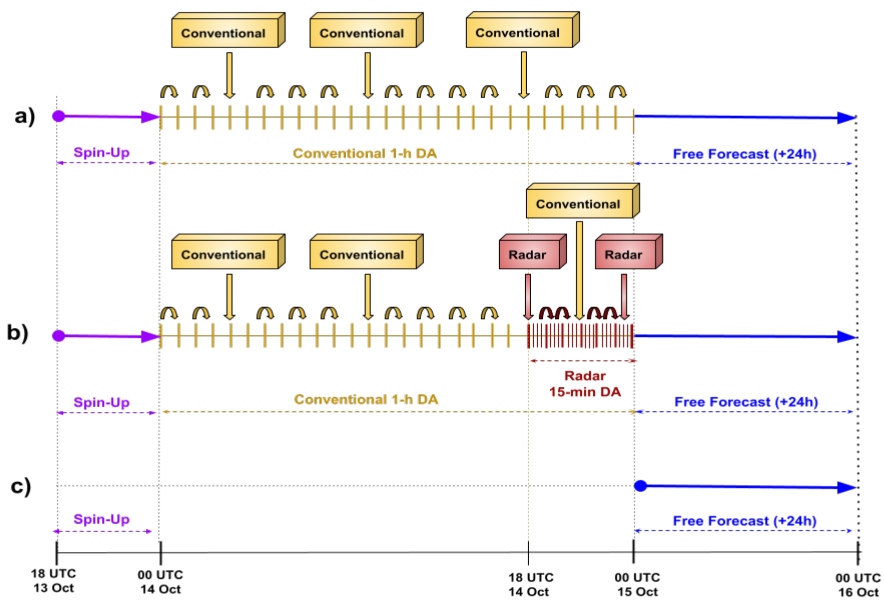
6.3. NODA Experiments

For the IOP13, NODA experiment is a direct downscaling from EPS-ECMWF boundary and initial conditions valid at 00 UTC 15 October to 00 UTC 16 October 2012. To the aim of simulating an operational framework, the NODA experiment starts at 00 UTC 15 October, instead of starting at 18 UTC 14 October (Fig. 6c). With this choice of the starting time, one could answer the question of which forecast system we should use to predict a 24-48 h forecast. Should we simply perform a simple downscaling using the last analysis obtained from a global model, or should we start our simulation with a previous analysis but now using DA at high temporal and spatial resolution to enhance the estimation of the initial conditions? The comparison among NODA, CNTRL and SYN will provide us with valuable information on the impact of assimilating different sources of observations.

For Qendresa, NODA experiment is simply a direct downscaling of 36 hours from EPS-ECMWF at 00 UTC 7 November to 12 UTC 8 November 2014 (Fig. 6f). Here again, it is important to note that the choice of starting NODA at 00 UTC 7 November instead of starting at 12 UTC 6 November was made intentionally to extract general conclusions applicable to an operational framework.



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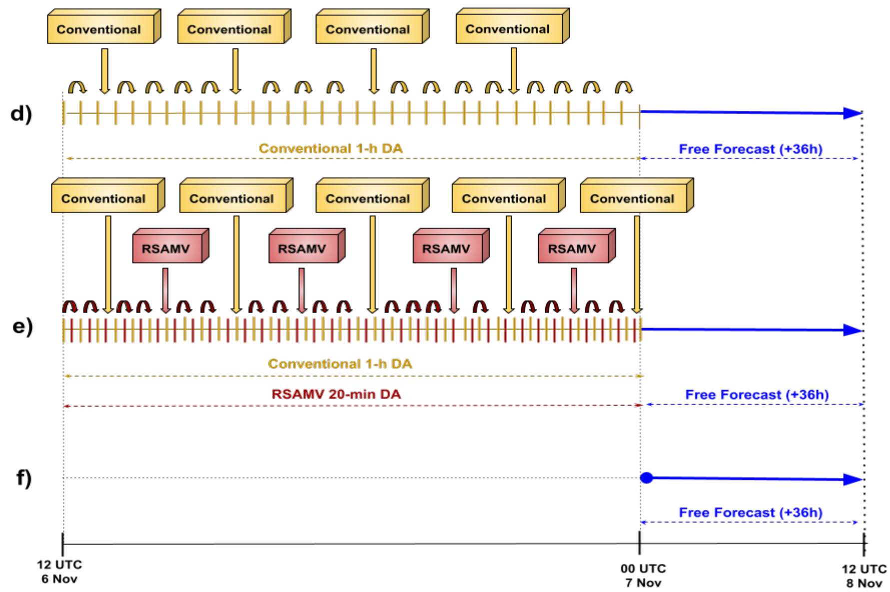

Figure 6. Schematic representation of the main numerical experiments performed in this study for the IOP13 and Qendresa episodes, respectively. SYN, CNTRL and NODA experiments for the IOP13 are shown in (a), (b) and (c) panels, respectively, meanwhile the ones corresponding to Qendresa are shown in (d), (e) and (f), respectively.

7. Verification Methods

To quantitatively evaluate the performance of the EnKF and the 3DVar and their impact on the short-term forecasting of these two extreme weather events, various verification scores are used. Given the different nature of the weather phenomena associated with these episodes, the selection of verification scores is tailored specifically to each event. For the IOP13 heavy precipitation event (Fig. 7a), the model verification was performed using the observed accumulated precipitation field over different time windows (e.g., 3 hours, 6 hours or 9 hours). More specifically, the accumulated precipitation was computed using observations from the *Italian Department of Civil Protection*. However, the spatial distribution of rain gauges is not homogenous and there are regions where a lack of rain gauges is present. To address these issues, three sub-regions are chosen where the heavy precipitation event was well recorded by the weather stations (see R1, R2 and R3 in Fig. 7b). Conversely, for the Qendresa tropical-like cyclone, a limited number of *in-situ* observations were present since it initiated and moved over the sea during its lifecycle, and radar-data were not available. Consequently, IR satellite imagery was the primary source of data to approximately estimate Qendresa's trajectory (Fig. 7c). Regarding the intensity of Qendresa, since the cyclone's center passed over Malta island, reaching its minimum mean sea level pressure (MSLP) of 985 hPa, METAR data from Malta's airport was also used to verify the cyclone's intensity (Fig. 7d).

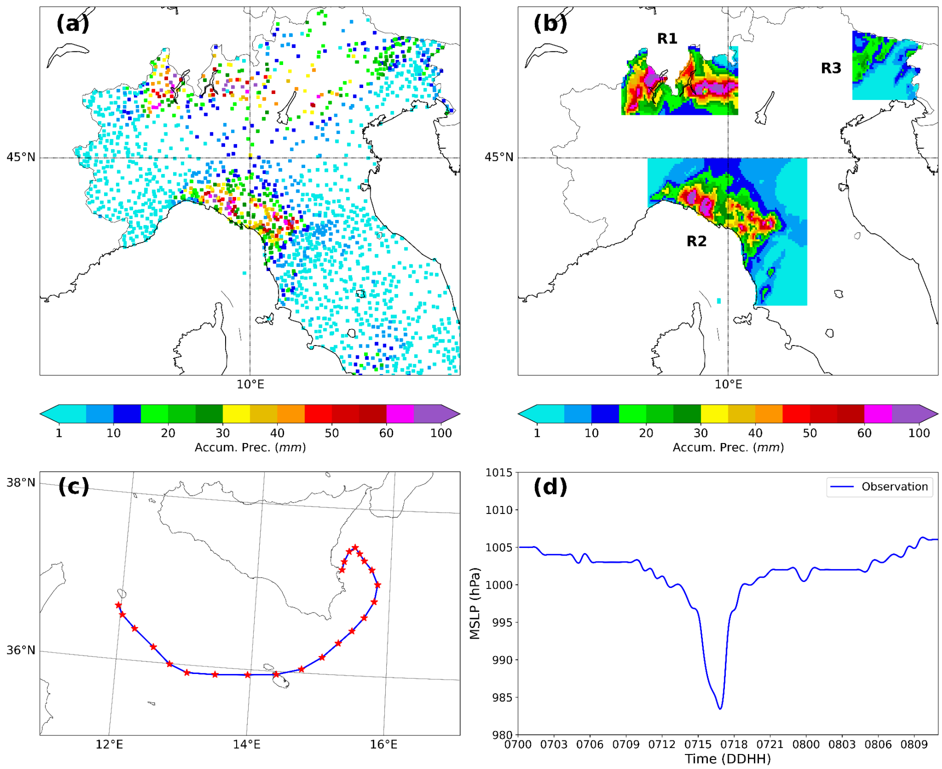

Figure 7. (a) Example of the 12-h accumulated precipitation estimated values and their spatial distribution from the *Italian Department of Civil Protection* rain gauges. (b) Linear interpolation of 12-h accumulated precipitation values into the three target areas where verification has been performed. (c) Observed track of Qendresa medicane viewed from infrared satellite imagery. (d) Surface pressure (hPa) data obtained from the METAR station at Malta's airport.

To quantitatively assess the short-term (i.e., first 6-9 hours) precipitation forecast for the IOP13 initialized using the analysis from the 3DVar and EnKF DA techniques, the *Filtering Method*, the *Relative Operating Characteristics* (ROC; Mason, 1982; Stanski et al., 1989; Swets, 1973) and the *Taylor Diagrams* (Taylor, 2001) were used. We avoid using the conventional point-by-point approach, which has been shown to have serious limitations in the evaluation of high-grid spatial and temporal precipitation field resolutions (Roberts, 2003). More specifically, as *Filtering Method* we use the *Fraction Skill Score* (FSS; Roberts and Lean, 2008), which is commonly used to quantitatively assess precipitation. A preliminary interpolation of the forecast and the observations onto a common regular mesh of 3 km is performed to compute FSS. Then the comparison is carried out within a region of 3x3 grid cells around each grid cell. The FSS can be used to determine the scale over which a forecast system has sufficient skill (Mittermaier, 2010). The FSS ranges from 0 to 1, being 1 a perfect match between model and observations. In addition to the ROC curves, the *Area Under the ROC Curve* (AUC; Stanski et al., 1989; Schwartz et al., 2010), which is also widely used to quantitatively assess the quality of weather forecasts, will be also used in this study. For a perfect forecast, AUC is equal to 1.

For Qendresa, the *Whisker diagrams* (Tukey, 1977) and the *Probability Distribution of the Cyclone Center Occurrence* **(PCCO)**, which was based on the *Kernel Density Estimation*

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(KDE; Bowman and Azzalini, 1997; Scott, 2015; Silverman, 2018), were used to validate the simulations. More specifically, the KDE is used to compute the probability of having the center of the cyclone over the entire numerical domain. The main idea behind KDE is to place a "kernel" (i.e., a probability distribution function) at each data point, and then sum up the kernels to estimate the overall probability density function. The kernel is typically chosen to be a smooth function, such as a Gaussian, that decays to zero as the distance from the data point increases. The width of the kernel is controlled by a parameter called the bandwidth, which it turns out to be one of the limitations of the KDE technique. In this case, we found that the optimal bandwidth is 20 km, which is within the meso β scale, i.e. a typical length scale for convective cells. Here, a 2-dimensional KDE will be applied over each cyclone center (*lat*, *lon* coordinates) identified for the different simulations (i.e., EnKF vs 3DVar). In this way, we will infer the most probable track of Qendresa for the different simulations, thereby identifying which is the best DA technique and which provides better estimations of Qendresa medicane's track.

8. Results

To quantitatively estimate the impact on the short-range forecast from assimilating the different types of observations considered in this study, using the 3DVar and the EnKF, the abovementioned verification techniques were applied for the two extreme events. Because of the differences in their features, we used the *Filtering method*, the *Relative Operating Characteristics* (ROC) and *Area Under the ROC curve* and the *Taylor diagrams* for IOP13, and the *Whisker diagrams* and the *Probability Distribution of Cyclone Center Occurrence* for Qendresa. The results are described in the following subsections.

8.1. Statistical analysis: IOP13 Episode

Because IOP13 was a heavy rainfall episode, to quantitatively assess the impact on the short-range forecasts from assimilating both *in-situ* conventional and reflectivity observations from Doppler weather radars using the 3DVar and the EnKF DA algorithms, the accumulated precipitation field will be used here.

8.1.1. Filtering Method

The FSS associated with the accumulated precipitation field is computed independently for the three sub-regions R1, R2 and R3 highlighted in Fig. 7b, where the density of observation was higher, using as threshold 1 $mm \cdot h^{-1}$. In general, the comparison in terms of FSS (Fig. 8 a-c) shows that EnKF outperforms 3DVar during the first 7 hours of free forecast in the three sub-regions. As it was expected, the CNTRL experiments for both the EnKF and 3DVar outperform the SYN experiments, where reflectivity observations were not considered. Moreover, Fig. 8a shows that the 3DVar-CNTRL provides the worst scores, except for the first few hours of simulation where 3DVar-CNTRL performs better than 3DVar-SYN. This is because the information ingested from the radar using the 3DVar in that region is lasting no longer than 2 hours. Something similar happens with the EnKF after 4 hours. These results would agree with past studies, showing similar behaviors (Carrió et al., 2016; Carrió et al., 2019).

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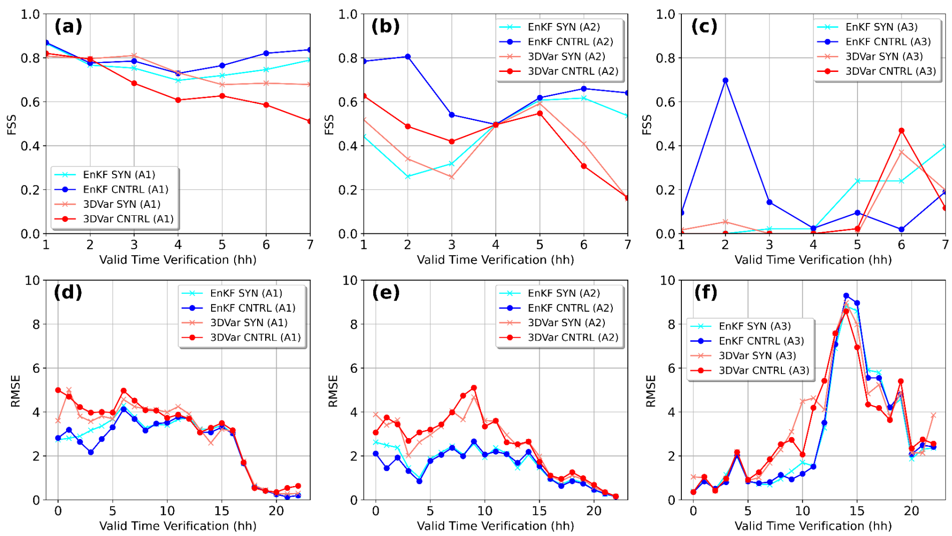

Figure 8. Upper panels: Evolution of the FSS during the first 7 hours of free forecast in the Italian sub-regions (a) R1, (b) R2 and (c) R3, using a threshold > 1 $mm \cdot h^{-1}$. Lower panels: Evolution of the RMSE during the first 24 hours of free forecast in the sub-regions (d) R1, (e) R2 and (f) R3. Simulations assimilating both conventional and radar observations (CNTRL) and simulations assimilating only conventional observations (SYN) associated with the 3DVar and the EnKF are shown here.

In addition to the FSS, we also compute the typical and widely used root-mean-squared-error (RMSE) on the precipitation field for the first 24 hours for both EnKF and 3DVar simulations. In general, the EnKF provides the lowest (best) RMSE scores, with respect to 3DVar. Also, note that the impact of the assimilation of reflectivity observations does not last more than 4-6 hours, in accordance with past studies.

8.1.2. ROC and AUC

To strengthen how skillful are the different simulations performed by the 3DVar and the EnKF, the *Receiver Operating Characteristic* (ROC) curve is used. The probability of exceeding a given threshold is computed and verified against dichotomous observations. The ROC curve is computed as follows: the model variable is interpolated to the observation locations and if the model variable exceeds a given threshold, that model grid point is assigned a value of 1. On the contrary, if the model value does not exceed that threshold, the assigned value is 0. The same method is applied for the observations. Then, using these dichotomous values, the Hit Rate and False Alarm scores are computed. This process is repeated, varying the threshold value. Gathering the Hit Rate and False Alarm scores for the different thresholds, we obtain the ROC curve. For the 3DVar, we get the Hit Rate and False Alarm scores by simply interpolating the model values to the observation locations and apply the threshold criteria explained above. In the case of the EnKF, the ensemble mean is used as the field to be interpolated to the observation locations. The area under the ROC curve (AUC), which measures the ability of the system to discriminate between the occurrence or nonoccurence of the event, is also computed.

For the sake of brevity and because the results from the three sub-regions are similar, the ROC and the area under the ROC curve are computed, accounting for all the observations within the

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inner numerical domain. Specifically, to compute the ROC curves, we use the 3-hour (from 00 UTC - 03 UTC 15 Oct) and 6-hour (from 00 UTC - 06 UTC 15 Oct) accumulated precipitation fields from the numerical model and the observed values registered by the rain gauges, using 1 mm and 10 mm as thresholds (Fig. 9).

Results show that EnKF clearly outperforms 3DVar for the different accumulated precipitation rates and thresholds, depicting larger values of AUCs. An even bigger improvement is obtained using a larger threshold (i.e., bottom row of Fig. 9) for EnKF, where the benefits of assimilating radar observations are noticeable, in comparison with 3DVar. To better understand this result, we inspected in more detail the 1-h and 6-h accumulated precipitation fields obtained from the EnKF (CNTRL) and the 3DVar (CNTRL) and we compared those fields against the corresponding observations (see Fig. A1 in the Appendix). The 1-h accumulated precipitation (first row, Fig. A1) shows that the EnKF is localizing with high accuracy the regions where the most intense precipitation was observed, that is near Tuscany and northern Italy. Also, 3DVar correctly reproduces the rainfall in the regions affected by observed precipitation, although the maximum amounts are centered over Liguria, instead of near Tuscany. In addition, the 3DVar is also showing a tongue area of weak precipitation from Liguria to northern Italy, that does not fit with the observations. Hence, although there are some differences between 3DVar and EnKF for the 1-h accumulated precipitation field, because the accumulated precipitation values are small, the ROC verification scores from the EnKF and 3DVar do not differ significantly. However, in the case of the 6-h accumulated precipitation (second row, Fig. A1), the 3DVar produces higher values of accumulated precipitation near Liguria, Tuscany and northern Italy than the observed ones. Moreover, 3DVar is also misplacing the locations of the precipitation for some places. On the contrary, the EnKF can (a) locate with enough accuracy the regions where the accumulated precipitation was actually observed, (b) properly estimate the observed intensity and (c) avoid spatial errors associated with the location where the precipitation was produced. This is why ROC for the 6-hour accumulated precipitation obtained from the EnKF produced a much better score than the 3DVar. We hypothesize that this difference could be associated with the *static/climatological* background error covariance matrix used by the 3DVar. Because of the fast changes in the flow associated with the IOP13 case, using a climatological background error covariance could not be as good as using a flow-dependent background error covariance matrix, which is used in the EnKF.

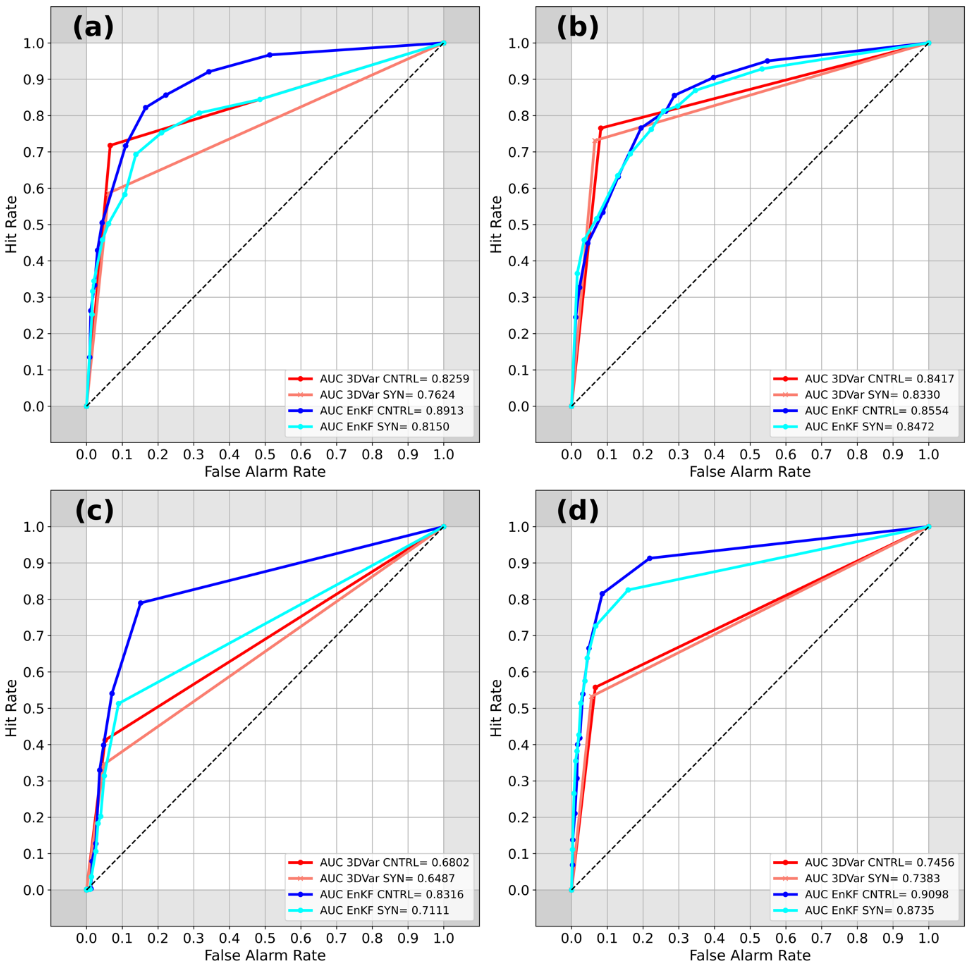

Figure 9. ROC curves and AUC associated with the 3DVar (red colors) and EnKF (blue colors) for the 3-hour accumulated precipitation using (a) 1 mm and (b) 10 mm threshold and 6-hour accumulated precipitation using (c) 1 mm and (d) 10 mm threshold, computed over the entire inner domain.

8.1.3. Taylor Diagrams

To strengthen the comparison of the DA schemes, the Taylor Diagram is used. This tool provides us with extra information about the skill of each ensemble member in the case of the EnKF. Here, we compute the Taylor diagram over the 6-hour accumulated precipitation field, which is the range where the observations assimilated have more impact on the forecast. Results show that the 3DVar and the ensemble mean of the EnKF provide similar results, with similar correlations (0.50-0.61), similar root mean squared error and standard deviation that are distributed symmetrically about the observation value, with the 3DVar overestimating the standard deviation and the EnKF underestimating it (Fig. 10). However, if we consider each ensemble member, we can observe that there is a cluster of the ensemble members of the EnKF that provide better scores than the 3DVar. Although the difference between the EnKF and the 3DVar in this case is small, we can point out that the EnKF provides additional information

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from their individual ensemble members. For instance, the individual ensemble members showing higher correlation and standard deviation similar to the observations for this study are the ones using Grell-Freitas cumulus parameterization in combination with the Yonsei University planetary boundary layer scheme. Ensemble members associated with the lower scores are those using Kain-Fritsch for the cumulus parameterization and the Mellor-Yamada-Janjic for the planetary boundary layer scheme.

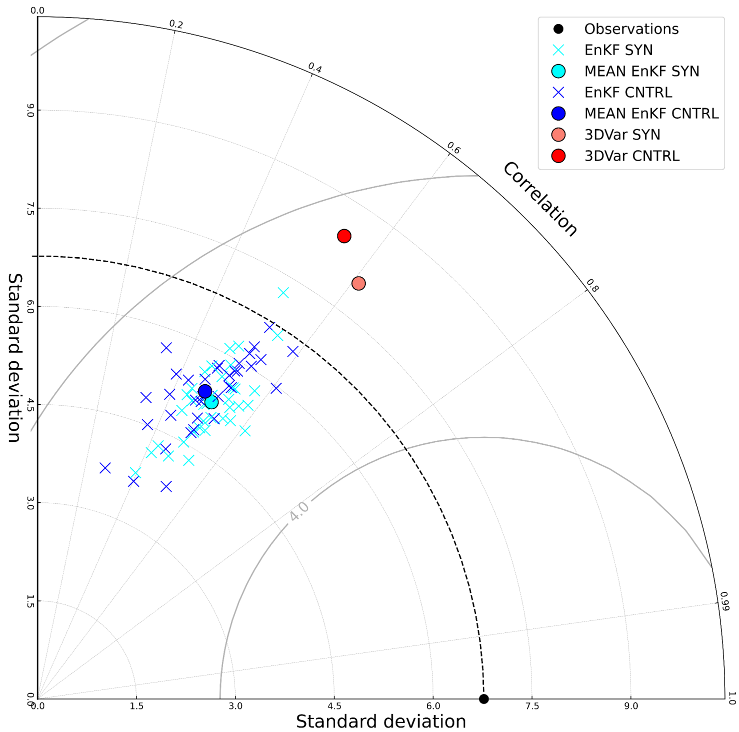

Figure 10. Taylor diagram performed by the 3DVar (reds) and EnKF (blues) for the 6-hour accumulated precipitation valid at 06 UTC 15 October 2012.

8.2. Statistical analysis: Qendresa event

Typically, two key factors are investigated for Tropical cyclone forecasts: (a) the intensity and (b) the trajectory followed by the cyclone. Therefore, to assess the impact of assimilating both *in-situ* conventional and remote RSAMV observations using the 3DVar and the EnKF, these two factors are considered.

8.2.1. Whisker Diagrams

For this event, the lack of *in-situ* observations over maritime regions poses a main challenge to properly verify the triggering and intensification of cyclones. Fortunately, the Qendresa medicane crossed just over Malta island, where a pressure drop greater than 20 hPa in 6 h, was registered by METARs at Malta airport, reaching a minimum of surface pressure of 985 hPa. Therefore, this METAR is used to quantitatively assess the skill of the different DA simulations. To compare the surface pressure registered at Malta with the different simulations, the full cyclone trajectory is used, and the grid point closest to Malta airport is selected. Finally, the surface pressure time series associated with that model grid point is compared with the values registered at Malta airport. Specifically, the surface pressure time series measured by METAR is compared with the different DA simulations from 3DVar and EnKF, such as the 3DVar_SYN, 3DVar_CNTRL, EnKF_SYN, and the EnKF_CNTRL (Fig. 11).

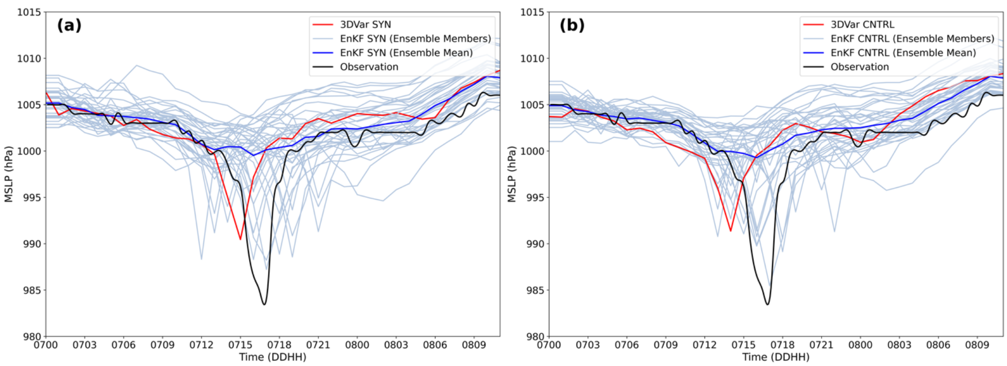

Figure 11. Temporal surface pressure evolution at the closes grid point to Malta for the (a) SYN and (b) CNTRL experiments associated with the EnKF (blue lines) and 3DVar (red lines), compared to the observed surface pressure registered by METARs in Malta's airport (black line).

Results from the assimilation of *in-situ* conventional observations show that the ensemble mean of the EnKF_SYN accurately fits the observations during the first hours of the forecast, from 00 UTC to 13 UTC 7 November (Fig. 11a), performing slightly better than 3DVAR_SYN. However, during the intensification phase, the ensemble mean of the EnKF_SYN barely shows the intensification of Qendresa, reaching minimum MSLP values of 1002 hPa. On the contrary, the 3DVar_SYN simulation depicts the intensification of the medicane, by deepening the MSLP and reaching values of 992 hPa, although a time shift of 3 hours is found (i.e., 15 UTC 7 November) (Fig. 11a). Finally, during the dissipation phase of Qendresa, the ensemble mean of EnKF_SYN is performing a bit better than the 3DVar_SYN (Fig. 11a). This interesting result clearly shows a limitation of the EnKF when applied to low-predictable weather events, such as Qendresa. The low predictability and the high sensitivity to the different physical parameterization schemes used for the forecast of this kind of event, lead to a very different behavior of each ensemble member. Consequently, some members could completely fail in the prediction of the weather event. In this situation, our small-to-moderate ensemble will probably produce a poor flow-dependent background error covariance matrix, which is key in DA, resulting in an analysis ensemble with large spread, for which ensemble mean will be smoothed out significantly. On the other hand, in such situations, we could think of using a climatological/static background error covariance matrix, as the one used in the 3DVar. If this climatological background error covariance matrix is obtained with a large enough statistical sample, it could produce much better results than using the flow-dependent background error covariance computed with ensemble members that are not accurate enough, as we see in Fig. 11a when we compared the 3DVar (red line) with the EnKF ensemble mean analysis (blue line). Also, it is important to note that although the ensemble mean of the EnKF_SYN is not correctly reproducing the intensification of Qendresa, some of the ensemble members accurately reproduce the observed MSLP both in deepening and timing. This suggests that using an ensemble system, even having the above-mentioned problems, is still more useful than using only a fully deterministic system such as the 3DVar, which cannot provide information about the uncertainties of the system. Therefore, we can speculate that for extreme weather events with low numerical predictability, a better approach could be using a Hybrid error covariance model, where the forecast error covariance matrix is obtained linearly combining ensemble-based covariance with static climatological error covariances (Hamill and Snyder (2000); Lorenc (2003); Clayton et al., 2013; Carrió et al., 2021). The impact of using hybrid DA to improve this kind of small-scale extreme weather events could be of great interest in the weather forecast community, although it is beyond the scope of this study. For this reason, the authors leave as future work the benefits of using hybrid error covariance models to improve the forecast of extreme weather events in the Mediterranean basin.

Then, we evaluated the impact of assimilating both *in-situ* conventional and RSAMV observations in the improvement of Qendresa intensity forecast. In this case, the results show large similarities with the assimilation of only *in-situ* observations (Fig. 11b). In terms of the 3DVar, the MSLP signature is basically the same, without showing a clear signal of improvement or diminishing, suggesting that the assimilation of RSAMVs is not enough to significantly improve the low level relevant dynamical structures associated with the genesis and intensification of Qendresa. However, in terms of the EnKF a clear improvement for a few members is found, even if it is not affecting the mean value. Indeed, some of the ensemble members depicting an intense cyclone far from the time when it was observed (approx. at 18 UTC 7 November), were corrected reducing spurious cyclones and the deepening of at least one ensemble member close to the observed value (Fig. 11b). It can be observed that in the EnKF_CNTRL, there are more ensemble members depicting a deep cyclone at the observed time than in the case of the EnKF_SYN, showing the benefits of assimilating RSAMVs to improve the intensification estimation of Qendresa.

To quantitatively assess the performance of the different DA experiments, we use the *lagged correlation* technique computed between the model MSLP signatures and the observations. This technique allows us to measure how the shape of the surface pressure evolution obtained from the different simulations fits the shape of the observed MSLP, taking also into account temporal shifting. The correlation is computed for the deterministic 3DVar, and for each ensemble member from the EnKF. These results are shown using Whisker plots (Fig. 12). Notice that a correlation of one means that the specific model field has the same 'V' pressure shape evolution as the observation, and that the minimum for both is found at the same time. For the 3DVar_SYN, the correlation is maximum and approximately equal to one when 1-hour delay is applied to forecasts (Fig. 12a). Whiskers from EnKF_SYN show that none of the ensemble members overcomes the maximum correlation value found in 3DVar_SYN. However, when the assimilation of RSAMVs is added to the *in-situ* conventional observations, it is found that the maximum correlation value associated with 3DVar_CNTRL using 2h of delay applied to the forecasts, is surpassed by some of the ensemble members of the EnKF_CNTRL, when a 3 or 4 hour of delay is applied (Fig. 12b).

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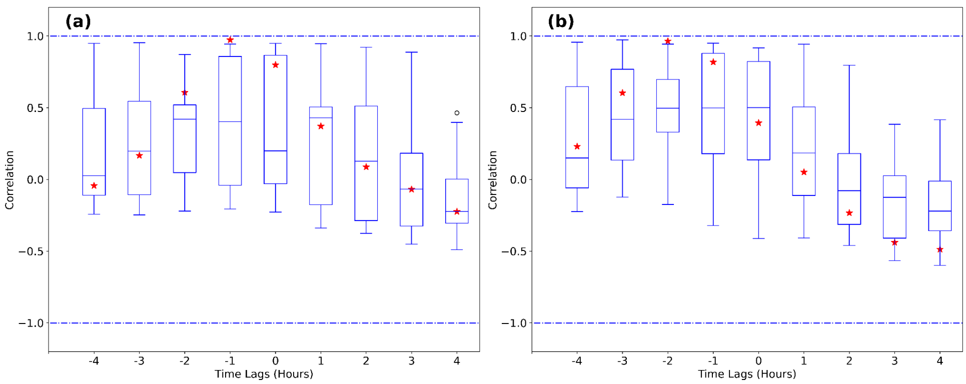

Figure 12. Whisker plots depicting the lagged correlation values between the observations and the EnKF (blue boxes) and the 3DVar (red stars) for the (a) SYN and (b) CNTRL experiments. The correlation is computed considering that the observed V-shape pressure signature associated with the observations is shifted 4 hours to the left and 4 hours to the right.

8.2.2. Probability Distribution of Cyclone Center Occurrence

Due to the difficulty to accurately predict the observed trajectory of Qendresa (Pytharoulis et al., 2018), the impact of assimilating different kinds of observations on the trajectory of the medicane is investigated.

The 3DVar_SYN is capturing with enough accuracy the track of Qendresa during the first hours (Fig. 13b). However, for 3DVar_SYN the trajectory of Qendresa leaving Malta diverges from the observed trajectory, moving north-eastwards without showing the track-loop signal observed by satellite imagery. To quantify the benefits of assimilating *in-situ* conventional observations using the 3DVar or the EnKF, the probability of occurrence of a cyclone following the track observed via satellite imagery is computed. For instance, we can see that the probability of cyclone occurrence eastwards Sicily, where Qendresa made landfall while it was doing a loop, is too small according to 3DVar_SYN (Fig. 13b). On the other hand, some of the ensemble members depict a cyclone trajectory for EnKF_SYN that is largely shifted southward, whereas some of them reproduce the loop trajectory that deterministic numerical weather models miss performing (Fig. 13a). In addition, the probability of Qendresa occurrence eastwards Sicily, is in this case larger than for 3DVar_SYN, showing the benefits of using the EnKF against the 3DVar (Fig. 13a). Moreover, the EnKF_SYN ensemble trajectories, in general, follow a 'V' shape (i.e., first moving towards the southeast, then moving to the east and finally moving towards the northeast) similar to the trajectory observed via satellite imagery. Although the shape of most of the EnKF_SYN trajectories agree with the observations, the location is not accurate, showing a general shift towards the southeast.

If both *in-situ* conventional and RSAMV observations are assimilated, some of the ensemble members from the EnKF_CNTRL shows more accurate trajectories in comparison with EnKF_SYN: the loop trajectory is close to the observed region of eastern Sicily (Fig. 13c). An improvement of the 3DVar_CNTRL trajectory by increasing the probability of cyclone occurrence following the observed track is observed, especially eastern of Sicily. However, 3DVar experiments are not able to reproduce the looping trajectory observed via satellite imagery (Fig. 13b-d). Hence, EnKF outperforms 3DVar showing some of the ensemble

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members depicting a loop trajectory, although shifted southwards and producing a probability of cyclone occurrence smaller than the 3DVAR ones.

Both the EnKF and the 3DVar still have difficulties in depicting accurately the track observed by Qendresa, even after the assimilation of *in-situ* conventional and RSAMV observations. Because RSAMVs are more useful in describing dynamical features on the upper levels of the atmosphere, we hypothesize that ingesting them via DA may not be enough to correct key low-level dynamical features. In this case, the assimilation of surface wind observations may help to even improve these results. However, this is beyond the scope of this study and the authors leave this question as future work, where other sources of information from satellites will be assimilated to improve low-level thermodynamic aspects of extreme weather events, such as medicanes.

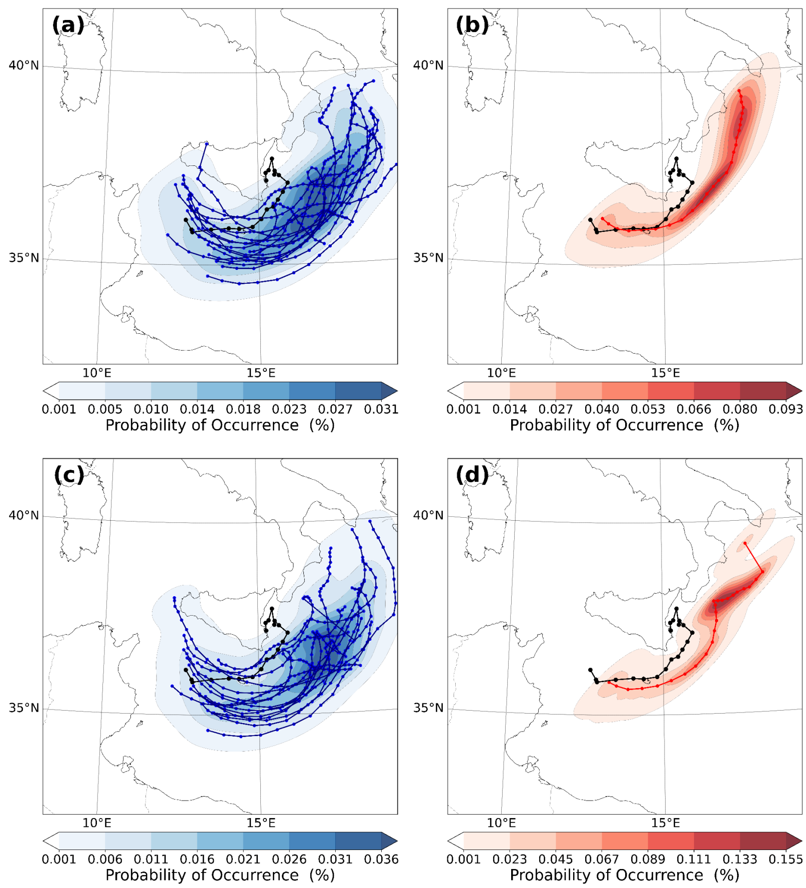

Figure 13. Probability of cyclone center occurrence computed using Gaussian KDE for (a) EnKF (SYN), (b) 3DVar (SYN), (c) EnKF (CNTRL) and (d) 3DVar (CNTRL), from 11 UTC 7 November to 12 UTC 8 November 2014. Qendresa's trajectory observed via satellite imagery is depicted in black.

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9. Summary and Conclusions

In this study, we quantitatively assess the impact of two high-resolution DA techniques. Here, we focus on the impact of assimilating observations to improve warning lead times of extreme weather events. While previous studies often assimilate observations during the mature stage of a weather event, when it is fully developed and no time for action remains, here the observations are assimilated hours before the mature stage of the convective system is reached, during the pre-convective stage. This approach enhances the accuracy of the pre-convective environment, thereby increasing the time available for reaction and preparedness. To quantitatively evaluate their forecast skill in improving the predictability of maritime events, two extreme weather events triggered over the sea affecting populated coastal regions are used. Nowadays, these weather events represent a serious challenge for the numerical weather prediction community in terms of their accurate predictability, due to their initialization over the sea, which are regions with a lack of in-situ observations, and thus their initial conditions are poorly estimated. Furthermore, these convective systems evolved towards complex terrain regions, increasing the predictability challenges. These two extreme weather events are known as (a) the high precipitation event registered during the 13th Intensive Observation Period (IOP13) affecting the western, northern and central parts of Italy, and (b) the intense Tropical-like Mediterranean Cyclone (medicane) known as Qendresa, that affected the islands of Pantelleria, Lampedusa, Malta and Sicily.

The two DA methods compared in this study for IOP13 and Qendresa are the variational 3DVar and the ensemble-based EnKF, which are currently used in operational National Weather Services worldwide. For the two events, both DA methods are used, and the type and number of assimilated observations changes depending on the data availability. For Qendresa, we assimilated (a) hourly *in-situ* conventional observations and (b) wind speed and wind direction profiles of the entire atmosphere (RSAMVs) derived from geostationary satellites every 20-min, providing high spatial and temporal resolution observations covering the Central Mediterranean Sea, where Qendresa initiated and evolved. On the other hand, for the IOP13, we assimilated (a) hourly *in-situ* conventional observations and (b) 15-min 3D reflectivity observations from two type-C Doppler Weather Radars.

Because of the different thermodynamic characteristics associated with Qendresa and IOP13, a set of different verification metrics were used for each of these extreme weather events. The *Filtering method* (FSS and RMSE), the ROC/AUC and the *Taylor diagram* were used to verify the numerical simulations from 3DVar and EnKF associated with IOP13. In the case of Qendresa, we used the *Whisker diagrams* and the *Probability Distribution of Cyclone Center Occurrence* verification scores. For the IOP13 event, the *Filtering method* and the *Taylor diagram* verification scores indicate that the skill performance of the 3DVar and the EnKF is similar, although the EnKF slightly overcomes the 3DVar. In addition, it was observed that the assimilation of spatial and temporal high-resolution reflectivity observations significantly improved the forecast for both 3DVar and EnKF, showing the key role of this type of observation. On the other hand, the ROC and AUC scores clearly show that EnKF outperforms 3DVar. For the Qendresa event, although the ensemble mean of EnKF provides the worst results, in terms of the intensity of the medicane with respect to 3DVar, some of the EnKF ensemble members provide better results than 3DVar. This result suggests how important it is using an ensemble forecast system to predict extreme weather events at high spatial and temporal resolution. In terms of the trajectory of the cyclone, it is also shown that using the EnKF provides a more realistic insight of the real trajectory Qendresa followed.

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Although the EnKF technique has shown in general better performance against the 3DVar for the two extreme weather events analyzed in this study, it is also important to account for the computational resources required to use them. In this sense, the 3DVar requires much less computational resources than the EnKF because it does not need to build an ensemble of considerable size, and it does not need either to simulate model trajectories between the assimilation of a set of observations at time t_1 and the subsequent set of observations valid at t_2. This makes the 3DVar appealing because it is much faster and cheaper than the EnKF, and it makes this technique particularly suitable for operational purposes at the small weather forecast centers.

Another interesting result that we have shown in this study is that depending on the level of predictability of the weather event and its sensitivity to numerical physical parameterizations used to build our ensemble, the 3DVar performs better than the EnKF ensemble mean. We speculated that this is linked to the way the background error covariances from these two methods are built. Based on this, we suppose that a better approach could be using Hybrid error covariance models, where the forecast error covariance matrix is obtained linearly combining the ensemble-based error covariance from the EnKF and the static climatological error covariance matrix from the 3DVar. Further work will investigate the impact of using hybrid DA schemes in comparison to use standard 3DVar or EnKF. As a case study, a catastrophic and deadly flash flood event affecting the Balearic Islands will be used to quantitatively assess the skill performance of the hybrid DA scheme against the EnKF and a more advanced version of the 3DVar, which is known as the 4DVar. In this case, most of the ensemble members of the EnKF did not reproduce the convective cells that later resulted in the flash flood episode. This is a key problem in current ensemble-based DA research. In this scenario, it is expected that the hybrid error covariance matrix will be more precise than the one derived from the ensemble members or from climatology, which on their own are not properly reproducing key aspects of this extreme weather episode. High temporal and spatial observations from Doppler Weather radars, such as reflectivity and radial wind velocities, will be assimilated for this case to obtain accurate analysis and thus, improve the short-range forecast of this catastrophic flash-flood event.

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Appendix

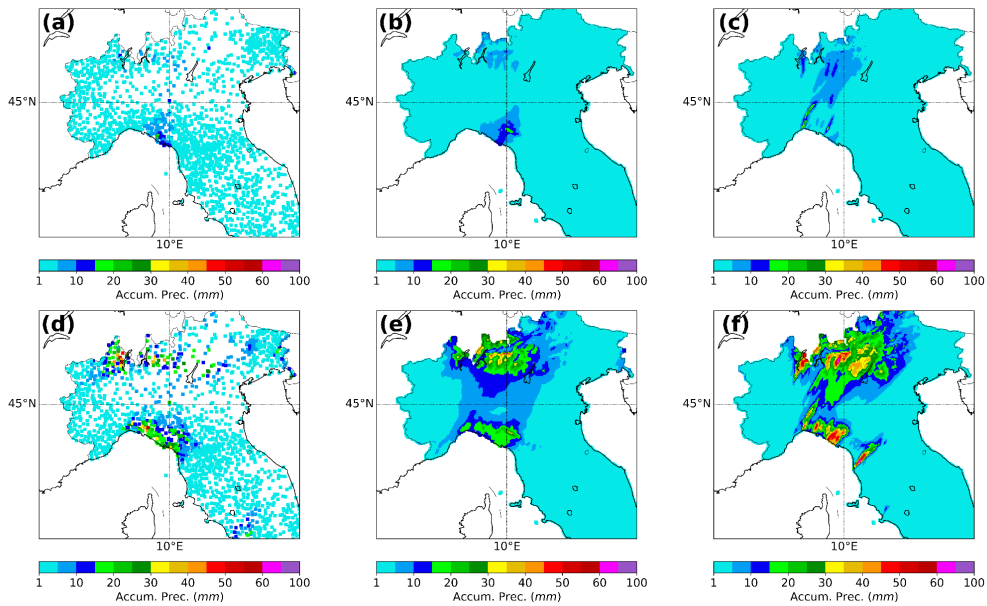

Fig. A1. 1-h accumulated precipitation computed from 00-01 UTC 15 October 2012 associated with (a) Observations, (b) EnKF (CNTRL) and (c) 3DVar (CNTRL). 6-h accumulated precipitation computed from 00-06 UTC 15 October 2012 associated with (d) Observations, (e) EnKF (CNTRL), (f) 3DVar (CNTRL).

Author Contribution

D. S. Carrió: Conceptualization, Methodology, Software, Validation, Formal analysis, investigation, writing-original draft, writing-review & editing, visualization, supervision; **V. Mazzarella:** formal analysis, writing-review; **R. Ferretti**: formal analysis, writing-review, supervision.

Competing Interests

The authors declare that they have no conflict of interest.