

Editor

Dear Authors,

both Reviewers have sent a further report about your second version. You will see that whilst both Reviewers appreciate the relevance of your work and have found satisfactorily your revision, they still have major concerns. In particular they both agree, sometimes in a complementary way, that the paper has to provide further comparisons/results in order to fulfil its goal of analysing the impact of radar data over, for instance, experiments where reflectivity data are not assimilated at all, or on short forecast lead-times.

I also agree with them that, addressing those concerns is necessary and overall will further strength and improve the manuscript.

I hope that you will consider submitting a revised version where the issues arisen by the Reviewers are considered and properly responded. I strongly encourage to do that and I will be happy to receive your revised version and responses.

Dear Editor,

As reported in the answers to the Reviewers, following their indications and reconsidering some of the previous suggestions, we decided to radically revise our manuscript. First of all, the number of forecasts for each experiment has been increased from 5 to 22: forecasts are now initialized each 3 hours from February 3 at 12 UTC to February 6 at 06 UTC instead of each 12 hours from February 4 at 00 UTC to February 6 at 00 UTC. In this way, results are much more significant from a statistical point of view. Furthermore, verification is performed considering hourly (instead of 3 hourly) precipitation to evaluate if the assimilation of radar volumes has an impact in the first few hours of forecast. Moreover, verification has been extended by introducing the Fractions Skill Score (FSS) to compare the QPF of the experiments. This score is applied to the precipitation field over the whole Italian country employing a 1 mm and a 5 mm thresholds. Finally, an experiment in which only conventional data are assimilated without LHN (conv60_nolhn) has been added to evaluate the case in which no radar information is employed in the data assimilation system. At the same time, the experiment rad60_Bm has been removed since we think that further investigation is needed to properly evaluate the impact of the additive inflation.

Due to these modifications, some results are changed. The assimilation of reflectivity volumes improves QPF accuracy compared to the conventional set-up (conv60) and to conv60_nolhn, even if the impact lasts only for the first few hours of forecast. Furthermore, the assimilation of observations collected in the last 15 minutes of each assimilation cycle (rad60_1st15) further enhances slightly the improvement. Other results are similar to those observed in the previous version of the manuscript but now they are much more significant from a statistical point of view: the assimilation of reflectivities with or without LHN does not substantially affects results, the shortening of the cycle length reduces QPF accuracy and the use of a too small value of the reflectivity observational error introduces imbalances which dramatically worsens results.

Finally, as a consequence of the modifications, some changes have been made in the introduction and in Section 2. Moreover, verification has been reorganized in a new section (section 3) while result and conclusions sections have been radically modified.

1) the authors might want to relate the general context of their study to a recent essay work: Yano et al., 2018: Scientific challenges of convective-scale numerical weather prediction. BAMS <https://doi.org/10.1175/BAMS-D-17-0125.1>.

Done.

2) I suggest the authors to include a brief mention of the conclusion they are drawing at the end of the abstract. In its present form it well describes the problem tackled and the methodology therein, but not much on the authors' main conclusion.

Done. These sentences are added at the end of the abstract:

Results show that the assimilation of reflectivity volumes has a positive impact on QPF accuracy in the first few hours of forecast both when it is combined to LHN or not. The improvement is further slightly enhanced when only observations collected close to the analysis time are assimilated, while the shortening of cycles length worsens QPF accuracy. Finally, the employment of a too small value of roe introduces imbalances in the analyses resulting in a severe degradation of forecast accuracy, especially when very short assimilation cycles are used.

3) in relation with the somehow unexpected lack of improvement when the data assimilation interval is further reduced, the authors might want to relate/interpretate it based on the study on dynamical instabilities within a convective-resolving model by Uboldi and Trevisan, 2015: Multiple-scale error growth in a convection-resolving model. *Nonlinear Processes in Geophysics* 22, 1-13, 2015.

This sentence has been added to the conclusion:

A possible explanation, which needs further investigation, is that the more frequent assimilation reduces the analysis error making the ensemble too small to properly characterize the forecast error (Uboldi and Trevisan, 2015).

Referee #1

The authors did a great effort to address my comments. I found that the paper has improved, however some important aspects are still unclear.

Major points

One of the main objectives of this paper is to assess the impact of assimilation of reflectivity data in a convective scale data assimilation system. However all the experiments presented in this paper assimilate reflectivity data either using nudging or using direct reflectivity assimilation. An experiment in which only conventional observations are assimilated would be very useful to properly assess the impact of assimilating reflectivity. If this experiment is performed then it would be possible to evaluate if nudging and direct reflectivity assimilation provides equivalent results or if we are in a case in which the assimilation of reflectivity do not produce a significant impact upon the forecast skill. In the later case it would also interesting to provide some hypothesis about the causes for such behavior (for example if the complex terrain over the study region is significantly enhancing rain predictability reducing the impact of initial conditions at the mesoscale over the short range forecast skill, or perhaps the impact of reflectivity upon forecast skill is limited to lead times under 3 hours and is not clearly seen beyond that time). The sensitivity experiments will also became more meaningful if the authors can demonstrate that including reflectivity data is producing a positive impact upon forecast skill in this case.

Following the indications of both referees and reconsidering some of the previous suggestions, we decided to radically revise our manuscript. First of all, the number of forecasts for each experiment has been increased from 5 to 22: forecasts are now initialized each 3 hours from February 3 at 12 UTC to February 6 at 06 UTC instead of each 12 hours from February 4 at 00 UTC to February 6 at 00 UTC. In this way, results are much more significant from a statistical point of view. Furthermore, verification is performed considering hourly (instead of 3 hourly) precipitation to evaluate if the assimilation of radar volumes has an impact in the first few hours of forecast. Moreover, verification has been extended by introducing the Fractions Skill Score (FSS) to compare the QPF of the experiments. This score is applied to the precipitation field over the whole Italian country employing a 1 mm and a 5 mm thresholds. Finally, an experiment in which only conventional data are assimilated without LHN (conv60_nolhn) has been added to evaluate the case in which no radar information is employed in the data assimilation system. At the same time, the experiment rad60_Bm has been removed since we think that further investigation is needed to properly evaluate the impact of the additive inflation.

Due to these modifications, some results are changed. The assimilation of reflectivity volumes improves QPF accuracy compared to the conventional set-up (conv60) and to conv60_nolhn, even if the impact lasts only for the first few hours of forecast. Furthermore, the assimilation of observations collected in the last 15 minutes of each assimilation cycle (rad60_1st15) further enhances slightly the improvement. Other results are similar to those observed in the previous version of the manuscript but now they are much more significant from a statistical point of view: the assimilation of reflectivities with or without LHN does not substantially affects results, the shortening of the cycle length reduces QPF accuracy and the use of a too small value of the reflectivity observational error introduces imbalances which dramatically worsens results.

Finally, as a consequence of the modifications, some changes have been made in the introduction and in Section 2. Moreover, verification has been reorganized in a new section (section 3) while result and conclusions sections have been radically modified.

Minor points

Page 3, line 25 ((LHN - Remove the extra parenthesis.

Done.

Page 7, Why 3D data is available only for radars over Northern Italy? Is because how data is archived?

Meteorological radar in Italy belong to different institutions. For the case study presented in this manuscript, only those of our institution (Arpae Emilia-Romagna) and of Arpa Piemonte were available to us. Anyway, note that in the period examined (3-7 February 2017) precipitations mainly interested Northern Italy.

Page 8, line 10 observed precipitation

Done.

Page 8, line 23 every 3 hours

Done.

Page 8, line 26 and

Done.

Page 10, line 7 February 5 line 8 February 6.

Done.

Page 10, Line 7 On February 5 / new precipitating systems

Done.

Page 10, Line 15 Spatially averaged forecasted precipitation is compared against ...

Done.

Page 10, Line 29 precipitating systems instead of precipitation nuclei

Done.

Page 12, Line 18 reflectivity data is

The sentence, as well as the entire section, has been completely modified.

Page 12, Line 20 Spatially averaged

The sentence, as well as the entire section, has been completely modified.

Page 18, lines 20-21 The experiment assimilating only conventional data is not described in this work. All the experiments assimilate reflectivity either using nudging or direct assimilation. This is explained in the followings entences, but it would be better to state the conclusion in a clearer way from the beginning instead of makingthis clarification later.

The sentences, as well as the entire section, have been completely modified. Note also that now an experiment in which only conventional data are assimilated (conv60_nolhn) has been discussed in the manuscript.

Page 19, For the case study considered in this work... Since the experiments provided in this work shows little sensitivity to the different strategies used to assimilate reflectivity, the lack of sensitivity reported here might be a consequence of the general lack of sensitivity of these forecast to the assimilation of reflectivity.

As stated previously, to investigate this lack of sensitivity, in the new version of the manuscript the verification of results has been radically enhanced by considering much more forecasts, by implementing FSS and by applying both SAL and FSS to hourly precipitation. It is still true that the impact of the assimilation of reflectivity volumes is not extremely marked, but however it is present in the first few hours of forecast.

To further reduce the number of figures, Figure 1 and 2 can be combined if the color scale is changed accordingly.

Done.

I still think that including some examples of the precipitation or reflectivity forecast in the paper would be useful. Statistical metrics are powerful and useful, but having such examples also gives a good subjective idea of how good is the fit between the forecast and the observations. This is particularly useful in the context of novel high resolution convective scale data assimilation systems. If the results changes from case to case, then two examples can be provided.

Hourly maps of precipitation for the first 3 hours of forecasts initialized on February 3 at 12 UTC are shown in Figure 4.

Referee #2

Based on the evidence presented in this study, it is difficult to draw a solid conclusion about positive impact from assimilating radar reflectivity. I think it is mainly because the authors are focusing on the one-day QPF, which is claimed to be the operational interest. However, it is well recognized by the literature that the impact of radar data is identified for (very) short-term forecast. I would like to suggest the authors that since this work is the new component for the KENDA system, it is essential to identify and justify the impact of the radar data, even though the impact may only last few hours. Also, I'd think that it is important to explain why additionally assimilating radar data doesn't seem to gain more benefit than applying LHN. Is this because the information is double used or redundant? Based on these concerns, I suggest major revision for this manuscript.

Following the indications of both referees and reconsidering some of the previous suggestions, we decided to radically revise our manuscript. First of all, the number of forecasts for each experiment has been increased from 5 to 22: forecasts are now initialized each 3 hours from February 3 at 12 UTC to February 6 at 06 UTC instead of each 12 hours from February 4 at 00 UTC to February 6 at 00 UTC. In this way, results are much more significant from a statistical point of view. Furthermore, verification is performed considering hourly (instead of 3 hourly) precipitation to evaluate if the assimilation of radar volumes has an impact in the first few hours of forecast. Moreover, verification has been extended by introducing the Fractions Skill Score (FSS) to compare the QPF of the experiments. This score is applied to the precipitation field over the whole Italian country employing a 1 mm and a 5 mm thresholds. Finally, an experiment in which only conventional data are assimilated without LHN (conv60_nolhn) has been added to evaluate the case in which no radar information is employed in the data assimilation system. At the same time, the experiment rad60_Bm has been removed since we think that further investigation is needed to properly evaluate the impact of the additive inflation.

Due to these modifications, some results are changed. The assimilation of reflectivity volumes improves QPF accuracy compared to the conventional set-up (conv60) and to conv60_nolhn, even if the impact lasts only for the first few hours of forecast. Furthermore, the assimilation of observations collected in the last 15 minutes of each assimilation cycle (rad60_lst15) further enhances slightly the improvement. Other results are similar to those observed in the previous version of the manuscript but now they are much more significant from a statistical point of view: the assimilation of reflectivities with or without LHN does not substantially affects results, the shortening of the cycle length reduces QPF accuracy and the use of a too small value of the reflectivity observational error introduces imbalances which dramatically worsens results.

Finally, as a consequence of the modifications, some changes have been made in the introduction and in Section 2. Moreover, verification has been reorganized in a new section (section 3) while result and conclusions sections have been radically modified.

My comments are as follows:

- Based on the verification merits used in this study, it is difficult to justify the impact of radar data. Have the authors consider adopting other verification merits such as POD, FAR, TS and BIAS to identify whether there is clearer signal about the data impact? Or, illustrate the results with a case study (from the 4-day assimilation)?

As indicated previously, we decided to implement FSS, a completely different score compared to SAL (it is also applied over a larger domain) which, at the same time, allows to overcome the problems of traditional grid-point based score like POD, FAR, Ts etc. The FSS score is explained in Section 3 and results are shown in Section 4.

- Discussion about Fig. 4 is vague. Line13, Page11: “Overall, the correspondence of rad60 to observations is equal or better than that of conv60 (red)”. Also, by eye, rad60_nolhn is slightly better than rad60. rad60_Bm tends to have the least rainfall among all the rad60-related experiments shown on Fig. 4 but the authors claim that the impact of the additive inflation cannot be judged. To quantify such statement. I suggest to summarize Fig. 4 in terms of RMS error.

The RMSE error has been introduced to evaluate the correspondence between experiments and observations. Note also that the experiment rad60_Bm has been removed and the section radically modified.

- As mentioned in my general comments, I'd think that it is important to explain why additionally assimilating radar data doesn't seem to gain benefit than applying LHN. Is this somewhat related to the fact that the SRI product uses the radar reflectivity? The authors can illustrate the result with even a case demonstration. Should we expect a large difference between radar data assimilation and LHN with heavy rainfall events?

As suggested by the referee, verification is now applied to hourly precipitation and FSS score has been added, Thanks to this, is possible to assess that the assimilation of reflectivity volumes improves QPF accuracy between lead time +2h and +4h compared to the assimilation of only conventional observations combined to LHN (conv60).

- Although the authors focus on the impact of radar data on 1-day QPF, it is undeniable that the impact is mostly evident within 6 hours. Therefore, I suggest that the authors should address the impact of radar data on short-range forecast (< 6h).

Done, considering a forecast range of 8 hours.

- It is concluded that the radar data only slightly improve QPF both during the assimilation procedure and for the subsequent forecasts, compared to the assimilation of only conventional data (Line3, Page 18). This sentence should be modified for 1-day QPF.

Done. Note that the whole section has been radically modified.

- Why does rapid update (15-min) with a small observation actually lead to a dry condition over northern Italy (Fig. 9)? Fig. 9 should be also compared with results from rad15 with rad15_roe0.5.

We decided to substitute rad60 with rad15 in the figure. As stated previously, the differences between rad15 and rad60 are very small but we agree with the referee that it make more sense to compare rad15_roe0.5 to rad15 rather than to rad60. We decided to not put both rad15 and rad60 in the same figure because, otherwise, it would have been unreadable.

The dry conditions over Northern Italy are, in our opinion, an effect of the big amount of imbalances in the analyses, as verified by evaluating KE spectra. However, how this results in a reduction of humidity is still an open problem. Anyway, please keep in mind that rad60_roe0.5 is an unrealistic experiment (the value of roe is extremely small), performed only to evaluate the sensitivity of results to the value of roe.

Minor comments:

Since radar reflectivity is the main focus in this work, the authors should briefly comment or summarize what are the issues/difficulties with assimilation of reflectivity volumes in the introduction.

Problems associate to the assimilation of radar data are explained, approximate lively, between P2 L35 and P3 L23

“Grater” is often used in the text. But, I think the authors meant “greater”.
Done.

Data assimilation of radar reflectivity volumes in a LETKF scheme

Thomas Gastaldo^{1,2}, Virginia Poli¹, Chiara Marsigli¹, Pier Paolo Alberoni¹, and Tiziana Paccagnella¹

¹Arpae Emilia-Romagna Hydro-Meteo-Climate Service - Bologna, Italy

²University of Bologna - Bologna, Italy

Correspondence to: Thomas Gastaldo (thomas.gastaldo2@unibo.it)

Abstract. Quantitative precipitation forecast (QPF) is still a challenge for numerical weather prediction (NWP), despite the continuous improvement of models and data assimilation systems. In this regard, the assimilation of radar reflectivity volumes should be beneficial, since the accuracy of analysis is the element that most affects short-term QPFs. Up to now, few attempts have been made to assimilate these observations in an operational set-up, due to the large amount of computational resources needed and to several open issues, like the arise of imbalances in the analyses and the estimation of the observational error. In this work, we evaluate the impact of the assimilation of radar reflectivity volumes employing a Local Ensemble Transform Kalman Filter (LETKF), implemented for the convection permitting model of the Consortium for Small-scale **Modelling** **MOdelling** (COSMO). A 4 days test case on February 2017 is considered and the verification of QPFs is performed using the Fractions Skill Score (FSS) and the SAL technique, an object-based method which allows to decompose the error in precipitation fields in terms of structure (S), amplitude (A) and location (L). Results obtained assimilating both conventional data and radar reflectivity volumes are compared to those of the operational system of the Hydro-Meteo-Climate Service of the Emilia-Romagna region (Arpae-SIMC), in which only conventional data-observations are employed and latent heat nudging (LHN) is applied using surface rainfall intensity (SRI) estimated from the Italian radar network data. The impact of assimilating reflectivity volumes using LETKF in combination or not to LHN is assessed. Furthermore, some sensitivity tests are performed to evaluate the effects of additive-inflation, of the length of assimilation-windows the assimilation window and of the reflectivity observational error. Finally (roe). Moreover, balance issues are assessed in terms of kinetic energy spectra and providing some examples of how these affect prognostic fields. Results show that the assimilation of reflectivity volumes has a positive impact on QPF accuracy in the first few hours of forecast both when it is combined to LHN or not. The improvement is further slightly enhanced when only observations collected close to the analysis time are assimilated, while the shortening of cycles length worsens QPF accuracy. Finally, the employment of a too small value of roe introduces imbalances in the analyses resulting in a severe degradation of forecast accuracy, especially when very short assimilation cycles are used.

1 Introduction

Numerical weather prediction (NWP) models are widely used in meteorological centres to produce forecasts of the state of the atmosphere. In particular, they play a key role in the forecast of precipitation (Cuo et al., 2011), which arouses a great interest due to the many applications in which it is involved, from the issue of severe weather warnings to decision making in several

branches of agriculture, industry and transportation. Therefore, an accurate quantitative precipitation forecast (QPF) is of great value for society and economic activities.

In recent years, the increase of available computing resources has allowed to increment NWP spatial resolution and to improve the accuracy of parametrization schemes, enabling to develop convection-permitting models (Clark et al., 2016).

5 Despite that, QPF is still a challenge since it is affected by uncertainties in timing, location and intensity (Cuo et al., 2011; Röpnick et al., 2013). These errors arise partly from the chaotic behaviour of the atmosphere and from shortcomings in the model physics (Berner et al., 2015), but the main factor which affects the quality of QPF, especially in the short range (3-12 hours), is the accuracy of initial conditions (Dixon et al., 2009; Clark et al., 2016).

The initial condition (analysis) is generally produced by a data assimilation procedure which combines model state (back-
10 ground or first guess) and observations to provide the best estimate of the actual state of the atmosphere at a given time. In the last decades, different assimilation schemes have been proposed and implemented operationally in meteorological centres around the world. They can be divided in different families: those based on a variational approach, like three-dimensional variational data assimilation (3D-Var: Courtier et al., 1998) and four-dimensional variational data assimilation (4D-Var: Buehner et al., 2010b), those based on the ensemble Kalman filter (EnKF: Evensen, 1994; Houtekamer and Mitchell, 1998) and those
15 based on the particle filter (PF; see van Leeuwen, 2009 for a review). At the convective scale, EnKF methods seem to be preferable to variational schemes (Schraff et al., 2016). In fact, they determine explicitly the background error covariance, which is highly flow-dependent at the convective scale. Furthermore, in a variational scheme it is not straightforward to update any variable of a NWP model since an explicit linear and adjoint relation to the control vector of prognostic variables is needed. These problems ~~are can be~~ partly addressed by employing hybrid EnKF-Variational techniques (like Wang et al., 2008; Gustafsson and Bojarova, 2014) but these approaches have mostly been applied to larger scale NWP. ~~Another option may A~~
20 ~~more preferable option would~~ be to employ ~~particle filters but a~~ PF ~~which is also considered to be the most promising technique to deal with the non-linear and non-Gaussian characters of dynamics and error statistics~~ (Yano et al., 2018). ~~Unfortunately,~~ despite the efforts to overcome the dimensionality challenges of ~~these assimilation techniques this assimilation technique~~ (e.g. Poterjoy, 2016), ~~it PF~~ is still not feasible for operational applications. ~~Several variants of EnKF~~ ~~Returning to EnKF methods,~~
25 ~~several variants~~ have been suggested (for a survey refer to Meng and Zhang, 2011) and one of the most popular is the local ensemble transform Kalman filter (LETKF), proposed by Hunt et al. (2007). It is used operationally in several meteorological centres like at COMET (Bonavita et al., 2010), at MeteoSwiss employing the version of the scheme developed for the COSMO consortium (Schraff et al., 2016) and for research purposes at the Japan Meteorological Agency (JMA; Miyoshi et al., 2010) and at the European Centre of Medium-Range Weather Forecasts (ECMWF; Hamrud et al., 2015).

30 The quality of the analysis is not determined only by the data assimilation scheme employed, but also by the quality and amount of observations that can be assimilated. With this aim, the assimilation of radar observations can be very beneficial, since they are highly dense in space (both horizontally and vertically) and in time. Up to now, several attempts have been made to improve the quality of analyses and subsequently the accuracy of QPFs by assimilating rainfall data estimated from radar reflectivity observations (Jones and Macpherson, 2006; Leuenberger and Rossa, 2007; Sokol, 2009; Davolio et al., 2017). Conversely, only few tries have been made to directly assimilate reflectivity volumes in a convection permitting model employing

EnKF techniques (e.g. Snyder and Zhang, 2003), especially in an operational framework (Bick et al., 2016). Despite some promising results, many issues affect the assimilation of reflectivity volumes at high spatial resolution and several aspects need to be further investigated.

5 First of all, the length of the assimilation window, which is one of the key aspects of any data assimilation system, has to be examined. In EnKF methods, a short window would be desirable to avoid that dynamical features leave the area where computed localized increments are significant (Buehner et al., 2010a) and to better preserve the gaussianity of the ensemble which can be compromised by non-linearities (Ferting et al., 2007). On the other hand, a too short window would lead to an increase of imbalances in the analysis, since the model has no the time to filter spurious gravity waves, introduced at each
10 initialization, ~~throughout~~ through the forecast step of the assimilation cycle. When reflectivity volumes are assimilated, the window length becomes even more crucial since these observations allow to catch small scale features of the atmosphere (Houtekamer and Zhang, 2016). In order to exploit the high temporal frequency of these data, which is essential to properly characterize fast developing and moving precipitation systems, it seems reasonable to employ short windows to assimilate, in each cycle, only observations collected very close to the analysis time. Furthermore, the choice of a short window is encouraged
15 by the use of short localization scales, which has to be employed since small scales features are observed. Conversely, the big amount of radar observations enhances the imbalance issue and, therefore, the imbalances generated in the model by each initialisation should be checked and kept under control.

Another important issue is how to determine the observational error for radar reflectivities. As for any other observation, this is influenced by three different sources: instrumental errors, representativity errors and observation operator errors. Since none
20 of these are known, the choice of its value is not straightforward and can be estimated only in a statistical sense. Considering the amount of radar data, a correct estimation of the observational error is crucial, since even a small departure from the correct value can have a large impact on the quality of the analyses. Moreover, it should be taken into account that the use of the radar data is highly dependent on the observation operator adopted and its biases should also be studied and ideally removed. Finally, a further challenge is the estimation of the observational error correlation especially when dealing with radar data assimilation,
25 due to the high density of this type of observations..

At Arpaè-SIMC, the Hydro-Meteo-Climato Service of the Emilia-Romagna region, in Italy, a LETKF scheme is used to provide the initial conditions to the convection-permitting components of the operational modeling chain, consisting of one deterministic run and of one ensemble system both at 2.2 km of horizontal resolution. Currently, only conventional data are assimilated ~~throughout~~ through the LETKF scheme and latent heat nudging (LHN; Stephan et al., 2008) is performed using
30 rainfall intensity estimated from the Italian radar network data. The purpose of this paper is to present the first results obtained when also reflectivity volumes are assimilated using the LETKF scheme. In particular, the impact of assimilating reflectivity volumes in combination or not with LHN is evaluated. Furthermore, it is studied the sensitivity of the obtained analysis to two important characteristics of the assimilation cycle: the length of each cycle and the observational error attributed to the radar reflectivities.

This paper is organised as follows. In section 2, ~~the model and the data assimilation system employed~~ are described, as well as the observations employed ~~and the~~. Furthermore, the operational set-up implemented at Arpaè is reported in conjunction

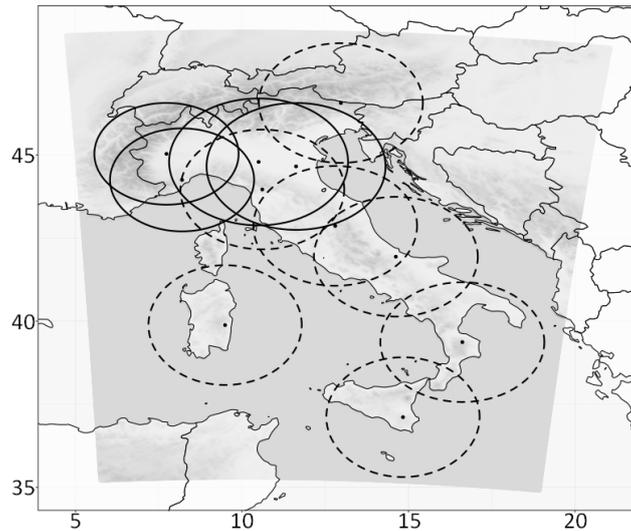


Figure 1. Integration domain ~~and corresponding orography (grayscale)~~ of the COSMO model employed in this study with the Italian radar network overlapped. For each radar the approximate coverage area is shown with a dashed line if the radar system contributes only to the SRI composite employed in LHN and with a solid line if it is used also to directly assimilate reflectivity volumes through KENDA.

5 with the set-up of the experiments performed ~~.Furthermore, the verification method is in this study.~~ In section 3 the verification methods are explained. In section ~~3~~4 results are shown and discussed. In section ~~4~~5 some conclusions are drawn.

2 Data, model and methodology

2.1 The COSMO model

The COSMO model (Baldauf et al., 2011) is a non-hydrostatic limited-area model developed by the multi-national Consortium
 10 for Small-scale ~~Modelling~~MOdelling (COSMO) and it is designed for both operational NWP and several research applications. It is based on the primitive equations describing compressible flows in a moist atmosphere and the continuity equation is replaced by a prognostic equation for the pressure perturbation (deviation from a reference state). The prognostic variables involved in these equations are the three dimensional wind vector, temperature, pressure perturbation, turbulent kinetic energy (TKE) and specific amount of water vapour, cloud water, cloud ice, rain, snow and graupel.

15 In the present study, the COSMO model is run at 2.2 km horizontal resolution over a domain covering Italy and part of the neighbouring countries (Figure ~~??~~1) and employing 65 terrain-following hybrid layers. The model top is at 22 km.

Regarding set-up and parametrizations, deep convection is resolved explicitly while the shallow convection is parametrized following the non-precipitating part of Tiedtke scheme (Tiedtke, 1989). Cloud formation and decay is controlled by a Lin-type one moment bulk microphysics scheme which includes all the prognostic microphysical species (Lin et al., 1983; Seifert and Beheng, 2001). The turbulent parametrization is based on a TKE equation with a closure at level 2.5, according to Raschendor-

5 fer (2001). Radiative effects are described by the δ -two-stream radiation scheme of Ritter and Geleyn (1992) for short-wave and long-wave fluxes. Finally, the lower boundary conditions at the ground are provided by the multi-layer soil model TERRA (Doms et al., 2011).

2.2 The KENDA system

The KENDA system (Schraff et al., 2016) implements for the COSMO model the LETKF scheme described by Hunt et al. (2007). In this implementation, the method is fully four dimensional, that is all observations collected during the assimilation window contribute to determine the analysis and the related model equivalents are computed using the prognostic variables at the proper observation time. To avoid spurious long-distance correlations in the background error covariance matrix, analyses are performed independently for each model grid point taking into account only nearby observations (observation localization). Observations are weighted according to their distance from the grid point considered using the Gaspari-Cohn correlation function (Gaspari and Cohn, 1999). In the present work, two different values of the Gaspari-Cohn localization length-scale are employed for conventional and radar observations: 80 km for the former, 16 km for the latter (as done by Bick et al., 2016).

The limited size of the ensemble, combined to the assumption of a perfect model made in the LETKF scheme, leads to an underestimation of the background and analysis variances (e.g. Anderson, 2009) and, as a consequence, the quality of analyses is negatively affected. To address this issue, KENDA provides some techniques to enlarge the spread of the ensemble (for a complete description of each of them refer to Schraff et al., 2016). Here, multiplicative covariance inflation (Anderson and Anderson, 1999) and the relaxation to prior perturbation (RTPP; Zhang et al., 2004) are employed. The former consists in inflating the analysis error covariance by a factor ρ greater than one which is estimated following Houtekamer et al. (2005). The latter lies on the relaxation of the analysis ensemble perturbations towards the background ensemble perturbations by replacing at each grid point the analysis perturbation matrix in ensemble space \mathbf{W}^a by

$$25 \quad (1 - \alpha_p)\mathbf{W}^a + \alpha_p\mathbf{I} \tag{1}$$

where \mathbf{I} is the identity matrix and $\alpha_p = 0.75$ (see also Harnisch and Keil, 2015). Another approach provided by KENDA to account for model error is the additive inflation. ~~The basic idea is to add~~ It consists in adding random noise with mean $\mathbf{0}$ and covariance \mathbf{Q} to the analysis ensemble members, where \mathbf{Q} is the model error covariance matrix (Houtekamer and Mitchell, 2005). Since \mathbf{Q} is not known, it is assumed to be proportional (by a factor smaller than 1) to a static background error covariance \mathbf{B} (Mitchell and Houtekamer, 2000). ~~This technique has already been employed with a positive impact in convective-scale data assimilation (e.g. Dowell and Wicker, 2009). In the present work, additive inflation is used together with multiplicative inflation and to RTPP only in one experiment, employing a climatological \mathbf{B} -matrix from the 3D-VAR of the Icosahedral Nonhydrostatic (ICON) global model (Zängl et al., 2015). Although the use of a lower resolution \mathbf{B} -matrix may not allow to properly characterize the model error at the smallest scales, the same configuration has been gainfully employed at MeteoSwiss (Leuenberger and Merker, 2018).~~ At the present time, this method is not employed.

The KENDA suite also allows to compute the analysis weights on a coarsened grid (Yang et al., 2009). Weights computed on this coarsened grid are then interpolated to the model grid and afterwards used to calculate analysis increments. In this way,

the computational cost is decreased without affecting negatively the accuracy of analysis (Yang et al., 2009). In the present study, a coarsening factor equal to 3 is employed.

2.3 Assimilated data

KENDA allows the assimilation of both conventional and non conventional observations.

10 Conventional observations assimilated in this work include aircraft measurements (AMDAR) of temperature and horizontal wind, surface station measurements (SYNOP) of 10 m horizontal wind, 2 m temperature, 2 m relative humidity and surface pressure, radiosonde data (TEMP) of temperature, horizontal wind and humidity.

~~The Italian radar network. For each radar the approximate coverage area is shown. All radars contribute to the composite generation employed in LHN. Radars highlighted in red are used to directly assimilate reflectivity volumes throughout KENDA.~~

15 With regards to non conventional observation, KENDA allows also the assimilation of radar reflectivity volumes and radial winds. Radar data are assimilated through the Efficient Modular Volume RADAR Operator (EMVORADO) expressly designed for the COSMO model. It simulates the radar reflectivity factor and radial velocities processing the COSMO model fields one radar system at a time. Operator characteristics, resolution and the management of no-precipitation information are described in (Bick et al., 2016).

20 Although the operator gives the possibility to assimilate both radial winds and reflectivities, in the present work only reflectivity volumes are assimilated. Reflectivity volumes come from four different radar stations over Northern Italy (~~red~~ solid circles in Figure ~~??1~~): Bric Della Croce (Piedmont Region), Settepani (Liguria Region), Gattatico and San Pietro Capofiume (Emilia-Romagna Region). Due to the complex orography of the considered area, radar are placed at very different altitudes and have different acquisition strategies. Observations are acquired every 10 minutes for Bric Della Croce radar, every 5 min-
25 utes for Settepani radar, every 15 minutes for San Pietro Capofiume radar and every 15 minutes starting from minutes 5 and 10 of each hour for Gattatico radar.

Data have a range resolution of 1 km, while the azimuthal resolution is 1 degree for Bric Della Croce and Settepani and 0.9 degree for San Pietro Capofiume and Gattatico. Before assimilation raw reflectivity are pre-processed taking into account non meteorological echoes, beam blocking and attenuation to improve the quality of data. In particular, it is important to
30 eliminate the clutter signal that would affect the analysis retrieval introducing spurious observations. However, due to the fact that volumes from single radars undergo different pre-processing, it is not possible to define a homogeneous quality criterion. For this reason, all data in the volume that are not rejected from pre-processing step are supposed to have the same quality and are used into the assimilation cycle.

The high temporal and spatial density of observations is precious to estimate the initial state of numerical weather forecast. This allows to gather a lot of information on the real state of the atmosphere, but it determines an increase in analysis computational cost, in data transfer time and in memory disk occupation. Moreover, a spatial and/or temporal high density violates the assumption made in the most part of assimilation schemes: the non-correlation of observational errors. To reduce the total amount of data and to extract essential content of information, the superobbing technique is chosen. In this way, reflectivities
5 over a defined area are combined through a weighted mean into one single observation representative of the desired greater

spatial scale. As in Bick et al. (2016), the horizontal resolution chosen in this work for the superobbing is equal to 10 km. Furthermore, before performing superobbing on the observed and simulated fields, a threshold of 5 dBZ is applied to both fields in order to avoid that large innovations associated to non-precipitating signals would lead to large analysis increments without physical relevance.

10 To evaluate the observational error associated to reflectivity volumes, a diagnostic based on statistical averages of observations-minus-background and observations-minus-analysis residuals, as described in Desroziers et al. (2005), is used. Employing all radar data available during the test case, a reflectivity observational error (*roe*) equal to 5 dBZ is estimated, as found also by Tong and Xue (2005).

Finally, fields of surface rainfall intensity (SRI) are also assimilated in each member of the assimilation ensemble using a latent heat nudging scheme. SRI data come from the composite of the Italian radar network (all circles in Figure ??1) and are distributed by the National Department of Civil Protection. These data have a temporal resolution of 10 minutes and a spatial resolution of 1 km, but before the assimilation they are interpolated at the model resolution. Data coming from each station undergo a quality control that removes those with low quality. The quality depends on different factors such as ground clutter, beam blocking, range distance, vertical variability and attenuation as described in Rinollo et al. (2013). The composite is then obtained as a weighted average of surface rain rates from single radar stations, where weights are represented by quality. These fields are assimilated through the LHN scheme, based on the assumption that the latent heat, integrated along the vertical column, is approximately proportional to the ~~precipitation-observed~~ observed precipitation. The scheme, which is applied continuously during the integration of the model, acts in rescaling temperature profiles with an adjustment of the humidity field according to the ratio between observed and modelled rain rates. LHN has been gainfully employed in different frameworks, including forecasts over complex terrain (Leuenberger and Rossa, 2004; Leuenberger and Rossa, 2007). Our hypothesis is that, in the KENDA framework, LHN allows to have the model first guess closer to the observed atmospheric state, improving the analysis quality. For this reason, in all experiments (except one) presented here, LHN is applied together to the direct assimilation of reflectivity volumes through KENDA.

2.4 ~~Experimental~~ Operational set-up

30 The KENDA system is implemented operationally at Arpae using an ensemble of 20 members plus a deterministic run, which is obtained by applying the Kalman gain matrix for the ensemble mean to the innovations of the deterministic run itself. In principle, ensemble mean analyses can be deployed to initialize the deterministic forecasts, but this would lead to some inaccuracies since the mean of a non-Gaussian ensemble is generally not in balance (Schraff et al., 2016). For this reason the deterministic branch is added to the system, which differs from the ensemble ones only due to boundary conditions. The ensemble members use lateral boundary conditions provided ~~each~~ every 3 hours at a 10 km horizontal resolution by the ensemble of the data assimilation system of the Centro Operativo per la Meteorologia (COMet), based on a LETKF scheme (Bonavita et al., 2010). The deterministic run employs hourly boundary conditions provided by a 5 km version of COSMO run at Arpae (COSMO-5M) which domain covers a large part of the Mediterranean basin ~~ans~~ and surrounding countries.

~~In At Arpae, in~~ the operational set-up ~~employed at Arpae~~, the COSMO model configuration described in Section 2.1 is adopted for all the 21 members. At present, in the operational chain only conventional observations are assimilated and LHN is performed on each member of the ensemble. The KENDA analyses are used operationally to provide initial conditions to COSMO-2I, the 2.2 km ~~deterministic~~ deterministic run initialized twice a day at 00 UTC and 12 UTC and to COSMO-2I EPS, an ensemble which is run every day at 00 UTC for a 48 hours forecast range. ~~In this work, deterministic forecasts starting from the KENDA deterministic analysis are also performed, in-~~

2.5 Experimental set-up

~~In~~ order to evaluate the ~~quality of the analysis also from its impact when used to initialise a forecast.~~

~~To evaluate the impact~~ impact of the assimilation of reflectivity radar volumes, several experiments are performed ~~employing different configurations. The complete list is provided in Table 1. In the control experiment, called conv60, the. Each experiment has the same~~ set-up of the operational chain ~~, described in the previous two paragraphs, is replicated. In particular, this means that in~~ described in Section 2.4 regarding the number of members of the ensemble, boundary conditions and the COSMO model configuration. Therefore, they differ only due to the assimilation set-up. The complete list is provided in Table 1.

~~In conv60 experiment only conventional data and conv60_nolhn experiments only conventional observations~~ are assimilated using KENDA through cycles of 60 minutes ~~and the. Moreover, in the former,~~ LHN is performed during the forecast step of each assimilation cycle. ~~In the, replicating completely the operational set-up described in Section 2.4. Experiments rad60 experiment, radar and rad60_nolhn are the analogous of conv60 and conv60_nolhn when also radar reflectivity measurements are assimilated through KENDA, using a reflectivity observation error (roe) of 5 dBZ and a 60 minutes assimilation window is employed. A comparison with between conv60, from which and rad60 differs only due to the inclusion of radar data in the KENDA system, or between conv60_nolhn and rad60_nolhn allows an assessment of whether, under the same conditions, the assimilation of reflectivity observations improves the quality of analyses. In Furthermore, comparing rad60 to rad60_nolhn and rad60_Bm experiments the same set-up it is possible to evaluate if the assimilation of rad60 is employed, but in the former the LHN procedure is switched off in order to assess the impact of the assimilation of radar data only by means of KENDA, while in the latter additive inflation is applied to increase the spread of the ensemble reflectivity volumes combined with the LHN provides better results than the assimilation of only radar volumes.~~

All the other experiments involve the assimilation of both conventional data and reflectivity volumes, in addition to LHN. In order to test the impact of assimilating only observations which are not too far from the analysis time, experiments on the duration of the assimilation windows are performed. This is tested by comparing *rad60* to experiments *rad30* and *rad15* which differ from *rad60* only for the length of the assimilation window, equal to 30 and 15 minutes respectively. An alternative way to assimilate only the most relevant observations is to select in each cycle a subset of data including the closest to the analysis time. In the experiment *rad60_lst15* an assimilation window of 60 minutes is employed but only the observations (both conventional and radar reflectivities) collected in the last 15 minutes of the cycle are taken into account.

Trial	Window length [min]	Assimilated obs.	roe [dBZ]	Note
conv60	60	conv.	-	-
rad60_conv60_nolhn	60	conv. + radar	5-	<u>No LHN</u>
rad60_nolhn	60	conv. + radar	5	No LHN
rad60_Bm_nolhn	60	conv. + radar	5	Additive inflation <u>No LHN</u>
rad30	30	conv. + radar	5	-
rad15	15	conv. + radar	5	-
rad60_lst15	60	conv. + radar	5	Use obs. in the last 15 min. of the window
rad60_roe10	60	conv. + radar	10	-
rad60_roe0.5	60	conv. + radar	0.5	-
rad15_roe10	15	conv. + radar	10	-
rad15_roe0.5	15	conv. + radar	0.5	-

Table 1. Experimental set-up of each experiment including the length of the assimilation cycles, the type of observations assimilated, the reflectivity observation error (*roe*) associated to radar data and any additional feature.

5 Since the estimation of observation error is not straightforward and different techniques can be applied, it is worth to evaluate the sensitivity of the assimilation system to this parameter. In addition to the value of 5 dBZ employed in the previous experiments, two other values are selected: 10 dBZ or 0.5 dBZ. Both of them are tested employing a 60 minutes assimilation window (*rad60_roe10* and *rad60_roe0.5*) and using 15 minutes cycles (*rad15_roe10* and *rad15_roe0.5*).

The experiments described above are carried out over a period of almost 4 days from February 3rd at 06 UTC to February 7th at 00 UTC in 2017. During 3 and 4 February, middle tropospheric circulation over Northern and Central Italy was dominated by southwesterly divergent flows associated with the passage of some precipitating systems. ~~In 5 February~~ On February 5 a trough moved from France to Italy and this caused the formation of new ~~precipitations~~ precipitating systems in Northern Italy. During ~~6 February~~ February 6 the trough moved slowly from Central Italy to the southern part of the country and precipitation systems weaken gradually. For each experiment, ~~a set of 5 analyses of the deterministic member are used to initialize~~ forecasts up to ~~48 hours is initialized using the analyses generated during the assimilation procedure. Initialization times employed are~~ 04 February at 00 and 24 hours each 3 hours from February 3 at 12 UTC, ~~5 February at 00 and 12 UTC and to February 6 February at 00.~~ at 06 UTC with a total of 22 forecasts.

2.6 Verification

3 Verification

The performance of ~~each experiment~~ the experiments described in the previous section is assessed ~~in terms of QPF employing~~ two methods by the verification of precipitation employing three methods: comparison of areal average precipitation, SAL technique and Fractions Skill Score (FSS). The first ~~employed for the verification during assimilation cycles,~~ consists of

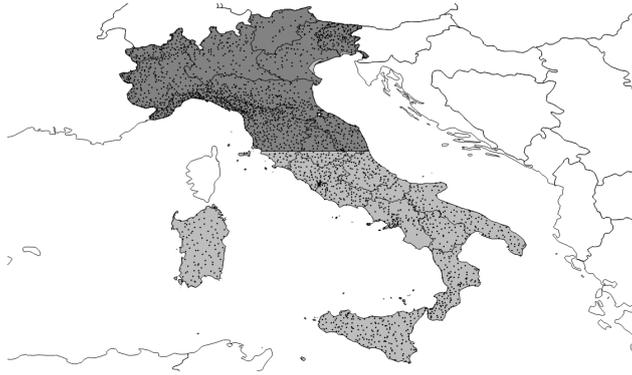


Figure 2. Verification domains employed to perform SAL (dark grey area) and FSS (union of dark grey and light grey areas). The rain-gauges (black dots) are used to correct precipitation estimated from the Italian radar network. Furthermore, rain-gauges over the black grey domain are employed for the verification of areal average precipitation during the assimilation procedure.

comparing the areal average values of 3-hourly precipitation: average precipitation forecasted by the model over an area is compared against method is applied only to the precipitation during the assimilation procedure for the deterministic member of the first 4 experiments in Table 1, while SAL and FSS are used to evaluate the QPF accuracy of the 22 forecasts initialized for each experiment.

3.1 Areal average precipitation

The method consists in comparing spatially averaged model precipitation to the average precipitation observed by rain-gauges over the same area. The rain-gauge stations used in this work (nearly 1500) are shown in Figure 2; note that they are approximately in the region where reflectivity volumes are assimilated. In order to have comparable samples, model precipitation is first interpolated on station location by selecting the value at the nearest grid point.

The second method, applied The rain-gauge stations employed for this verification method (nearly 1500) are the black dots in the dark grey region in Figure 2. This area is chosen to cover approximately the domain where reflectivity volumes are assimilated. Both model and rain-gauges precipitation are accumulated in 3 hours steps. Since this method is used for the verification of forecasts, employs the during the assimilation procedure and the duration of each assimilation cycle, for the experiments considered, is 1 hour, model hourly precipitation is accumulated in order to obtain the 3-hourly precipitation. To summarize the results, the correspondence between model and observations is evaluated in terms of root mean square error (RMSE).

3.2 SAL

The SAL metrics (Wernli et al., 2008) is an object based verification score which allows to overcome the limitations of traditional scores for convection-permitting models, like the double-penalty problem (Rossa et al., 2008). The detection of

5 individual objects in the accumulated precipitation fields is achieved by considering continuous areas of grid points exceeding a selected threshold. Comparing objects from observed and forecast fields, SAL provides information about the structure S , the amplitude A and the location L errors of QPF. A perfect match between forecast and observations would lead to $S = A = L = 0$; the more the values differ from 0, the greater the disagreement between model and observations. More in detail, a too sharp/flat (broad/small) structure of forecast precipitation compared to observations is associated to positive (negative) values of S ;
10 an overestimation (underestimation) of average rainfall over the domain is associated to positive (negative) values of A ; a misplacement of ~~precipitation-nuelei~~ precipitating systems leads to positive values of L . Note that L can range between 0 and 2, while S and A between -2 and 2.

Observations employed to perform SAL ~~consist in 3-hourly~~ are hourly accumulated precipitation estimated from the Italian radar network (~~SRI~~) and corrected using rain-gauges data. The radar-raingauges adjustment, adapted for a radar composite,
15 derives from the method described in Koinstinen and Puhakka (1981). The original method comprises two terms: a range dependency adjustment and a spatial varying adjustment. In our case, only the second term is taken into account due to the fact that, in overlapping areas of the composite, rainfall estimation is obtained combining data from different radars and, therefore, the original information on the range distance from the radar is lost. The correction is based on a weighted mean of the ratio between rain gauges and estimated radar rainfall amount calculated over the station locations. Weights are a function of the
20 distance of the grid point from the station and of a filtering parameter calculated as the mean spacing between 5 observations. Then a smoothing factor is applied to the correction.

~~Raingauges (dots) used for the verification of area-average precipitation during the assimilation procedure. In gray the domain employed for SAL verification is depicted.~~

The verification area ~~is shown in~~, shown in dark gray in Figure 2. ~~This choice is made to assess the impact of the assimilation of radar reflectivity volumes in the region where these data are actually observed. Furthermore, regarding SAL, is the same as for the areal average precipitation. In this case, the rain-gauges inside it are employed to correct the rainfall estimation from the radar network. As mentioned before, this area covers approximately the domain where reflectivity volumes are assimilated. The choice of a larger domain would not be feasible. In fact,~~ in Wernli et al. (2009) it is recommended to use ~~a domain-an area~~ not larger than $500 \times 500 \text{ km}^2$ since, otherwise, the domain may include different meteorological systems making the
30 interpretation of results problematic. In fact, if the domain contains strongly differing meteorological systems, then results obtained using the SAL technique may not be representative for the weakest one.

3.3 FSS

The Fractions Skill Score is a verification method introduced by Roberts and Lean (2008) based on the neighbourhood approach and applied to fractional coverage, that is the fraction of grid points exceeding a threshold. The score consists in comparing forecast and observed fractional coverage over squared box (neighbourhoods) and it ranges between 0 (completely wrong forecast) and 1 (perfect forecast). Therefore, a perfect match between model and observations is obtained when the two fields
5 have the same frequency of events in each box. In this way, the method implicitly acknowledges that the actual resolution of a model is larger than the grid resolution and, at the same time, that also observations may contain random error at the model

grid scale. Like SAL, this approach allows to overcome the limitation of traditional grid point based scores. Furthermore, it can be applied over a domain larger than that employed for SAL since it is based on dichotomy events instead of being based on the amount of precipitation. For this reason, in this work FSS is applied over the whole Italian country (union of dark gray and light gray domains in Figure 2) considering boxes of 0.2° in both latitude and longitude and, as for SAL, observations consist in hourly accumulated precipitation estimated from the Italian radar network corrected using rain-gauges data (all black dots in Figure 2).

4 Results

4.1 Impact of assimilating the radar reflectivities

A preliminary assessment of the impact of assimilating radar reflectivity volumes with the KENDA system is provided by comparing two pairs of experiments: *conv60_nolhn* with *rad60_nolhn* and *conv60* ,~~in which~~ with *rad60*. In the experiment named *conv60_nolhn* only conventional observations are employed, and *rad60*, in which radar reflectivity data are added. It is reminded that LHN using assimilated while in the *rad60_nolhn* experiment both conventional and radar reflectivity volumes are employed. The same dichotomy is preserved in the second pair of experiments but, in this case, LHN of SRI data is also applied in both experiments. Areal average performed additionally in both *conv60* and *rad60*.

The areal average of 3-hourly precipitation ~~forecasted~~ during the assimilation procedure is displayed in Figure 3 for these experiments, employing precipitation recorded by rain-gauges (black line) as independent observation. Since the duration of each assimilation cycle is 1 hour, the precipitation forecasted by the model during each hour is accumulated in order to obtain the 3-hourly precipitation. Overall, the correspondence of reference observation. Comparing *rad60_nolhn* (solid orange line) to *conv60_nolhn* (dashed blue line), the correspondence between forecast and observed precipitation is improved when reflectivity volumes are assimilated in combination with conventional data through KENDA. In fact, the root mean square error (RMSE) is reduced from 0.38 mm of *conv60_nolhn* to 0.26 mm of *rad60_nolhn* experiment. The same conclusion holds when the assimilation through KENDA is combined to LHN: the RMSE is reduced from 0.37 mm of *conv60* (dashed red line) to 0.29 mm of *rad60* (~~green, which~~ solid green line; this colour will be used from here onwards to identify uniquely this experiment) to observations is equal or better than that of. Note that the LHN substantially unaffected the overall agreement between forecast and observed precipitation when it is combined to the assimilation of only conventional data (RMSE equal to 0.38 mm for *conv60_nolhn* experiment and to 0.37 mm for *conv60*(red). In some cases the improvement is particularly relevant, like at 21 UTC on 3 February and at 15 UTC on 4 February. Only at 00 UTC on 4 February the performance of *conv60* is clearly better than that of) while slightly degrades the correspondence when also reflectivity volumes are employed (RMSE equal to 0.26 mm for *rad60_nolhn* experiment and to 0.29 mm for *rad60*).

~~Since in~~ Verification of areal average precipitation during the assimilation procedure suggests that the quality of analyses is improved when radar reflectivity volumes are assimilated. To validate this result, the accuracy of QPF for the 22 forecasts initialized for each experiment is evaluated. In order to give an insight about how analysis affects a forecast, hourly forecast precipitation from analyses on February 3 at 12 UTC are shown in Figure 4. Each column represents different lead times, from

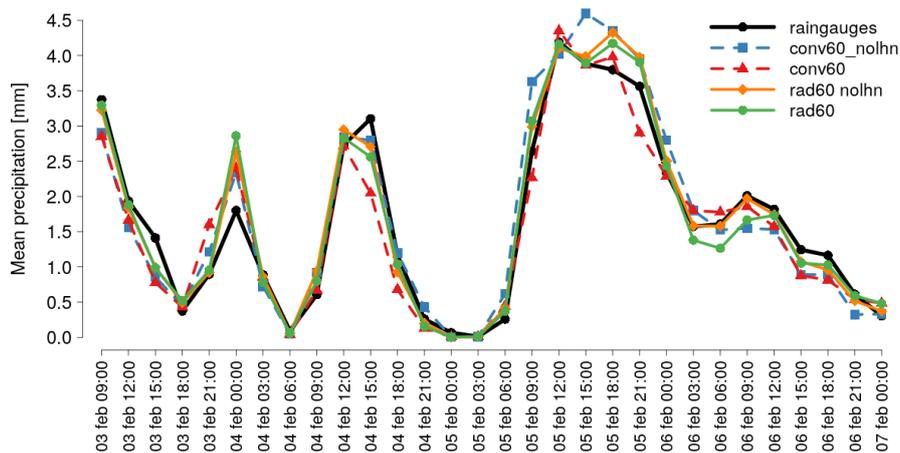


Figure 3. Areal average 3h-3 hourly precipitation for rain-gauges (black) in the verification area shown in dark grey in Figure 2 and at-for the corresponding model forecast, during the assimilation procedure, relative to experiments conv60 conv60_nolhn (reddashed blue line), rad60 conv60 (greendashed red line), rad60_nolhn (solid orange line) and rad60_Bm rad60 (bluesolid green line), during the assimilation procedure.

+1h to +3h going from left to right. The first row is the observed rainfall estimated from radars corrected by rain-gauges, that is the observed field employed for SAL and FSS described in Section 3. The shaded yellow area highlights the acquisition domain of the Italian radar network. The other rows are, in the order from top to bottom, the forecasts of the experiments conv60_nolhn, conv60, rad60_nolhn and rad60 experiment both reflectivity volumes and surface rainfall intensity are assimilated (the former using KENDA, the latter by LHN), the impact of assimilating reflectivity volumes may be hidden. To avoid this and to assess the influence of reflectivity observations in the assimilation procedure, LHN is switched off in rad60_nolhn experiment. Results displayed in Figure 3 show that average precipitation during assimilation cycles of. Forecast precipitation of conv60_nolhn is too weak and too spread, especially at lead time +2h in which large nuclei are forecast west of 12°E. A significant improvement at +1h is obtained when considering conv60, even if a strong unobserved nucleus is forecast near 45.5°N 13.5°E, while at +2h and especially at +3h the precipitation is completely misplaced. When considering forecasts initialized from rad60_nolhn (orange line) is similar to that of and rad60 with an improvement on February 6th between 03 UTC to 09 UTC.

The same set-up of rad60 is used in the experiment rad60_Bm, but with the addition of additive inflation to enlarge the ensemble spread. Mean precipitation during the assimilation cycles (blue line in Figure 3) differs from that of, rainfall accuracy at +1h is further enhanced in terms of location. Moreover, a significant improvement of both experiments compared to conv60_nolhn and conv60 can be noticed in location and intensity at lead times +2h and +3h. In particular, rad60 but, since slight improvements at some instants are compensated by slight deteriorations at others, the overall impact of the use of additive inflation cannot be judged. is the only one able to forecast nuclei of the correct intensity with just a slight misplacement error.

For the five-

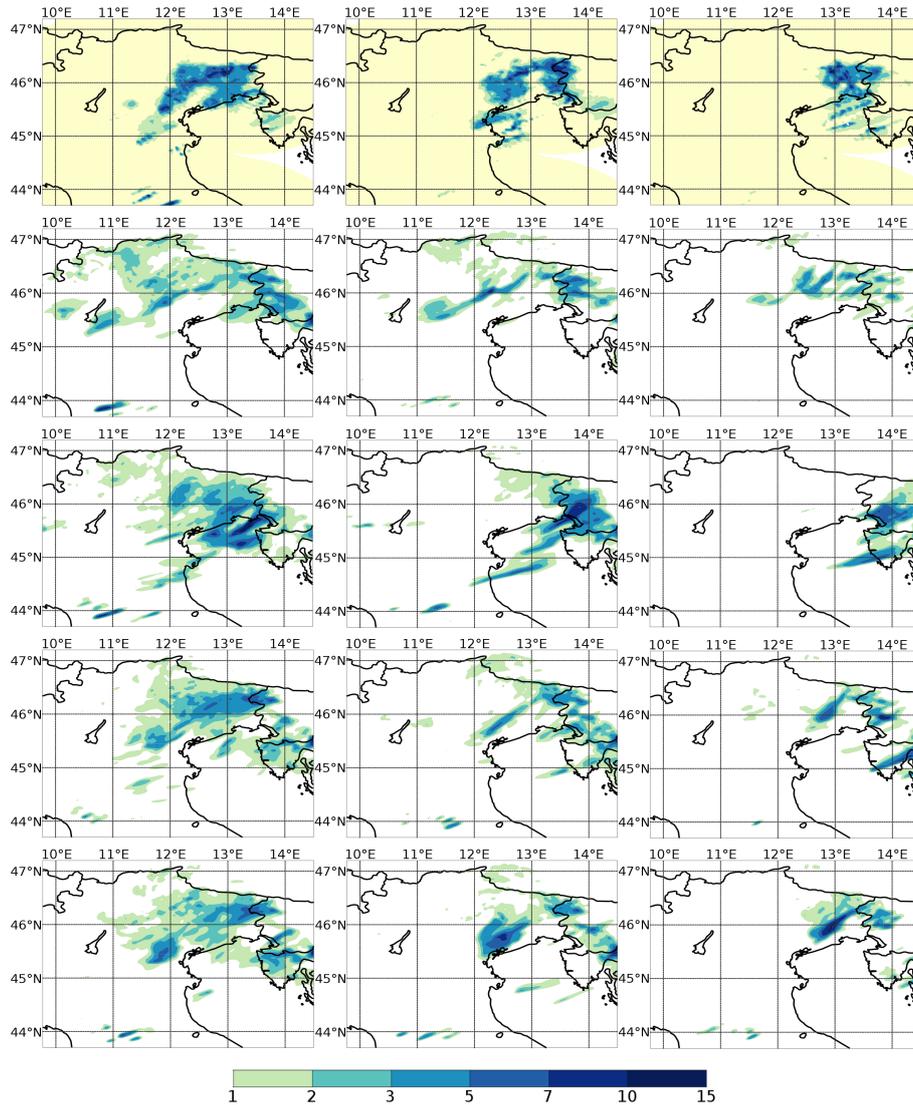


Figure 4. In the first row, the observed field, consisting in hourly rainfall estimated from radars corrected by rain-gauges, is shown for February 8 at 13, 14 and 15 UTC; the shaded yellow area highlights the acquisition domain of the Italian radar network. In the subsequent rows, forecast hourly precipitation of experiments *conv60_nolln* (second row), *conv60* (third row), *rad60_nolln* (fourth row) and *rad60* (fifth row) initialized on February 3 at 12 UTC is shown. Each column represents different lead times, from +1h to +3h going from left to right.

5 For an objective verification of QPF, hourly precipitation of the 22 forecasts initialized from the analyses of each experiments, the precipitation experiment is verified using SAL and employing; to detect rainfall objects a 1 mm threshold to identify rainfall objects. Verification using a is set. The verification using a threshold of 3 mm threshold was is also performed but, since results do not differ significantly from those obtained with a 1 mm threshold, they are not shown here. In Following the approach of Davolio et al. (2017), in Figure 5 the average of the absolute value of each component of SAL is plotted as a function of lead

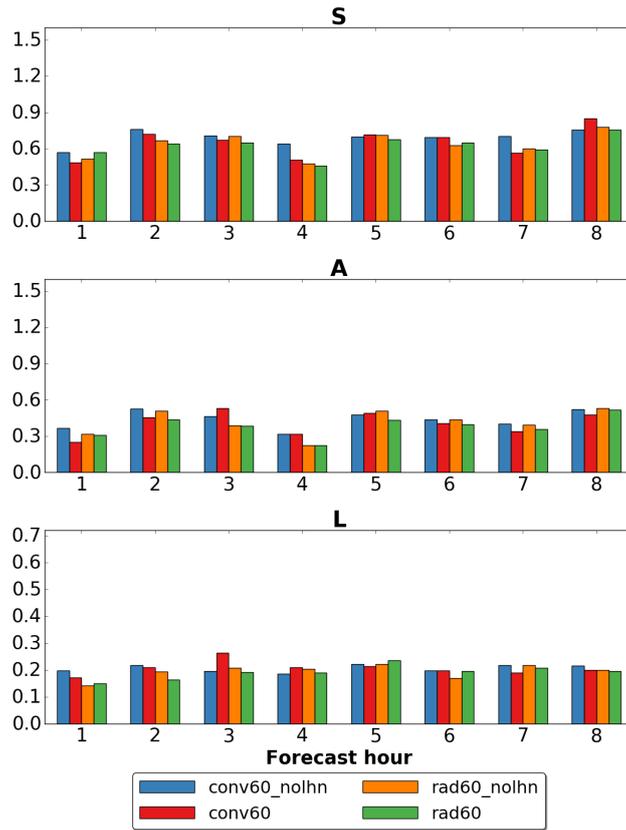


Figure 5. Average of the absolute value of each component of SAL over the 22 forecasts initialized from *conv60_nolhn* (blue), *conv60* (red), *rad60_nolhn* (orange) and *rad60* (green) analyses. Objects are selected using a threshold of 1 mm in hourly accumulated precipitation fields. Cases in which the observed precipitation field consists of less than 1000 points are not taken into account in the average.

5 time. Although forecasts are up to 48-24 hours, the verification is shown only for the first 24-8 hours, since after this lead time scores of the different experiments become very close. The average is computed considering only cases in which the observed or forecast rainfall field consists of at least 1000 grid points (3 events at lead time +6h, 4 otherwise), which is approximately equal to an area of $50 \times 50 \text{ km}^2 = 50 \times 50 \text{ km}^2$. Using the absolute value of the components of SAL, only the magnitude of the error is considered, losing the information on the type of error (e.g., for A, an overestimation of forecast precipitation cannot be distinguished from an underestimation). This choice slightly limits the potential of SAL but provides an intuitive picture of the overall performance of each experiments (a similar approach is employed by Davolio et al., 2017). Differences between forecasts initialized from experiment.

Comparing *conv60_nolhn* to *rad60_nolhn*, QPF accuracy is slightly improved when forecasts are initialized from analyses obtained by assimilating both conventional data and reflectivity volumes instead of employing only conventional data. In fact, at lead times +1h and +2h values of each component of SAL of *rad60_nolhn* are smaller than those of *conv60_nolhn*. An

5 improvement can be noticed also at +3h in the A component, while S and L are substantially unaffected. At +4h S and A are improved while L is very slightly deteriorated. From +5h onwards, slight improvements and deteriorations alternate in an incoherent manner, therefore we can assess that the impact on QPF of using conv60_nolhn or rad60_nolhn analyses is substantially neutral.

10 The accuracy of QPF obtained by assimilating conventional data is improved at lead times +1h and +2h by activating LHN during the assimilation procedure: all components of SAL for conv60 and from rad60 analyses are very small. Overall, the location of precipitations (experiment are smaller than those of conv60_nolhn. The positive impact of LHN is already lost at +3h (in particular, a significant degradation in L component)is observed) but, again, a benefit can be obtained by assimilating also reflectivity volumes. In fact, although at +1h the structure and amplitude errors of rad60 forecasts is only slightly improved compared to are larger than those of conv60 forecasts. The amplitude error A is generally smaller in the first 12 hours, but from 15h onward the conv60 forecasts outperform the rad60 forecasts(while location error is slightly smaller), from +2h to +4h each component of SAL is smaller indicating a clear improvement in QPFs accuracy. Again, from +5h onwards, the impact of initializing forecasts from different analyses becomes neutral. Regarding the structure component S, smaller errors combined use of LHN and the assimilation of reflectivity volumes through KENDA, at +1h the S component for rad60 forecasts at some lead times are counterbalanced by smaller errors for conv60 at other lead times, in a non-coherent way. Therefore, even if the use of analyses obtained by assimilating reflectivity volumes affects the structure of forecast precipitation, it is not possible to state if it is improved or deteriorated is slightly larger than that of rad60_nolhn, while A and L are almost equal. From +2h to +4h each component of SAL of rad60 is always equal or slightly smaller than the corresponding one of rad60_nolhn.

25 Finally, to strengthen the results obtained using SAL over Northern Italy, the verification of QPF is extended to the whole Italian country employing FSS. Results are shown in Figure 6 for two thresholds: 1 mm (solid lines) and 5 mm (dashed lines). Regarding the 1 mm threshold, a strong improvement in QPF accuracy can be noticed at +1h when reflectivity volumes are assimilated (rad60_nolhn and rad60 experiments). At this lead time also only the use of LHN (conv60) is able to improve significantly the assimilation of conventional data (conv60_nolhn). At +2h the FSS value of the two experiments in which reflectivities are assimilated is still slightly larger than that of conv60_nolhn, while from +3h onwards differences become very small. Regarding conv60, the QPF accuracy strongly worsen between +2h and +4h and it is the worst among the 4 experiments. Similar conclusions hold when the 5 mm threshold is considered but, in this case, QPF of experiments in which reflectivity volumes are assimilated outperforms conv60 even at the first hour of forecast. Furthermore, values of FSS of rad60_nolhn are slightly larger than those of rad60 between +2h and +4h.

35 When LHN is not performed and radar data are assimilated only using KENDA, results (orange bars in Figure 5) are not significantly affected. Only a meaningful improvement can be noticed in the structure component at lead time. In conclusion, summarizing the verification with SAL and FSS, at lead time +6h, but, at the same time, the error in the location component is increased. Since the combined 1h the assimilation of both conventional data and reflectivity volumes (rad60 and rad60_nolhn) has a positive impact on QPF accuracy compared to the assimilation of only conventional data (conv60_nolhn). The improvement is seen not only where reflectivities are assimilated (Northern Italy), but also over a much larger area (the whole Italian country). Verification with SAL shows that a slight positive impact over Northern Italy holds up to +4h, while FSS scores reveal a benefit

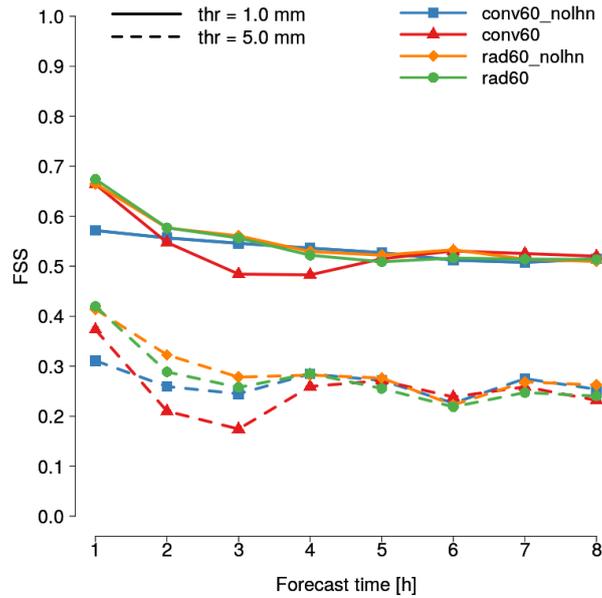


Figure 6. Average Fractions Skill Score as a function of the absolute value of each component of SAL over the 5 forecasts initialized from *conv60* lead time for *conv60_nolhn* (redblue), *rad60_conv60* (greenred), *rad60_nolhn* (orange) and *rad60_Bm rad60* (bluegreen) analyses. Three-hourly precipitation Verification is considered employing a threshold of 1mm. Cases in which the observed performed considering hourly precipitation field consist of less than 1000 points are not taken into account in the average and 1 mm (solid lines) and 5 mm (dashed lines) thresholds.

5 up to +2h over Italy for both 1 mm and 5 mm thresholds. The two experiments in which reflectivity volumes are assimilated do not substantially improve the QPF accuracy at +1h of the experiment in which only conventional data are assimilated in combination to LHN (*conv60*). However, they remarkably outperform it from +2h to +4h, as highlighted by both SAL and FSS. In this case, the positive impact is even enhanced when the 5 mm threshold is considered.

10 Finally, regarding the use of LHN combined to the assimilation of reflectivity volumes with KENDA and SRI by LHN does not have a negative impact on the quality of precipitation forecasts compared to the assimilation of only reflectivity observations, SAL shows comparable results between *rad60* and *rad60_nolhn* at +1h, while QPF accuracy of *rad60* is very slightly enhanced compared to *rad60_nolhn* between +2h and +4h. Verification with FSS does not show significant differences between the two experiments for the 1 mm threshold, while *rad60_nolhn* very slightly outperforms *rad60* at +2h and +3h for the 5 mm threshold. Therefore, we can assess that QPF accuracy is substantially unaffected by assimilating twice an information derived from radar. On the basis of this result, even if we recognize that the combined assimilation of reflectivity volumes through KENDA and SRI by LHN may not be a rigorous process from a theoretical point of view, it is decided to not switch-off-keep the LHN for the other subsequent experiments. In fact, this choice does not affect negatively the results of the sensitivity tests that are presented in this work and, at the same time, the LHN allows to use radar derived information on

5

the state of the atmosphere in the whole Italian country, despite reflectivity volumes can be assimilated, at present, only over Northern Italy.

Finally, the addition of the additive inflation (*rad60_Bm*, blue bars in Figure 5) does not show a positive impact. At lead time +6h a clear worsening of each of the 3 components of SAL can be noticed.

10 4.2 Impact of the length of the assimilation cycles

To obtain some insights about this topic, assimilation cycles of 15 and 30 minutes (respectively *rad15* and *rad30*) are tested and the results are compared with those obtained with the 60 minutes window (*rad60*), discussed in the previous subsection. Furthermore, an experiment in which observations are assimilated only if collected during the last 15 minutes of hourly assimilation cycles is performed (*rad60_1st15*). Accordingly, the total amount of assimilated data is reduced and the increments computed by the LETKF scheme should be more appropriate for computing the analysis, since the observations time is always very close to the analysis time.

In the same way as described in the previous subsection, SAL verification is computed and averaged over the 5 forecasts initialized from the analyses of each trial. QPF accuracy of the 22 forecasts initialized for each experiment is verified employing SAL and FSS. Results are shown, respectively, in Figure 7 where the green bars are associated to and Figure 8 for *rad15* (red), *rad30* (orange), *rad60* while red and orange to (green) and *rad60_1st15* (blue). Considering SAL verification, at lead time +1h the shorter the cycle the smaller the error in structure and amplitude; however, the smallest location error among the experiments which differ only for the cycle length is associated to *rad30* while *rad15* and *rad60* are almost equal. Moreover, at lead time +1h also QPF of *rad60_1st15* is more accurate than that of *rad60* in each component. Between +2h and +4h, both *rad15* and *rad30* respectively. Regarding the location error, during the first 6 hours of forecast the performance of *rad15* is similar to that of *rad30* have always larger errors than *rad60*, with the only exception of S at +4h. In particular, a relevant worsening in the location of rainfall nuclei is observed at +3h. Regarding *rad60_1st15*, the comparison with *rad60* in the same forecast range reveals that the differences are always small but, except for S at +2h and both are worse than +3h, *rad60*. Afterwards, slightly outperforms *rad60_1st15*. From lead time +5h onwards, differences among the 4 experiments become small and the 3 experiments provides a very similar performance. In terms of structure and amplitude components, the differences among the 3 different window lengths are generally small and non-coherent over the 24 hours of forecast results are mixed.

In a further test, conventional and radar observations are assimilated only if collected during the last 15 minutes of each assimilation cycle of 60 minutes. (Extending the verification to the whole Italian country employing FSS, at +1h no significant differences can be noticed among the 4 experiments when the 1 mm threshold is considered. Between +2h and +4h, as observed with SAL verification, the shortening of the assimilation cycle worsens the QPF accuracy. Similarly, the differences between *rad60* and *rad60_1st15*). In this way, the total amount of assimilated data is reduced and the increments computed by the LETKF scheme should be more appropriate for computing the analysis, since the observations time is always very close to the analysis time. Actually, verification shown in Figure 7 (blue bars) does not point out an improvement of *rad60_1st15* if compared to are very small but, contrary to what observed with SAL, in this case the latter very slightly outperforms the former. From +5h onwards, FSS values of all the experiments are almost equal. When the 5 mm threshold is considered, the

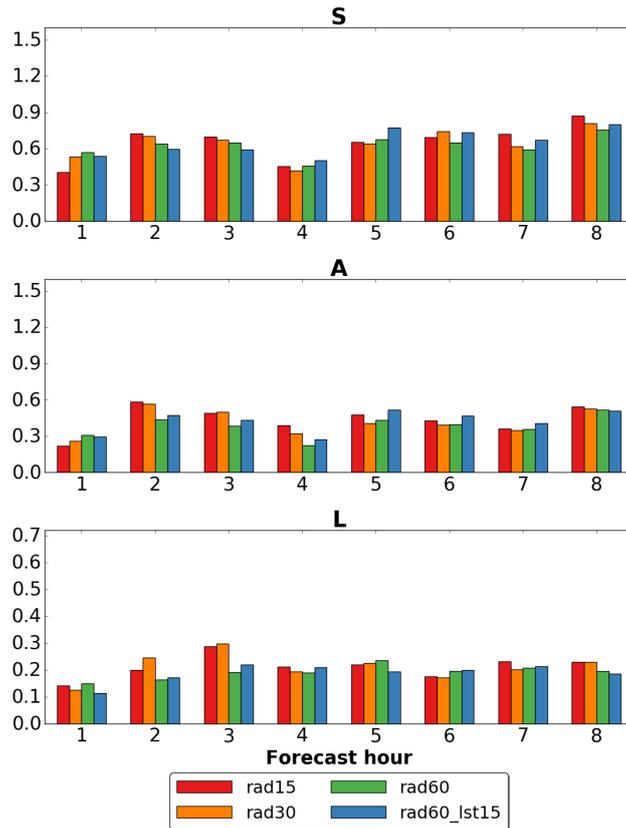


Figure 7. As in Figure 5 but considering experiments *rad15* (red), *rad30* (orange), *rad60* (green) and *rad60_lst15* (blue).

- 5 comparison between *rad15*, *rad30* and *rad60*. In fact, except for a worsening in the *S* component at forecast time leads to the same results as those observed for the 1 mm threshold with even more pronounced differences at lead times +3h-2h and +6h, performance of both experiments is very similar. Therefore, the assimilation of data closer to analysis time does not improve the forecast quality-3h. Regarding *rad60_lst15*, a significant improvement compared to *rad60* is noticed at +1h and a slight positive impact still holds at the subsequent lead times.
- 10 In order to evaluate-
- In summary, assimilating observations collected in the last 15 minutes of hourly cycles does not affect significantly the QPF accuracy when a 1 mm threshold is considered: at +1h a slight improvement is observed only over Northern Italy, while from +2h onwards the mixed results obtained with FSS and SAL suggest a neutral impact. However, *rad60_lst15* slightly outperforms *rad60* over the whole Italian country when the 5 mm threshold is considered. Regarding the length of assimilation cycles, when it is shortened a slight improvement on QPF accuracy is observed at +1h over Northern Italy, but the impact over Italy is neutral. Thereafter, from +2h to +4h, a clear worsening is observed both where assimilation is performed and
- 5 in the rest of Italy. To investigate if this worsening is due to the imbalance issue, the kinetic energy (KE) spectra of the

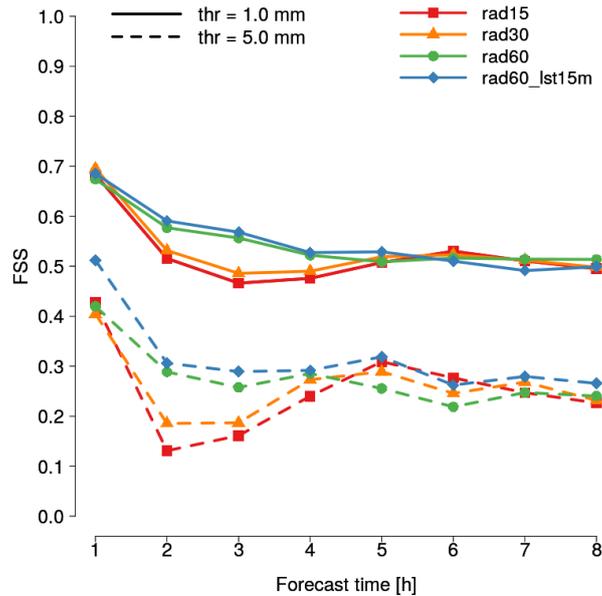


Figure 8. As in Figure 6 but considering experiments *rad15* (red), *rad30* (orange), *rad60* (green) and *rad60_1st15m* (blue).

experiments is computed following the method described in Errico (1985). Curves displayed in Figure 9 are obtained as an average over the whole assimilation period (from 3 February at 06 UTC to 7 February at 00 UTC) of KE spectra computed each hour using analysis values of u , v and w over the whole domain. Kinetic energy spectra of *rad15* (red) and *rad60* (green) are almost overlapping, even at very small wavelength, indicating that shortening the length of cycles from 60 to 15 minutes does not introduce imbalances in the analyses (Skamarock, 2004). Furthermore, both spectra have a $-5/3$ dependence on the wavenumber beyond a wavelength of 15-20 km, in agreement with observed spectra at the mesoscale (Nastrom and Gage, 1985). Same considerations apply also to KE spectra of *rad30* and to *rad60_1st15m*, which are which is not shown.

As a conclusionTherefore, with the current set-up, the use of a sub-hourly window length does not introduce degrades QPF accuracy but this is not due to the introduction of imbalances in the analysis. It is anyway observed a slightly worsening of the precipitation forecast, especially in terms of location of rainfall nucleiA possible different explanation is that the reduced analysis error associated to *rad15* and *rad30* compared to *rad60* makes the ensemble employed for the LETKF scheme too small to correctly characterize the forecast error, as suggested in Uboldi and Trevisan (2015).

4.3 Impact of changing the reflectivity observational error

A set of experiments is performed to investigate the impact of the reflectivity observation observational error in the assimilation scheme. In addition to the value of 5 dBZ employed so far, which was estimated applying the diagnostic described in Desroziers et al. (2005) to this case study, two other values of roe are tested: 10 dBZ and 0.5 dBZ. The former is employed by Bick et al. (2016) for the assimilation of reflectivity volumes from the German radar network using KENDA and COSMO and, therefore,

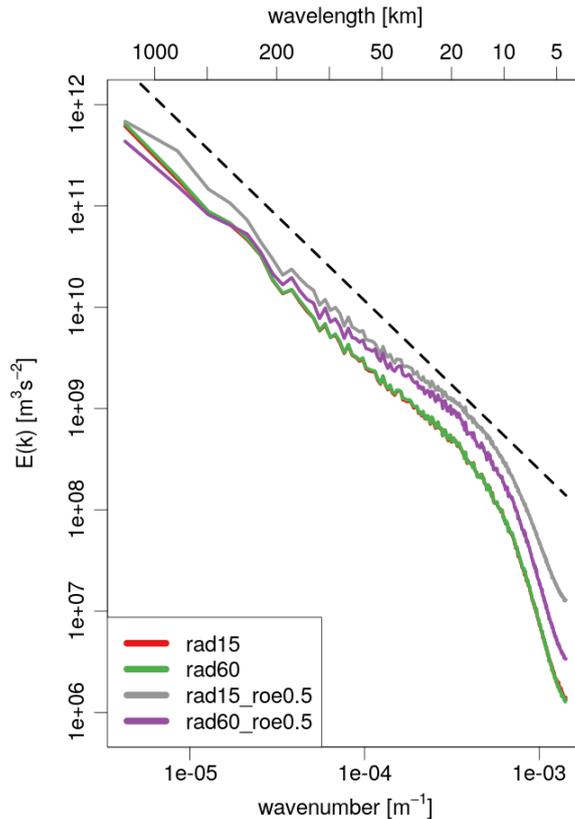


Figure 9. Kinetic energy (KE) spectra computed following the method described by Errico (1985). Each curve is obtained averaging KE spectra ~~computed~~ with a frequency of one hour during the assimilation procedure and employing analysis values of u , v and w over the whole model domain. The spectra are displayed for experiments *rad15* (red), *rad60* (green), *rad15_roe0.5* (~~yellow~~grey) and *rad60_roe0.5* (violet). The dashed black line represents a function with a dependence to the wavenumber equal to $-5/3$.

should be reasonable also for the present study. The latter is a deliberately extreme value that may be chosen in the case of a great confidence in the quality of radar observations. These two different values of *roe* are used in assimilation cycles of 60 minutes (*rad60_roe0.5* and *rad60_roe10*) and 15 minutes (*rad15_roe0.5* and *rad15_roe10*). Therefore, they can be compared with the experiments with our standard value of *roe* = 5dBZ, respectively *rad60* and *rad15*.

~~Verification of forecasts initialized from the analyses of these experiments is reported~~

~~Results of QPF verification in terms of SAL and FSS are reported, respectively, in Figure 10 and Figure 11. Regarding the experiments with a 60 minutes assimilation cycle, SAL verification (left panel) ,the performance of *rad60_roe0.5* is clearly worse than that of *rad60*. In fact, up to the lead time of reveals that *rad60_roe0.5* slightly reduces structure and amplitude errors on QPF at lead time +15h, each component of SAL for the former (violet) is almost equal or greater than that of the~~

5

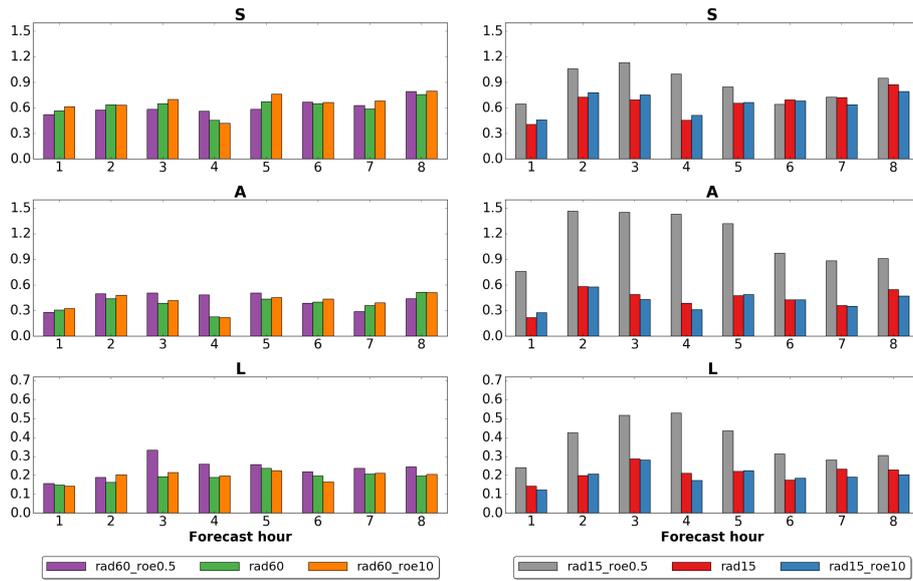


Figure 10. As in Figure 5 but considering, in the left panel, experiments *rad60_roe0.5* (violet), *rad60* (green) and *rad60_roe10* (orange) while, in the right panel, experiments *rad15_roe0.5* (grey), *rad15* (red) and *rad15_roe0.5* (blue).

latter (green) with the only exception for 1h compared to *rad60*, but the location error is very slightly increased. From +2h to +4h, *rad60_roe0.5* has a larger error in all components, except S at +2h and +3h. In particular, the A component is remarkably worsened at +4h and the SL component at +2h and +3h. From As observed for the previous experiments, from +18h onwards, differences between the two become very small. On the other hand, the performance of 5h onwards the results become mixed. When comparing *rad60_roe10* forecasts (orange) is very similar to that of to *rad60* at any lead-time, apart for the error in the structure of precipitation at, differences are small and mixed in the whole forecast range. The FSS verification carried out over the whole Italian country substantially confirms what observed with SAL: *rad60_roe0.5* worsens QPF accuracy from +6h and 2h to +9h which is significantly greater for roe = 10dBZ. When considering assimilation cycles of 4h and the differences compared to *rad60* are even enhanced and extended to +1h when the 5 mm threshold is considered; at the same time, the impact of using a value of roe equal to 10 dBZ instead of 5 dBZ as a neutral impact over the whole forecast range.

In regards with 15 minutes assimilation cycles, *rad15_roe0.5* dramatically worsens QPF accuracy over Northern Italy in terms of structure (right panel in Figure 10), the worsening of forecast precipitation employing a roe = 0.5dBZ (yellow) compared to roe = 5dBZ (red) is further enhanced. In particular, precipitation in the first 12 hours is largely mis-placed and its total amount is widely different from observations up to +5h and up to +12h in terms of amplitude and location (the range between +9h and +12h is not shown). In this regard, the verification of individual forecasts (not shown here) reveals that the large error in A component is due to a systematic underestimation of the average precipitation over the domain. Regarding *rad15_roe10* (blue), similarly to what observed for 60 minutes cycles, the use of roe = 10dBZ instead of 5 dBZ does not affect radically the quality of forecasts, even if a slight improvement in each component of SAL can be observed at This marked

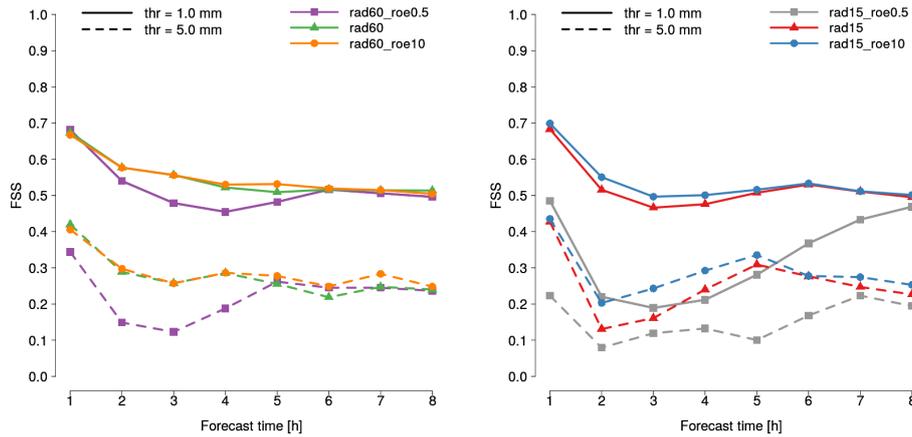


Figure 11. As in Figure 5-6 but considering, in the left panel, experiments *rad60_roe0.5* (violet), *rad60* (green) and *rad60_roe10* (orange) while, in the right panel, experiments *rad15_roe0.5* (yellowgrey), *rad15* (red) and *rad15_roe10* (blue).

worsening can be appreciated also with FSS verification (right panel in Figure 11), especially for the 1 mm threshold. When comparing results of SAL verification for *rad15_roe10* and *rad15*, differences are small and mixed over the whole forecast range. However, in this case, FSS reveals that the former slightly outperforms the latter between +3h and +4h when the 1 mm threshold is considered and this is enhanced when considering the 5 mm threshold.

The overall poor quality of *rad15_roe0.5* forecasts is the direct consequence of the poor quality of the analyses from which they are initialized. As an example, in Figure 12 it is shown the mean sea level pressure (MSLP) and specific humidity at 850 hPa of *rad15_roe0.5* (right column) analysis on February 5 at 12 UTC and it is compared with the same quantities for the analysis of *rad60rad15* (central column) and of the Integrated Forecasting System (IFS) of ECMWF (left column). Slight variations can be observed between IFS and *rad60rad15* analyses and it seems reasonable that they may simply arise from differences between models and assimilation systems. Conversely, *rad15_roe0.5* analysis exhibits a noticeable increase in MSLP and a decrease in specific humidity over Northern Italy. This is in agreement with the decrease in forecast precipitation previously described.

In the same way as described in Section 4.2, KE spectra are computed for *rad15_roe0.5* and *rad60_roe0.5* and displayed in Figure 9. In both cases, at the smallest wavelength the KE is significantly greater than that of *rad15* or *rad60* and this is particularly evident for *rad15_roe0.5*. This behaviour is indicative of the presence of some undesired noise at small scales (Skamarock, 2004). Therefore, employing a value of *roe* equal to 0.5 dBZ, the assimilation system is not able to correctly remove small scale noise, especially when really short cycles are employed. Furthermore, the excess of energy associated to the highest wavenumber modes propagates to the larger scales and the slope of the curves at wavelengths greater than 15 km differs from $-5/3$.

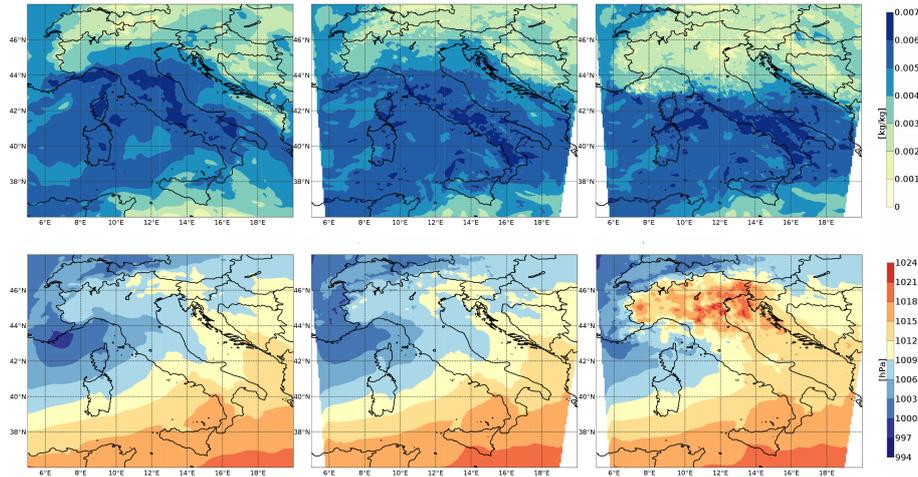


Figure 12. Mean sea level pressure (top) and specific humidity at 850 hPa (bottom) analysis on February 5 at 12 UTC for IFS (left) *rad60* (middle) and *rad15_roe0.5* (right).

5 Conclusions

In the present work, the assimilation of reflectivity volumes in a high resolution model employing a LETKF scheme is evaluated. Assimilation of radar data in an operational set-up is a challenging issue and most of the previous studies is devoted to the assimilation of rainfall estimation, while few to the direct employment of reflectivity estimated from radar data and it is currently widely employed in meteorological centres all over the world. The continuous increase of computer resources now allows to directly assimilate reflectivity volumes, but few studies have been dedicated to test the assimilation of these observations in an operational data assimilation system. Here, results in terms of QPF obtained assimilating reflectivity volumes context. In the present work, the assimilation of reflectivity volumes using the LETKF scheme developed for the high resolution COSMO model is evaluated. A case study of 4 days in February 2017 is carried out using data from 4 radars of the Italian network are shown and compared to those produced with the current operational assimilation system of Arpae, in which only conventional data are employed. Furthermore, some sensitivity tests are performed to investigate the impact of some parameters which can substantially affect the quality of analyses over Northern Italy. The quality of the analyses generated by the data assimilation system is assessed in terms of the accuracy of QPF which is verified using SAL (approximately in the region where reflectivity volumes are assimilated) and FSS (over the whole Italian country).

The assimilation of both conventional data and radar reflectivity volumes with our selected set-up in combination to LHN (*rad60*) only slightly improves QPF both during the assimilation procedure and for the subsequent forecasts, compared to the assimilation of improves QPF accuracy compared to our operational set-up (*conv60*), in which only conventional data are employed together with LHN, and to *conv60_nolhn*, in which conventional observations are assimilated without performing LHN. The improvement

5 ~~compared to *conv60* experiment, in form of LHN of radar precipitation estimate. In fact, even if the precipitation estimate is only a product derived by applying a complex algorithm to is remarkable between lead times +2h and +4h and observed both with SAL and FSS. Regarding the comparison with *conv60_nolhn*, the volume of reflectivities, nevertheless its ingestion could influence the analysis so much that it is difficult to add benefit with the assimilation of reflectivities themselves. However, when LHN is not applied and radar data are assimilated only through KENDA improvement is consistent at +1h and holds~~
10 ~~(attenuated) up to +4h over Northern Italy, while it becomes irrelevant over Italy from lead times +3h. Similar improvements are observed when both conventional data and reflectivity volumes are assimilated without LHN (*rad60_nolhn*), QPF accuracy is not improved. As a consequence, at this stage, the direct assimilation of reflectivity volumes does not outperform significantly LHN and the two techniques may be applied together without loss in QPF accuracy. It has also been shown that, even if the spread of the ensemble is very small (not shown), its enlargement by employing additive inflation does not improve the~~
15 ~~performance, instead, it leads to a modest worsening of the results. One possible reason for this behaviour can be suggesting that the combined use of radar volumes and SRI, not rigorous from a theoretical point of view, does not degrade the results. This can be due to the different nature of the use of a climatological B matrix generated from the ICON model run at a very different resolution. This test should be repeated when a B matrix provided by the COSMO model over the Italian domain will be available.~~
20 ~~observed values: in case of reflectivity volumes the measure is direct while for SRI the field is indirectly calculated using an empiric relationship between reflectivity and rain rate. Furthermore, also the assimilation schemes differ dramatically.~~

For the case study considered in this work ~~In this context, the assimilation of data close to analysis time (at most collected observations collected only in the last 15 minutes before) does not improve the quality of forecast obtained when all observations collected in the whole assimilation window are employed. Nevertheless, this results suggests of each assimilation cycles~~
25 ~~(*rad60_1st15*), further slightly enhances the positive impact of assimilating reflectivity volumes. This result is observed when considering precipitation more intense than 5 mm/h while the impact of using *rad60_1st15* instead of *rad60* analyses is neutral when a 1 mm threshold is employed. Taking into account that this configuration can be employed without evident downsides to reduce also reduces the computational cost of the KENDA system. Further associated to the assimilation of radar data, it seems to be the most promising for an operational implementation. However, further tests would be necessary to evaluate if the~~
30 ~~same conclusion arises when only observations at the analysis time are assimilated. Investigation of the instabilities generated with short assimilation eyeless shows that the use of a sub-hourly window length does not introduce imbalances in the analysis, but it slightly worsens the forecast of precipitation, especially in terms of location of rainfall nuclei. Regarding the length of assimilation cycles, the shortening of their length to 30 and 15 minutes slightly improves QPF accuracy at lead time +1h over the region where they are assimilated, but worsens results between lead times +2h and +4h both over Northern Italy and~~
35 ~~in the rest of the country. This is not due to the introduction of imbalances in the analyses. A possible explanation, which needs further investigation, is that the more frequent assimilation reduces the analysis error making the ensemble too small to properly characterize the forecast error (Uboldi and Trevisan, 2015).~~

With regards to the observational error, it is found that a value of *roe* equal to 0.5 dBZ negatively affects the quality of the analyses and of the subsequent forecasts, because the model is not able to remove noise at the smallest scales. This leads to

5 large errors in all prognostic fields in the area where radar data are assimilated and, as a consequence, to a very poor quality of the forecasts. This is particularly significant when 15 minutes assimilation cycles are employed, in which case forecast precipitation is strongly underestimated and ~~mis-located~~misplaced. Conversely, a value of 10 dBZ ~~does not degrade results both in 60 minutes and~~, that is a value which is twice that estimated using Desroziers statistics, lead to similar results obtained with $roe = 5$ dBZ but slightly improves QPF accuracy when 15 minutes cycles ~~and further~~ are employed.

The observed improvement on QPF accuracy associated to the assimilation of reflectivity volumes is promising, even if it is limited only to the first few hours of forecast. Other tests are necessary to ~~find out if a value grater than 5 dBZ can provide better results. Another improvement of results may be obtained~~ validate if this improvement holds in other synoptic conditions and for longer case studies. Furthermore, several tests need to be performed to extend the impact of the assimilation beyond the first few hours of forecast. In particular, the value of the reflectivity observational error seems to have a strong impact on QPF accuracy. Therefore, it seems reasonable that a further improvement can be achieved when roe is made dependent on the range, elevation ~~and radar station~~, radar station and meteorological condition, but a better comprehension and estimation of this value is mandatory before testing ~~this configuration~~ more complex configurations.

Competing interests. No competing interests.

Acknowledgements. TEXT

References

- 15 Anderson, J. L.: Spatially and temporally varying adaptive covariance inflation for ensemble filters, *Tellus A*, 61, 72–83, <https://doi.org/10.1111/j.1600-0870.2008.00361.x>, <http://dx.doi.org/10.1111/j.1600-0870.2008.00361.x>, 2009.
- Anderson, J. L. and Anderson, S. L.: A Monte Carlo Implementation of the Nonlinear Filtering Problem to Produce Ensemble Assimilations and Forecasts, *Monthly Weather Review*, 127, 2741–2758, [https://doi.org/10.1175/1520-0493\(1999\)127<2741:AMCIOT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1999)127<2741:AMCIOT>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(1999\)127<2741:AMCIOT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1999)127<2741:AMCIOT>2.0.CO;2), 1999.
- 20 Baldauf, M., Seifert, A., Förstner, J., Majewski, D., Raschendorfer, M., and Reinhardt, T.: Operational Convective-Scale Numerical Weather Prediction with the COSMO Model: Description and Sensitivities, *Monthly Weather Review*, 139, 3887–3905, <https://doi.org/10.1175/MWR-D-10-05013.1>, <https://doi.org/10.1175/MWR-D-10-05013.1>, 2011.
- Berner, J., Fossell, K. R., Ha, S.-Y., Hacker, J. P., and Snyder, C.: Increasing the Skill of Probabilistic Forecasts: Understanding Performance Improvements from Model-Error Representations, *Monthly Weather Review*, 143, 1295–1320, <https://doi.org/10.1175/MWR-D-14-00091.1>, <https://doi.org/10.1175/MWR-D-14-00091.1>, 2015.
- 25 Bick, T., Simmer, C., Trömel, S., Wapler, K., Hendricks Franssen, H.-J., Stephan, K., Blahak, U., Schraff, C., Reich, H., Zeng, Y., and Potthast, R.: Assimilation of 3D radar reflectivities with an ensemble Kalman filter on the convective scale, *Quarterly Journal of the Royal Meteorological Society*, 142, 1490–1504, <https://doi.org/10.1002/qj.2751>, <http://dx.doi.org/10.1002/qj.2751>, 2016.
- Bonavita, M., Torrisi, L., and Marcucci, F.: Ensemble data assimilation with the CNMCA regional forecasting system, *Quarterly Journal of the Royal Meteorological Society*, 136, 132–145, <https://doi.org/10.1002/qj.553>, <http://dx.doi.org/10.1002/qj.553>, 2010.
- 30 Buehner, M., Houtekamer, P. L., Charette, C., Mitchell, H. L., and He, B.: Intercomparison of Variational Data Assimilation and the Ensemble Kalman Filter for Global Deterministic NWP. Part I: Description and Single-Observation Experiments, *Monthly Weather Review*, 138, 1550–1566, <https://doi.org/10.1175/2009MWR3157.1>, <https://doi.org/10.1175/2009MWR3157.1>, 2010a.
- Buehner, M., Houtekamer, P. L., Charette, C., Mitchell, H. L., and He, B.: Intercomparison of Variational Data Assimilation and the Ensemble Kalman Filter for Global Deterministic NWP. Part II: One-Month Experiments with Real Observations, *Monthly Weather Review*, 138, 1567–1586, <https://doi.org/10.1175/2009MWR3158.1>, <https://doi.org/10.1175/2009MWR3158.1>, 2010b.
- 35 Clark, P., Roberts, N., Lean, H., Ballard, S. P., and Charlton-Perez, C.: Convection-permitting models: a step-change in rainfall forecasting, *Meteorological Applications*, 23, 165–181, <https://doi.org/10.1002/met.1538>, <http://dx.doi.org/10.1002/met.1538>, mET-14-0154.R1, 2016.
- Courtier, P., Andersson, F., Hackley, W., Vasiljevic, D., Hamrud, M., Hollingsworth, A., Rabier, F., Fisher, M., and Pailleux, J.: The ECMWF implementation of three dimensional variational assimilation (3D-Var). I: Formulation, *Quarterly Journal of the Royal Meteorological Society*, 124, 1783–1807, <https://doi.org/10.1002/qj.49712455002>, 1998.
- 5 Cuo, L., Pagano, T. C., and Wang, Q. J.: A Review of Quantitative Precipitation Forecasts and Their Use in Short- to Medium-Range Streamflow Forecasting, *Journal of Hydrometeorology*, 12, 713–728, <http://www.jstor.org/stable/24912965>, 2011.
- Davolio, S., Silvestro, F., and Gastaldo, T.: Impact of Rainfall Assimilation on High-Resolution Hydrometeorological Forecasts over Liguria, Italy, *Journal of Hydrometeorology*, 18, 2659–2680, <https://doi.org/10.1175/JHM-D-17-0073.1>, <https://doi.org/10.1175/JHM-D-17-0073.1>, 2017.
- 10 Desroziers, G., Berre, L., Chapnik, B., and Poli, P.: Diagnosis of observation, background and analysis-error statistics in observation space, *Quarterly Journal of the Royal Meteorological Society*, 131, 3385–3396, <https://doi.org/10.1256/qj.05.108>, <http://dx.doi.org/10.1256/qj.05.108>, 2005.

- Dixon, M., Li, Z., Lean, H., Roberts, N., and Ballard, S.: Impact of Data Assimilation on Forecasting Convection over the United Kingdom Using a High-Resolution Version of the Met Office Unified Model, *Monthly Weather Review*, 137, 1562–1584, <https://doi.org/10.1175/2008MWR2561.1>, <https://doi.org/10.1175/2008MWR2561.1>, 2009.
- Doms, G., Förstner, J., Heise, E., Herzog, H.-J., Mironov, D., Raschendorfer, M., Reinhardt, T., Ritter, B., Schrodin, R., Schulz, J.-P., and Vogel, G.: A Description of the Nonhydrostatic Regional COSMO Model, Part II: Physical Parameterization, Tech. rep., <http://www.cosmo-model.org/content/model/documentation/core/default.htm>, 2011.
- Dowell, D. C. and Wicker, L. J.: Additive Noise for Storm-Scale Ensemble Data Assimilation, *Journal of Atmospheric and Oceanic Technology*, 26, 911–927, <https://doi.org/10.1175/2008JTECHA1156.1>, <https://doi.org/10.1175/2008JTECHA1156.1>, 2009.
- Errico, R. M.: Spectra Computed from a Limited Area Grid, *Monthly Weather Review*, 113, 1554–1562, [https://doi.org/10.1175/1520-0493\(1985\)113<1554:SCFALA>2.0.CO;2](https://doi.org/10.1175/1520-0493(1985)113<1554:SCFALA>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(1985\)113<1554:SCFALA>2.0.CO;2](https://doi.org/10.1175/1520-0493(1985)113<1554:SCFALA>2.0.CO;2), 1985.
- Evensen, G.: Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics, *J. Geophys. Res.*, 99, 10 143–10 162, 1994.
- Ferting, E. J., Harlim, J., and Hunt, B. R.: A comparative study of 4D-VAR and a 4D Ensemble Kalman Filter: perfect model simulations with Lorenz-96, *Tellus A*, 59, 96–100, <https://doi.org/10.1111/j.1600-0870.2006.00205.x>, <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1600-0870.2006.00205.x>, 2007.
- Gaspari, G. and Cohn, S. E.: Construction of correlation functions in two and three dimensions, *Quarterly Journal of the Royal Meteorological Society*, 125, 723–757, <https://doi.org/10.1002/qj.49712555417>, <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.49712555417>, 1999.
- Gustafsson, N. and Bojarova, J.: Four-dimensional ensemble variational (4D-En-Var) data assimilation for the High Resolution Limited Area Model (HIRLAM), *Nonlinear Processes in Geophysics*, 21, 745–762, <https://doi.org/10.5194/npg-21-745-2014>, <https://www.nonlin-processes-geophys.net/21/745/2014/>, 2014.
- Hamrud, M., Bonavita, M., and Isaksen, L.: EnKF and Hybrid Gain Ensemble Data Assimilation. Part I: EnKF Implementation, *Monthly Weather Review*, 143, 4847–4864, <https://doi.org/10.1175/MWR-D-14-00333.1>, <https://doi.org/10.1175/MWR-D-14-00333.1>, 2015.
- Harnisch, F. and Keil, C.: Initial Conditions for Convective-Scale Ensemble Forecasting Provided by Ensemble Data Assimilation, *Monthly Weather Review*, 143, 1583–1600, <https://doi.org/10.1175/MWR-D-14-00209.1>, <https://doi.org/10.1175/MWR-D-14-00209.1>, 2015.
- Houtekamer, P. L. and Mitchell, H. L.: Data Assimilation Using an Ensemble Kalman Filter Technique, *Monthly Weather Review*, 126, 796–811, [https://doi.org/10.1175/1520-0493\(1998\)126<0796:DAUAEK>2.0.CO;2](https://doi.org/10.1175/1520-0493(1998)126<0796:DAUAEK>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(1998\)126<0796:DAUAEK>2.0.CO;2](https://doi.org/10.1175/1520-0493(1998)126<0796:DAUAEK>2.0.CO;2), 1998.
- Houtekamer, P. L. and Mitchell, H. L.: Ensemble Kalman filtering, *Quarterly Journal of the Royal Meteorological Society*, 131, 3269–3289, <https://doi.org/10.1256/qj.05.135>, <http://dx.doi.org/10.1256/qj.05.135>, 2005.
- Houtekamer, P. L. and Zhang, F.: Review of the Ensemble Kalman Filter for Atmospheric Data Assimilation, *Monthly Weather Review*, 144, 4489–4532, <https://doi.org/10.1175/MWR-D-15-0440.1>, <https://doi.org/10.1175/MWR-D-15-0440.1>, 2016.
- Houtekamer, P. L., Mitchell, H. L., Pellerin, G., Buehner, M., Charron, M., Spacek, L., and Hansen, B.: Atmospheric Data Assimilation with an Ensemble Kalman Filter: Results with Real Observations, *Monthly Weather Review*, 133, 604–620, <https://doi.org/10.1175/MWR-2864.1>, <https://doi.org/10.1175/MWR-2864.1>, 2005.
- Hunt, B. R., Kostelich, E. J., and Szunyogh, I.: Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter, *Physica D: Nonlinear Phenomena*, 230, 112 – 126, <https://doi.org/https://doi.org/10.1016/j.physd.2006.11.008>, <http://www.sciencedirect.com/science/article/pii/S0167278906004647>, data Assimilation, 2007.

- Jones, C. D. and Macpherson, B.: A latent heat nudging scheme for the assimilation of precipitation data into an operational mesoscale model, *Meteorological Applications*, 4, 269–277, <https://doi.org/10.1017/S1350482797000522>, <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1017/S1350482797000522>, 2006.
- Koistininen, J. and Puhakka, T.: An improved spatial gauge-radar adjustment technique, in: *Proc. 20th Conference on Radar Meteorology*, pp. 179–186, AMS, 1981.
- Leuenberger, D. and Merker, C.: Additive Covariance Inflation in an operational, convective-scale NWP Ensemble Kalman Filter Assimilation System, Poster contribution at the International Symposium on Data Assimilation (ISDA), https://isda2018.wavestoweather.de/program/poster_presentations/p6_1_leuenberger.pdf, 2018.
- Leuenberger, D. and Rossa, A.: Revisiting the latent heat nudging scheme for the rainfall assimilation in convective system, in: *Proc. of 3th European Radar Conference on Radar Meteorology and Hydrology (ERAD)*, pp. 162–167, Visby, Gotland, Sweden, 6–10 September 2004, 2004.
- Leuenberger, D. and Rossa, A.: Revisiting the latent heat nudging scheme for the rainfall assimilation of a simulated convective storm, *Meteorol. Atmos. Phys.*, 98, 195–215, 2007.
- Lin, Y.-L., Farley, R. D., and Orville, H. D.: Bulk Parameterization of the Snow Field in a Cloud Model, *Journal of Climate and Applied Meteorology*, 22, 1065–1092, [https://doi.org/10.1175/1520-0450\(1983\)022<1065:BPOTSF>2.0.CO;2](https://doi.org/10.1175/1520-0450(1983)022<1065:BPOTSF>2.0.CO;2), [https://doi.org/10.1175/1520-0450\(1983\)022<1065:BPOTSF>2.0.CO;2](https://doi.org/10.1175/1520-0450(1983)022<1065:BPOTSF>2.0.CO;2), 1983.
- Meng, Z. and Zhang, F.: Limited-Area Ensemble-Based Data Assimilation, *Monthly Weather Review*, 139, 2025–2045, <https://doi.org/10.1175/2011MWR3418.1>, <https://doi.org/10.1175/2011MWR3418.1>, 2011.
- Mitchell, H. L. and Houtekamer, P. L.: An Adaptive Ensemble Kalman Filter, *Monthly Weather Review*, 128, 416–433, [https://doi.org/10.1175/1520-0493\(2000\)128<0416:AAEKF>2.0.CO;2](https://doi.org/10.1175/1520-0493(2000)128<0416:AAEKF>2.0.CO;2), <https://journals.ametsoc.org/doi/abs/10.1175/1520-0493%282000%29128%3C0416%3AAAEKF%3E2.0.CO%3B2>, 2000.
- Miyoshi, T., Sato, Y., and Kadowaki, T.: Ensemble Kalman Filter and 4D-Var Intercomparison with the Japanese Operational Global Analysis and Prediction System, *Monthly Weather Review*, 138, 2846–2866, <https://doi.org/10.1175/2010MWR3209.1>, <https://doi.org/10.1175/2010MWR3209.1>, 2010.
- Nastrom, G. D. and Gage, K. S.: A Climatology of Atmospheric Wavenumber Spectra of Wind and Temperature Observed by Commercial Aircraft, *Journal of the Atmospheric Sciences*, 42, 950–960, [https://doi.org/10.1175/1520-0469\(1985\)042<0950:ACOAWS>2.0.CO;2](https://doi.org/10.1175/1520-0469(1985)042<0950:ACOAWS>2.0.CO;2), [https://doi.org/10.1175/1520-0469\(1985\)042<0950:ACOAWS>2.0.CO;2](https://doi.org/10.1175/1520-0469(1985)042<0950:ACOAWS>2.0.CO;2), 1985.
- Poterjoy, J.: A Localized Particle Filter for High-Dimensional Nonlinear Systems, *Monthly Weather Review*, 144, 59–76, <https://doi.org/10.1175/MWR-D-15-0163.1>, <https://doi.org/10.1175/MWR-D-15-0163.1>, 2016.
- Raschendorfer, M.: The new turbulence parametrization of LM, *COSMO newsletter*, 1, 89–97, 2001.
- Rinollo, A., Vulpiani, G., Puca, S., Pagliara, P., Kaňák, J., Lábó, E., Okon, L., Roulin, E., Baguis, P., Cattani, E., Laviola, S., and Levizzani, V.: Definition and impact of a quality index for radar-based reference measurements in the H-SAF precipitation product validation, *Natural Hazards and Earth System Sciences*, 13, 2695–2705, <https://doi.org/10.5194/nhess-13-2695-2013>, <https://www.nat-hazards-earth-syst-sci.net/13/2695/2013/>, 2013.
- Ritter, B. and Geleyn, J.-F.: A Comprehensive Radiation Scheme for Numerical Weather Prediction Models with Potential Applications in Climate Simulations, *Monthly Weather Review*, 120, 303–325, [https://doi.org/10.1175/1520-0493\(1992\)120<0303:ACRSFN>2.0.CO;2](https://doi.org/10.1175/1520-0493(1992)120<0303:ACRSFN>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(1992\)120<0303:ACRSFN>2.0.CO;2](https://doi.org/10.1175/1520-0493(1992)120<0303:ACRSFN>2.0.CO;2), 1992.

- Roberts, N. M. and Lean, H. W.: Scale-Selective Verification of Rainfall Accumulations from High-Resolution Forecasts of Convective Events, *Monthly Weather Review*, 136, 78–97, <https://doi.org/10.1175/2007MWR2123.1>, <https://doi.org/10.1175/2007MWR2123.1>, 2008.
- Röpnack, A., Hense, A., Gebhardt, C., and Majewski, D.: Bayesian Model Verification of NWP Ensemble Forecasts, *Monthly Weather Review*, 141, 375–387, <https://doi.org/10.1175/MWR-D-11-00350.1>, <https://doi.org/10.1175/MWR-D-11-00350.1>, 2013.
- Rossa, A., Nurmi, P., and Ebert, E.: Overview of methods for the verification of quantitative precipitation forecasts, pp. 419–452, Springer Berlin Heidelberg, Berlin, Heidelberg, https://doi.org/10.1007/978-3-540-77655-0_16, https://doi.org/10.1007/978-3-540-77655-0_16, 2008.
- Schraff, C., Reich, H., Rhodin, A., Schomburg, A., Stephan, K., Perriñez, A., and Pothast, R.: Kilometre-scale ensemble data assimilation for the COSMO model (KENDA), *Quarterly Journal of the Royal Meteorological Society*, 142, 1453–1472, <https://doi.org/10.1002/qj.2748>, <http://dx.doi.org/10.1002/qj.2748>, 2016.
- Seifert, A. and Beheng, K. D.: A double-moment parameterization for simulating autoconversion, accretion and selfcollection, *Atmospheric Research*, 59-60, 265 – 281, [https://doi.org/https://doi.org/10.1016/S0169-8095\(01\)00126-0](https://doi.org/https://doi.org/10.1016/S0169-8095(01)00126-0), <http://www.sciencedirect.com/science/article/pii/S0169809501001260>, 13th International Conference on Clouds and Precipitation, 2001.
- Skamarock, W. C.: Evaluating Mesoscale NWP Models Using Kinetic Energy Spectra, *Monthly Weather Review*, 132, 3019–3032, <https://doi.org/10.1175/MWR2830.1>, <https://doi.org/10.1175/MWR2830.1>, 2004.
- Snyder, C. and Zhang, F.: Assimilation of Simulated Doppler Radar Observations with an Ensemble Kalman Filter, *Monthly Weather Review*, 131, 1663–1677, <https://doi.org/10.1175//2555.1>, <https://doi.org/10.1175//2555.1>, 2003.
- Sokol, Z.: Effects of an assimilation of radar and satellite data on a very-short range forecast of heavy convective rainfalls, *Atmospheric Research*, 93, 188 – 206, <https://doi.org/https://doi.org/10.1016/j.atmosres.2008.11.001>, <http://www.sciencedirect.com/science/article/pii/S0169809508003402>, 4th European Conference on Severe Storms, 2009.
- Stephan, K., Klink, S., and Schraff, C.: Assimilation of radar-derived rain rates into the convective-scale model COSMO-DE at DWD, *Quarterly Journal of the Royal Meteorological Society*, 134, 1315–1326, <https://doi.org/10.1002/qj.269>, <http://dx.doi.org/10.1002/qj.269>, 2008.
- Tiedtke, M.: A Comprehensive Mass Flux Scheme for Cumulus Parameterization in Large-Scale Models, *Monthly Weather Review*, 117, 1779–1800, [https://doi.org/10.1175/1520-0493\(1989\)117<1779:ACMFSF>2.0.CO;2](https://doi.org/10.1175/1520-0493(1989)117<1779:ACMFSF>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(1989\)117<1779:ACMFSF>2.0.CO;2](https://doi.org/10.1175/1520-0493(1989)117<1779:ACMFSF>2.0.CO;2), 1989.
- Tong, M. and Xue, M.: Ensemble Kalman Filter Assimilation of Doppler Radar Data with a Compressible Nonhydrostatic Model: OSS Experiments, *Monthly Weather Review*, 133, 1789–1807, <https://doi.org/10.1175/MWR2898.1>, <https://doi.org/10.1175/MWR2898.1>, 2005.
- Uboldi, F. and Trevisan, A.: Multiple-scale error growth in a convection-resolving model, *Nonlinear Processes in Geophysics*, 22, 1–13, <https://doi.org/10.5194/npq-22-1-2015>, <https://www.nonlin-processes-geophys.net/22/1/2015/>, 2015.
- van Leeuwen, P. J.: Particle Filtering in Geophysical Systems, *Monthly Weather Review*, 137, 4089–4114, <https://doi.org/10.1175/2009MWR2835.1>, <https://doi.org/10.1175/2009MWR2835.1>, 2009.
- Wang, X., Barker, D. M., Snyder, C., and Hamill, T. M.: A Hybrid ETKF–3DVAR Data Assimilation Scheme for the WRF Model. Part I: Observing System Simulation Experiment, *Monthly Weather Review*, 136, 5116–5131, <https://doi.org/10.1175/2008MWR2444.1>, <https://doi.org/10.1175/2008MWR2444.1>, 2008.
- Wernli, H., Paulat, M., Hagen, M., and Frei, C.: SAL—A Novel Quality Measure for the Verification of Quantitative Precipitation Forecasts, *Monthly Weather Review*, 136, 4470–4487, <https://doi.org/10.1175/2008MWR2415.1>, <https://doi.org/10.1175/2008MWR2415.1>, 2008.

- Wernli, H., Hofmann, C., and Zimmer, M.: Spatial Forecast Verification Methods Intercomparison Project: Application of the SAL Technique, *Weather and Forecasting*, 24, 1472–1484, <https://doi.org/10.1175/2009WAF2222271.1>, <https://doi.org/10.1175/2009WAF2222271.1>, 2009.
- 765 Yang, S.-C., Kalnay, E., Hunt, B., and Neill, E. B.: Weight interpolation for efficient data assimilation with the Local Ensemble Transform Kalman Filter, *Quarterly Journal of the Royal Meteorological Society*, 135, 251–262, <https://doi.org/10.1002/qj.353>, <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.353>, 2009.
- Yano, J.-I., Ziemiański, M. Z., Cullen, M., Termonia, P., Onvlee, J., Bengtsson, L., Carrassi, A., Davy, R., Deluca, A., Gray, S. L., Homar, V., Köhler, M., Krichak, S., Michaelides, S., Phillips, V. T. J., Soares, P. M. M., and Wyszogrodzki, A. A.: Scientific Challenges of Convective-
770 Scale Numerical Weather Prediction, *Bulletin of the American Meteorological Society*, 99, 699–710, <https://doi.org/10.1175/BAMS-D-17-0125.1>, <https://doi.org/10.1175/BAMS-D-17-0125.1>, 2018.
- Zängl, G., Reinert, D., Rípodas, P., and Baldauf, M.: The ICON (ICOsahedral Non-hydrostatic) modelling framework of DWD and MPI-M: Description of the non-hydrostatic dynamical core, *Quarterly Journal of the Royal Meteorological Society*, 141, 563–579, <https://doi.org/10.1002/qj.2378>, <http://dx.doi.org/10.1002/qj.2378>, 2015.
- 775 Zhang, F., Snyder, C., and Sun, J.: Impacts of Initial Estimate and Observation Availability on Convective-Scale Data Assimilation with an Ensemble Kalman Filter, *Monthly Weather Review*, 132, 1238–1253, [https://doi.org/10.1175/1520-0493\(2004\)132<1238:IOIEAO>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<1238:IOIEAO>2.0.CO;2), [https://doi.org/10.1175/1520-0493\(2004\)132<1238:IOIEAO>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<1238:IOIEAO>2.0.CO;2), 2004.