



SBMcast – An ensemble nowcasting technique to assess the uncertainty in rainfall forecasts by Lagrangian extrapolation

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SUMMARY

Deterministic nowcasting based on Lagrangian extrapolation of recent radar observations is a technique used in many operational and research centers and has proven to be useful at extending the anticipation with which flows can be forecasted with a rainfall–runoff model. However, the improvement in flow forecasts is not known a priori and case-dependent, mostly depending on the predictability of the rainfall field.

In this work a probabilistic technique has been developed to automatically quantify the uncertainty in radar-based nowcasts obtained by Lagrangian extrapolation to be used in hydrology. The technique follows the ensemble approach: it generates a number of realizations of rainfall forecasts compatible with observations and that preserve the space and time structure of the rainfall field according to the String of Beads model.

The results show that the technique reasonably reproduces the evolution of the rainfall field, but that, overall, the errors are underestimated in part due to the fact that the uncertainty in rainfall forecasts due to errors in the motion field is neglected in this current version of the method.

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1. Introduction

A number of studies (among others, Sempere-Torres et al., 1999; Ogden et al., 2000; Giannoni et al., 2003; Germann et al., 2009; Gourley et al., 2010) have shown the benefit of coupling radar rainfall measurements with distributed rainfall–runoff models to improve the simulation of the response of small- to medium-sized catchments, thanks to the detailed description of the precipitation field provided by radar.

These schemes are of particular interest in the framework of real-time flood forecasting and warning systems. There, the anticipation of floods is crucial for emergency management (particularly, in medium-sized basins). In this sense, Dolcine et al. (2001), Berenguer et al. (2005), Van Horne et al. (2006) and Vivoni et al. (2006, 2007) showed the benefit of extending rainfall inputs to a rainfall–runoff model with rainfall forecasts obtained with radar-based nowcasting techniques.

However, most nowcasting techniques generate deterministic rainfall forecasts and thus do not provide assessments of their uncertainty. Consequently, the need for quantifying the uncertainty affecting rainfall nowcasts by means of probabilistic nowcasting techniques has been recently identified (e.g. Germann

and Zawadzki, 2004; Berenguer et al., 2005; Bowler et al., 2006). The idea is develop methodologies similar to those for probabilistic Quantitative Precipitation Estimation from radar observations (see the recent works of Lee et al., 2007; Llort et al., 2008; Germann et al., 2009; Villarini et al., 2009), based on the generation of ensembles of possible scenarios given the observations.

The first attempts at generating radar-based probabilistic nowcasts consisted of approaches similar to those of Andersson and Ivarsson (1991) or Germann and Zawadzki (2004). Those methods produced forecasts of the probability distribution function of precipitation at each point. However, the main disadvantage in using such techniques for flood forecasting is the fact that they do not provide a complete description of the spatial and temporal structure of precipitation, which plays a key role in the hydrological response of basins. This disadvantage is a major limitation for their use in the analysis of error propagation through rainfall–runoff models. That is why most authors have identified the ensemble approach, which consists in the generation of a number of “realistic” future rainfall scenarios (“members”) compatible with the observations. The main advantage of these ensembles is that they describe the uncertainty in Quantitative Precipitation Forecasts (QPF) and, at the same time, they respect the spatial and temporal structure of the rainfall field, which are crucial properties in analyses of error propagation through distributed rainfall–runoff models (see e.g. Zappa et al. (2010) and references therein).

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Table 1

Characteristics of the events selected for the analysis carried out in Section 2 of this work. Average and maximum accumulations correspond to the values accumulated along the events in the $160 \times 160 \text{ km}^2$ domain indicated with dash line in the different panels of Fig. 1.

Start [UTC]	End (UTC)	Average accumulation (mm)	Maximum accumulation (mm)	Nature of the event
15 January 2001 00:00	15 January 2001 24:00	9.7	70	Stratiform
19 July 2001 02:00	19 July 2001 13:00	13.0	30	Stratiform
14 November 2001 22:00	16 November 2001 16:00	38.5	95	Stratiform/ convective
16 April 2009 10:00	16 April 2009 20:30	2.4	55	Convective
16 June 2009 00:00	16 June 2009 21:30	1.9	50	Convective
19 June 2009 00:00	19 June 2009 24:00	5.6	160	Convective

The present work introduces and evaluates the performance of an extrapolation-based algorithm for probabilistic rainfall nowcasting with the aim of quantifying the uncertainty in nowcasting by Lagrangian extrapolation (i.e. advecting current radar observations according to the motion field of precipitation). This probabilistic algorithm is based on the assumptions of a model for the structure of rainfall in space and time. A follow-up paper will focus on the analysis of the impact of such uncertainty in flow simulation by means of a distributed rainfall–runoff model.

The paper is structured as follows: Section 2 describes the framework where the study has been carried out, providing descriptions of the data set, the deterministic version of the Lagrangian extrapolation algorithm and the scores used to assess the quality of rainfall forecasts. Section 3 presents the probabilistic nowcasting technique, and the performance of the deterministic and probabilistic algorithms is analyzed in Section 4. Finally, concluding remarks are summarized in Section 5.

2. Implementation of the nowcasting technique

2.1. Data set and framework of analysis

The study has been carried out in the vicinity of Barcelona, Catalunya (Spain). This region has a typical Mediterranean climate: it is affected by intense rainfall events that frequently lead to severe floods. In this area, during autumn, the land-sea temperature differences and mountain ranges near the coast, which act as natural barriers causing the updraft of warm wet air from the Mediterranean sea, trigger the generation of local intense convective storms. However, long-lasting, widespread systems are also common, especially in winter and spring.

The domain is covered by a number of radars. In particular, for this study we have used data collected with the Corbera de Llobregat and Creu del Vent C-band radars which belong, respectively, to the Spanish Meteorological Agency (AEMET) and the Meteorological Service of Catalunya (SMC). Raw radar data have been processed to produce 1-km resolution rainfall maps according to a chain of Quality Control and Quantitative Precipitation Estimation algorithms, including: (i) reduction of the effects of beam blockage by the orography using the approach of Delrieu et al. (1995), (ii) clutter elimination by combining the techniques of Berenguer et al. (2006) and Sánchez-Diezma et al. (2001), (iii) identification of the type of precipitation and extrapolation of elevated reflectivity measurements to the surface according to a double Vertical Profile of Reflectivity as described by Franco et al. (2006, 2008), and (iv) conversion of reflectivity into rain rate using a double Z-R relationship: Marshall–Palmer's $Z = 200R^{1.6}$ for stratiform rain (Marshall and Palmer, 1948), and $Z = 525R^{1.28}$ for convective rain (derived from disdrometer measurements in the area of study by Sempere-Torres et al., 1997).

In this study, we have analyzed data corresponding to six events, including both convective and stratiform situations

representative of the region and totaling 133 h of rainfall (some details are provided in Table 1, and the maps of accumulated radar rainfall are presented in Fig. 1). Data for the three events of year 2001 were collected with the Corbera de Llobregat C-band radar, and the three 2009 events, were collected with the Creu del Vent C-band radar (the rainfall accumulation maps of Fig. 1 are centered, correspondingly, at the radar locations).

2.2. The Lagrangian extrapolation algorithm

The deterministic version of the algorithm for rainfall forecasting by Lagrangian extrapolation uses radar rainfall maps generated as described in Section 2.1. The algorithm is the same as in Berenguer et al. (2005) and consists of two modules for:

- (1) Rainfall tracking: The algorithm implemented to estimate the motion field of precipitation is based on TREC (Rinehart and Garvey, 1978) to which continuity is imposed according to the algorithm COTREC proposed by Li et al. (1995). The motion field is obtained with a given resolution (in this case, 16 km) and it is finally transferred to the grid resolution (1 km) by linear interpolation.
- (2) Extrapolation of rainfall observations: Last observed rainfall field is advected according to the estimated motion field derived with the mentioned tracking technique. The motion field is kept stationary in time during the forecast, and it is implemented according to a semi-Lagrangian backward scheme (i.e. reflectivity forecasted at a given pixel is obtained by picking the observed reflectivity value at a location found by integrating the motion field backwards along the forecasting period – for further details see Germann and Zawadzki, 2002 and Berenguer et al., 2005).

2.3. Verification of the forecasts

The performance of the extrapolation-based nowcasting algorithms has been evaluated against radar rainfall observations over the events presented in Section 2.1. The quality of the forecasts has been assessed within the domain shown with a dashed line in the panels of Fig. 1, and according to the following scores:

- (1) Cross-correlation: We have chosen to use the formulation of cross-correlation introduced by Zawadzki (1973) without subtraction of the mean:

$$\text{corr}(\tau) = \frac{\sum_{x,y,t} \hat{Z}_t(x,y,t+\tau) \cdot Z(x,y,t+\tau)}{\left[\sum_{x,y,t} \hat{Z}_t(x,y,t+\tau)^2 \sum_{x,y,t} Z(x,y,t+\tau)^2 \right]^{\frac{1}{2}}} \quad (1)$$

where $Z(x,y,t+\tau)$ is the reflectivity (in dBZ) observed at $t+\tau$ at position (x,y) , and $\hat{Z}_t(x,y,t+\tau)$ is the reflectivity forecasted at t with a lead time τ at the same location.

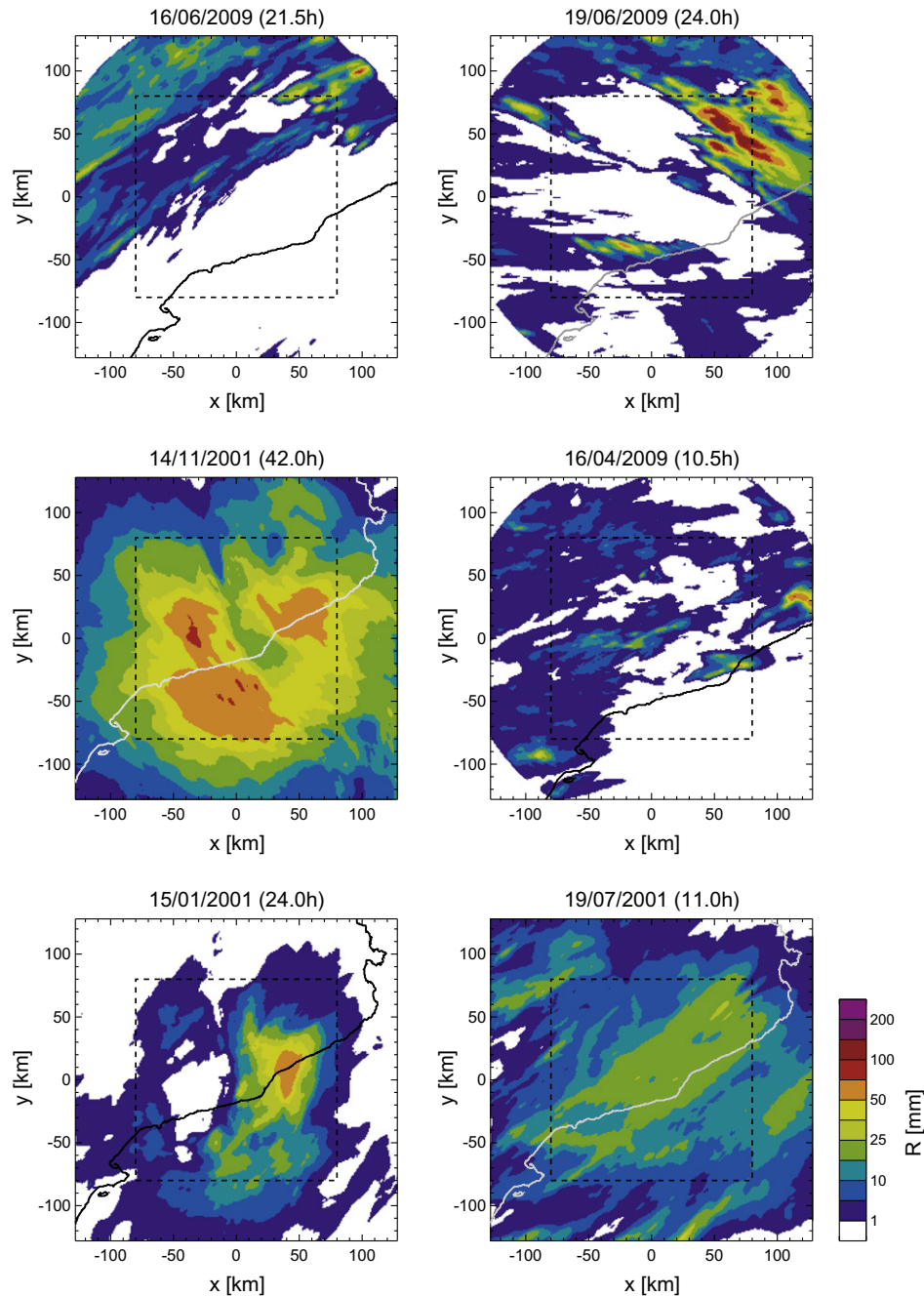


Fig. 1. Maps of accumulated rainfall corresponding to the events described in Section 2. The number in parentheses specifies the duration of the considered events in hours, and the dashed line indicates the $160 \times 160 \text{ km}^2$ analysis domain centered at the radar site.

(2) *Probability of Detection (POD)*, *False Alarm Ratio (FAR)* and *Critical Success Index (CSI)*: these are contingency-table scores (see e.g. Stanski et al., 1989) that are obtained after assigning the categories “event” (“no-event”) to each point of the grids of rainfall observations and forecasts provided that rain rate exceeds (does not exceed) a certain threshold. The scores are computed as:

$$POD = \frac{a}{a + b} \quad (2)$$

$$FAR = \frac{c}{a + c} \quad (3)$$

$$CSI = \frac{a}{a + b + c} \quad (4)$$

where a is the number of hits (both the forecast and the observation were classified as “event”), b is the number of misses (an ob-

served event was not forecasted), and c is the number of false alarms (where a forecasted event was not observed). Note that the sites where neither the forecast nor the observation exceed the chosen threshold are neglected in the computation of the CSI. In the results presented in this section, we used a rainfall threshold of 1 mm/h in the computation of the scores.

(3) *Conditional Mean Absolute Error*: We have analyzed the error in forecasted intensities in the areas where both observations and forecasts have an event (i.e. where rainfall rate exceeds 1 mm/h). This has been done by means of the Mean Absolute Error in terms of reflectivity (in dB) in such areas:

$$CMAE(\tau) = \frac{1}{a} \sum_{x,y,z \in A} |\hat{Z}_t(x,y,t+\tau) - Z(x,y,t+\tau)| \quad (5)$$

where a is the number of hits, and the summation is done in the areas A where hits have been obtained.

(4) **Brier Score:** The Brier score is also based on contingency tables.

It is principally used in the analysis of ensemble forecasts and is defined as:

$$\text{Brier}(\tau) = \frac{1}{n} \sum_{x,y,t} [f_t(x,y,t+\tau) - p(x,y,t+\tau)]^2 \quad (6)$$

where $p(x,y,t+\tau)$ is either 1 or 0 depending whether an event occurred or not; $f_t(x,y,t+\tau) = \frac{1}{n_m} \sum_{j=1}^{n_m} \hat{p}_{t,j}(x,y,t+\tau)$ and $\hat{p}_{t,j}(x,y,t+\tau)$ is either 1 or 0 for the events forecasted by the j th member of the ensemble at time t for a location (x,y) and with a lead time τ ; n is the number of points of the domain, and n_m are the number of members of the ensemble. A Brier score of 0 indicates a perfect forecast, and it increases as the forecasts worsen.

3. The extrapolation-based probabilistic nowcasting technique

As mentioned in Section 1, the main purpose of the probabilistic nowcasting technique presented herein is the description of the errors affecting rainfall forecasts obtained by Lagrangian extrapolation. Bowler et al. (2006) and Germann et al. (2006) identified the following as the two main factors resulting in errors in rainfall forecasts obtained by Lagrangian extrapolation:

- (1) growth and decay of rainfall intensity not explained by the apparent motion field, and
- (2) errors introduced by the motion field used to extrapolate recent observations; that is the result of the errors associated with (i) the estimation of the motion field due to an imperfect tracking algorithm (see Section 2.2), and (ii) the extrapolation of rainfall maps with this estimated motion field kept constant, meaning that the non-stationarity of the motion field in time is neglected.

Germann et al. (2006) showed that the relative importance of the two factors is case-dependent, but that the first one had a pre-dominant role in all their analyzed cases. Because of that, in the version of the probabilistic extrapolation-based nowcasting technique presented in this study, we have mainly focused on the errors introduced by the evolution of rainfall intensities (growth and decay) not explained by the apparent motion field.

In addition, our choice has been to develop the probabilistic technique according to the ensemble approach, which requires that the forecasts preserve the spatial and temporal structure of the rainfall field. To fulfill such requirements, we have decided to generate rainfall forecasts conditioned on the observations, and in which the evolution of the rainfall field is simulated according to a stochastic model of rainfall structure.

The spatial and temporal modeling of rainfall fields is a topic addressed by a number of authors (among others, Lovejoy and Schertzer, 1995; Menabde et al., 1997; Sivakumar, 2001; Ferraris et al., 2003; Franco et al., 2003; Deidda et al., 2005 – see the review of Seed 2003). In the present study, the “String of Beads” model (Pegram and Clothier, 2001a,b) has been constrained to the observations. The main hypotheses of the model can be summarized as follows:

- (1) the marginal distribution of reflectivity fields (in dBZ) at each time step follows a truncated Gaussian distribution with parameters $\mu(t)$ and $\sigma(t)$ (the mean and the standard deviation of the non-truncated Gaussian distribution, respectively). Clothier and Pegram (2001) showed how $\mu(t)$ and $\sigma(t)$ are directly related to the Wet Area Ratio [WAR(t), the proportion of the analysis domain experiencing a rainfall rate above a certain threshold – we used 1 mm/h] and the

Image Mean Flux [IMF(t), the average rainfall rate in mm/h], and they used the strongly correlated pair of WAR(t) and IMF(t) to model the evolution of rainfall fields;

- (2) the spatial Fourier spectrum of instantaneous reflectivity fields can be well characterized by a radially-averaged power-law of exponent β :

$$P(w) = c \cdot w^{-\beta} \quad (7)$$

where w is the wave number;

- (3) the temporal evolution of standardized reflectivity fields in Lagrangian coordinates can be well-described by a second-order autoregressive model, AR(2), with parameters $\phi_1(t)$ and $\phi_2(t)$;
- (4) the motion field of precipitation stays stationary in time along the forecasts (i.e. a unique motion field is used to generate the forecasts using the same algorithm as described in Section 2.2).

In summary, to generate a simulation of the evolution of the rainfall field in moving coordinates according to the String of Beads model, the required parameters are the time series of IMF(t) and WAR(t), the values of the exponent $\beta(t)$ of the power-law spectrum of equation (7), and the coefficients of the AR(2) model for the standardized reflectivity field, $\phi_1(t)$ and $\phi_2(t)$.

In our case, we have adapted Pegram and Clothier's model to generate ensembles of rainfall forecasts compatible with the observations, in such a way that the forecasts evolve from common initial conditions (i.e. the most recent observations). The technique is referred to as SBMcast and is based on using (i) real radar reflectivity fields as the first time steps of each time series of the ensemble, (ii) forecasts of IMF(t) and WAR(t) constrained with observed values, (iii) the observed values of $\beta(t)$ and $\phi_1(t)$ and $\phi_2(t)$, and (iv) the motion field estimated from recent observations (the full description of the theoretical core and equations of SBMcast are presented in Appendix A).

4. Results

4.1. Deterministic forecasts

The quality of the deterministic forecasts obtained with the Lagrangian extrapolation method presented above is presented in Figs. 2–4 (dashed lines) in terms of the cross-correlation, the CSI for intensities of 1 mm/h and the Conditional Mean Absolute Error (in dB), respectively.

The results show the different nature of the chosen events (see also Fig. 1): Fig. 2 shows that significantly higher cross-correlation values have been obtained for the two events of January and July 2001, consisting of widespread systems with moderate rainfall intensities, than for the two events of June 2009, where most of the rainfall was associated with small, fast-evolving convective cells with high rainfall intensities (the results obtained for the CSI – Fig. 3 – show a similar behavior). According to Germann and Zawadzki (2002) and Boudevillain et al. (2006), the higher cross-correlation indicates the more predictability of the latter two events with the Lagrangian extrapolation technique described in Section 2.2.

The results of the CMAE defined in Eq. (5) are presented in Fig. 4 as a function of lead time. Since a difference in logarithmic reflectivity can be interpreted as a factor in terms of linear rainfall units, the CMAE of reflectivity can be interpreted as a relative error in rainfall forecasts. As discussed by Germann and Zawadzki (2002), the CMAE is of particular interest, especially in combination with the probability of detection (also presented in Fig. 3). For instance, for the case of 19 July 2001, the 2-h forecasts correctly forecasted

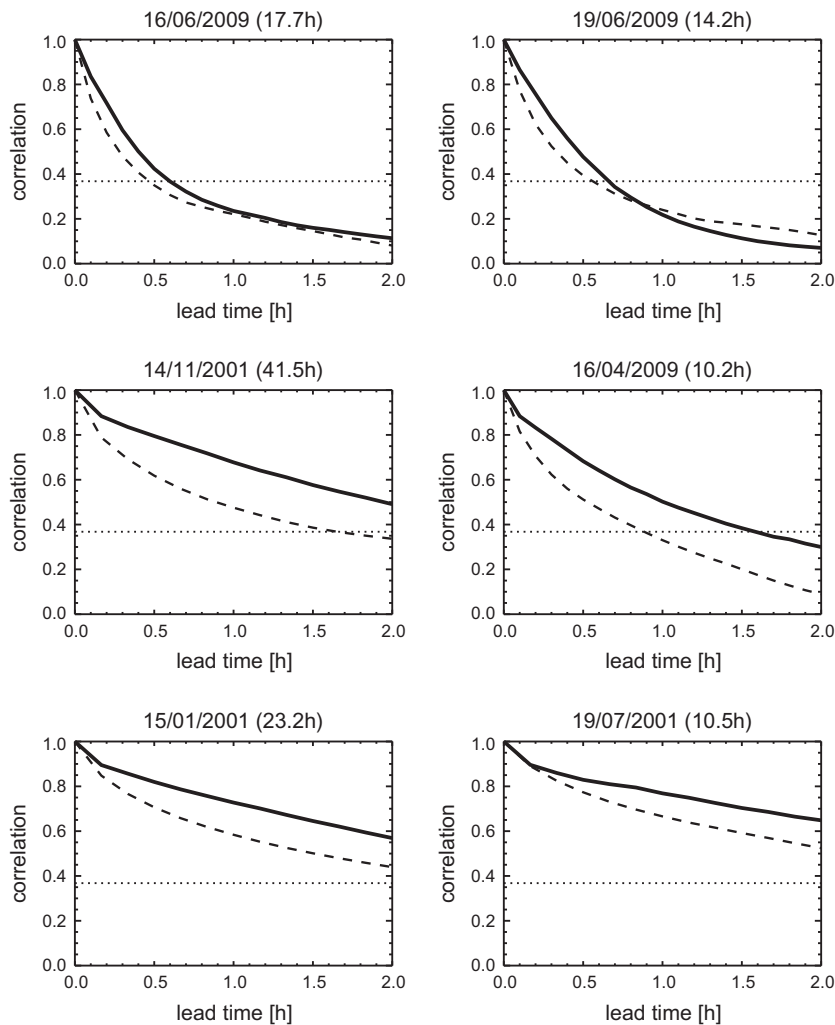


Fig. 2. Correlation between Lagrangian extrapolation forecasts and (1) observations (dashed line) and (2) the simulations obtained with SBMcast (solid line). The dotted line corresponds to a correlation of $1/e$.

50% of the area with precipitation over 1 mm/h (see Fig. 3), and in such areas the CMAE is 4.0 dB, which corresponds to an average factor of 1.78 in terms of rain rates if the Marshall–Palmer exponent $b = 1.6$ is assumed for the exponent of the reflectivity–rainfall relationship ($Z = aR^b$).

4.2. Probabilistic forecasts

Figs. 5 and 6 illustrate the first step necessary to generate an ensemble of rainfall forecasts n time steps Δt ahead, at a given time step t : forecasts of $WAR_t^*(t + n \cdot \Delta t)$ and $IMF_t^*(t + n \cdot \Delta t)$ are obtained as described in Appendix A.2 and constrained with observations (we note that throughout the whole paper the asterisk refers to forecasts of the variables). The figures show, for two of the analyzed events, 50 realizations of the pair $\begin{bmatrix} WAR_t^*(t + n \cdot \Delta t) \\ IMF_t^*(t + n \cdot \Delta t) \end{bmatrix}$. It can be noticed how the spread of these two variables increases with lead time, $n \cdot \Delta t$.

For the same two time steps, Figs. 7 and 8 show the rainfall fields forecasted for lead times up to 1 h with both the deterministic version of the Lagrangian extrapolation algorithm (left column) and three members generated with SBMcast (three central columns), and compare them against actual radar measurements (right column). While, by design, rainfall intensities stay constant along the forecasts obtained by Lagrangian extrapolation

(left column in Figs. 7 and 8), the nowcasting ensemble members simulate the evolution of rainfall intensities.

A quantitative analysis of the performance of the probabilistic version of the nowcasting technique has been done according to the following three criteria:

- (1) verification that the simulated rainfall forecasts correctly satisfy the imposed parameters of the String of Beads model;
- (2) analysis of the uncertainty in rainfall forecasting by Lagrangian extrapolation as simulated by SBMcast;
- (3) comparison of SBMcast forecasts against radar observations.

4.2.1. Analysis of the parameters of the ensembles

This section analyzes the simulations obtained with SBMcast in terms of the parameters that control its performance.

Figs. 9 and 10 show the evolution of IMF and WAR as obtained from the observed radar fields along two of the analyzed events. Observations are compared to the 10%- and 90%-percentiles corresponding to the 30-, 60- and 90-min forecasts for these two variables (i.e. simulated according to the model described in Appendix A.2). For the two cases, the presented confidence intervals cover, for most of the time, the observed values of IMF and WAR for the different lead times. However, the two cases show significantly different characteristics due to the nature of the events: for the case of July 2001 (a typical situation of long-lasting

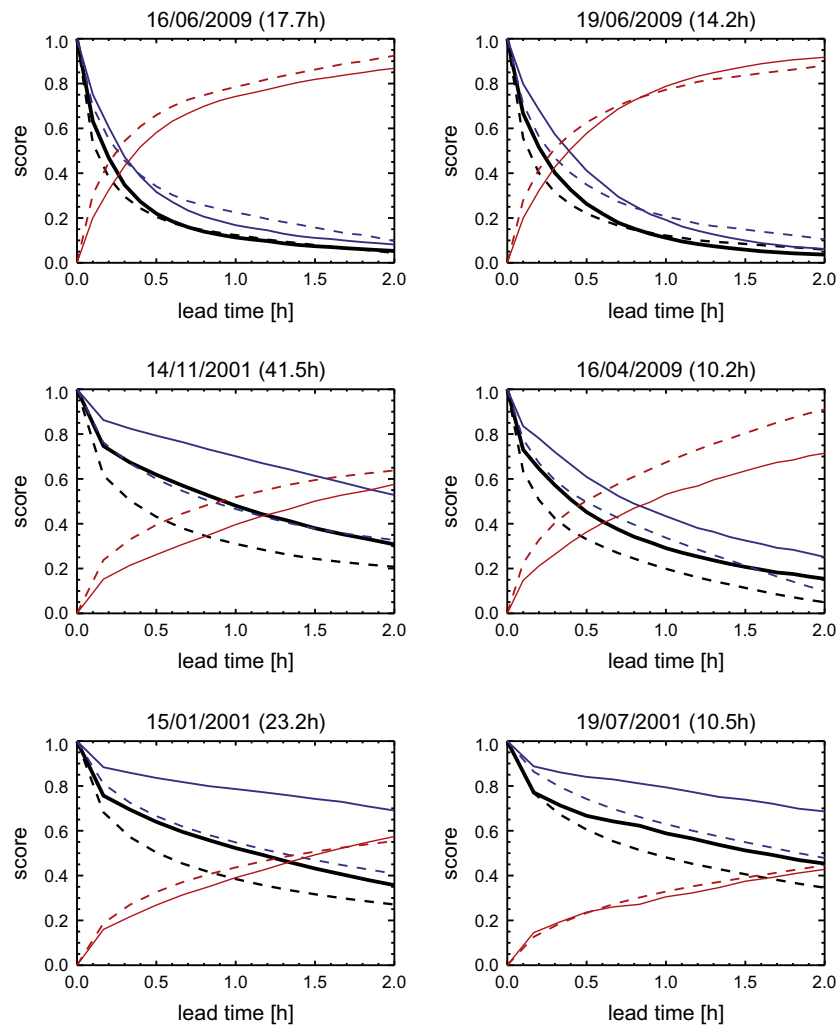


Fig. 3. Probability of Detection (blue), False Alarm Ratio (red) and Critical Success Index (black) between Lagrangian extrapolation forecasts and (1) observations (dashed line) and (2) the simulations obtained with SBMcast (solid line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

widespread rainfall sweeping the domain of analysis), the confidence intervals completely cover the observed values of the pair *IMF*–*WAR*, whereas for the case of June 2009 (a fast-evolving situation dominated by popping convective storms with high rainfall intensities) the sudden changes of *IMF* and *WAR* do not always fall within the range of the 10%–90%-percentiles of the simulations. Similar results have been obtained for the rest of the events reported in Table 1: during the stratiform periods, observed *IMF*–*WAR* values fall well within the 10%–90%-percentiles interval of simulations, which does not always occur during the periods of general convection initiation or dissipation, specially for longer lead times.

Steps (2) and (3) of Appendix A.1 show that the method guarantees, by construction, the values of *IMF** and *WAR** prescribed to the simulations. Therefore, here we have focused on verifying that the parameters of the correlation models in space and time (see Section 3 and the details in Appendix A.3) are well reproduced in the simulated ensembles.

Figs. 11 and 12 show the evolution of the parameter β (the exponent of the power-law fitted to the spatial Fourier spectrum of reflectivity fields) as estimated from radar observations and computed from the simulations. The results show that for both of the example cases (and similarly for the rest of the events of Table 1), the range of variability of the exponents is relatively small

(as reported by Pegram and Clothier, 2001a), and that the simulations reasonably respect the spatial correlation model of (7) and imposed as described in Appendix A.1.

Finally, the curves in Figs. 13 and 14 corroborate that the simulations reproduce, on average, the correlation model imposed according to equation (A3). On the other hand, it is also worth pointing out the higher correlation values for the case of widespread rainfall of 19 July 2001 compared to the convective case of 16 June 2009 (also evident in Fig. 2). Also, the evolution of correlation coefficients for the latter seem to vary according to the variation of the Wet Area Ratio (Fig. 10): the periods with less rainfall coverage seem to coincide with situations of low values of correlation in time.

4.2.2. Analysis of the simulated uncertainty

The final goal of SBMcast is to reproduce the uncertainty in rainfall forecasting by Lagrangian extrapolation. To verify if this goal has been accomplished, the following (perhaps counterintuitive) analysis has been carried out: The departures of SBMcast simulations from Lagrangian extrapolation forecasts have been compared with the real errors (i.e. the differences between observations and forecasts obtained by Lagrangian extrapolation). By doing this, we attempt to assess if the simulated SBMcast scenarios evolve away from Lagrangian extrapolation forecasts as

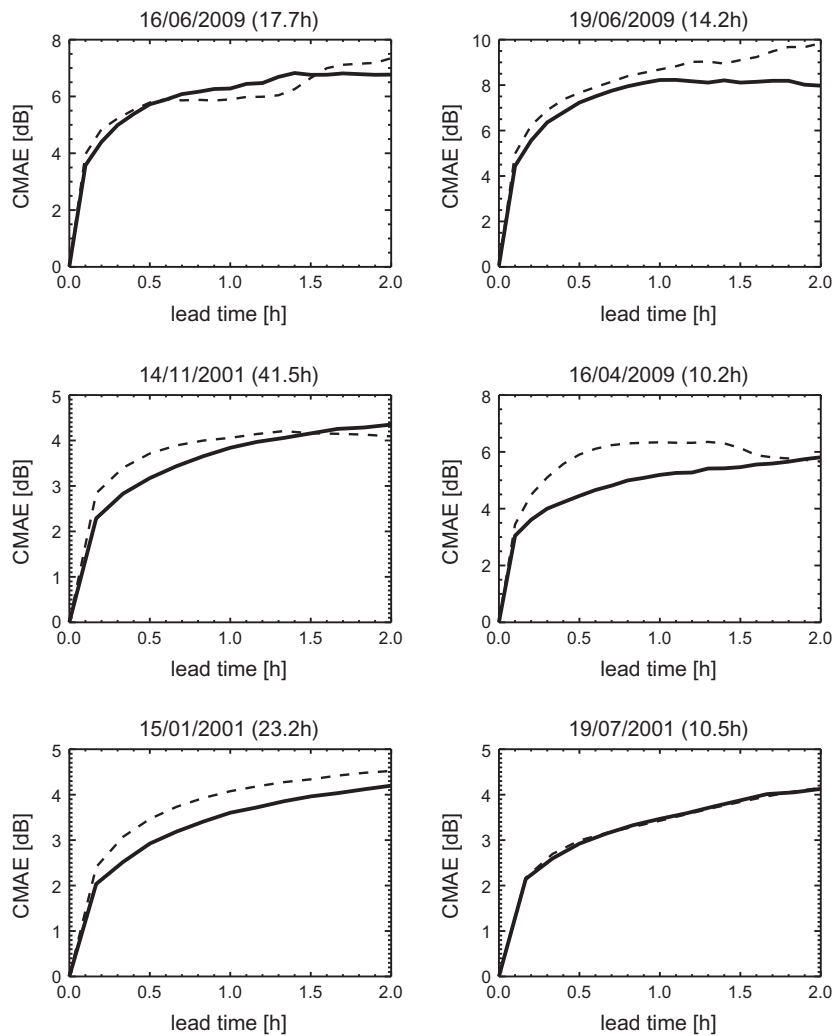


Fig. 4. Conditional Mean Absolute Error between Lagrangian extrapolation forecasts by and (1) observations (dashed line) and (2) the simulations obtained with SBMcast (solid line). Note that the y-axis is not the same for all the panels.

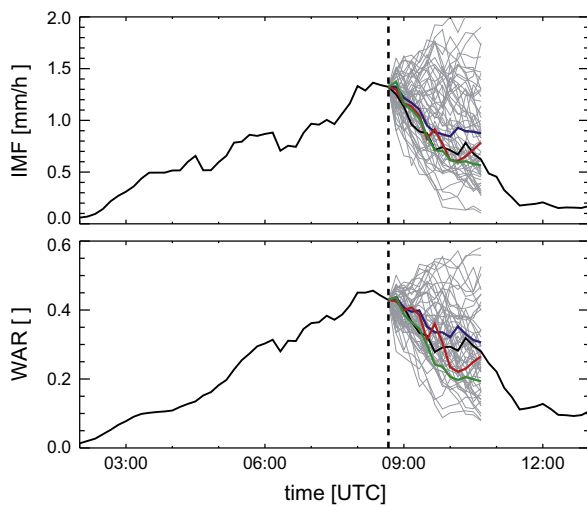


Fig. 5. Evolution of IMF and WAR (top and bottom, respectively) along the event of 19 July 2001. The solid black line shows the values computed from radar observations, and the thin grey lines correspond to 50 realizations obtained as described in Appendix A.1 for 19 July 2001 at 08:40 UTC. The blue, red and green lines in both panels correspond to ensemble members #1, #2 and #3 shown in Fig. 7.

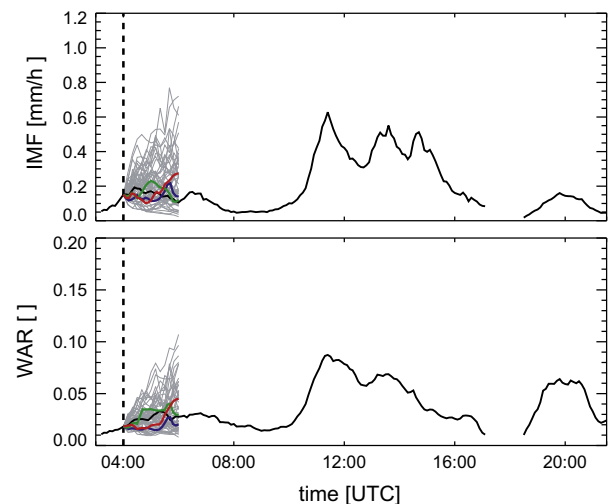


Fig. 6. Same as Fig. 5, but for the case of 16 June 2009 and the simulations generated for 16 June 2009 at 04:00 UTC (Fig. 8).

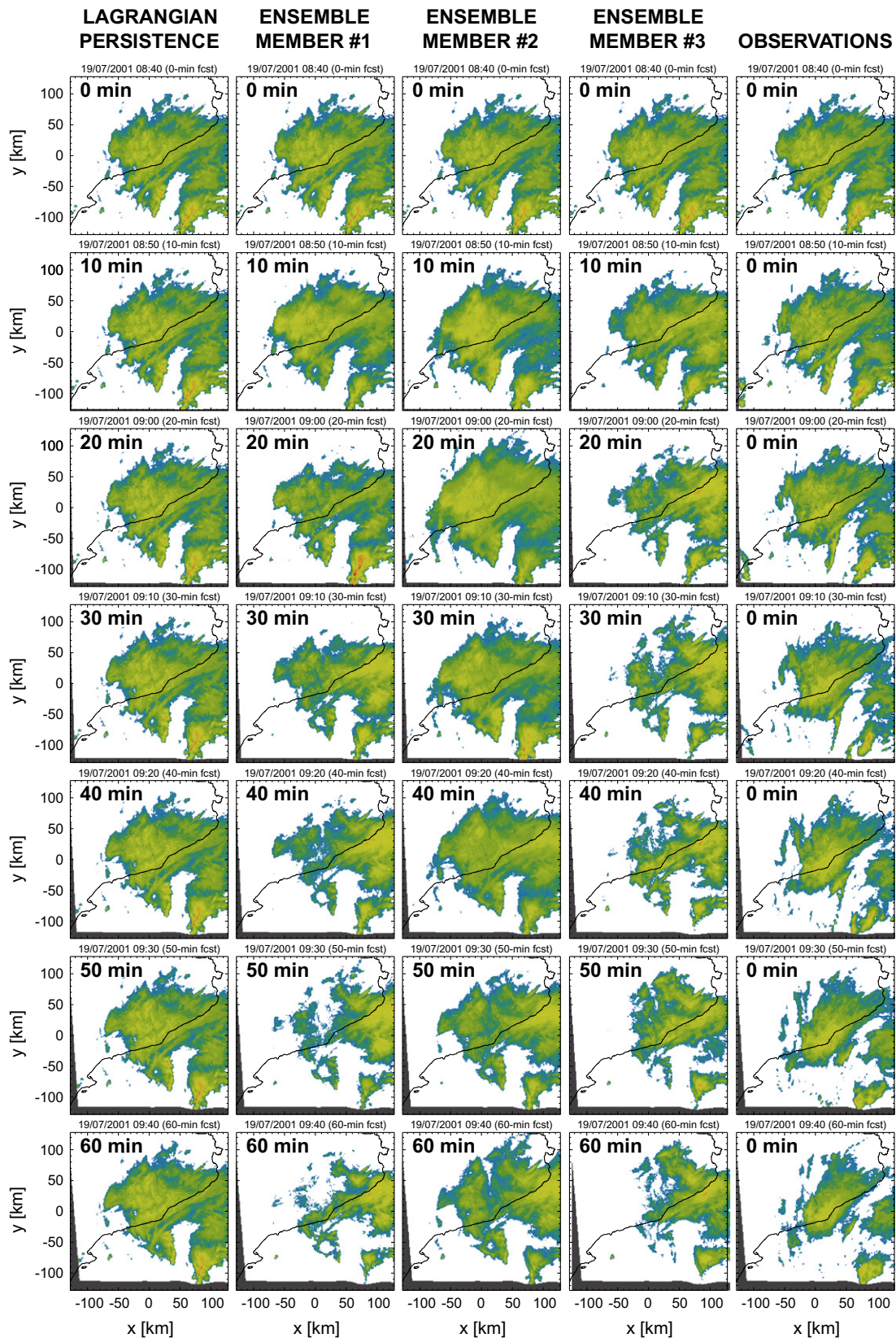


Fig. 7. Evolution of the rainfall field as forecasted with the deterministic version of the Lagrangian extrapolation algorithm (left column), as simulated by three members of the probabilistic nowcasting algorithm (central columns), and as estimated from real radar observations (right column). The numbers in each panel show the lead-time (0-min forecasts are observations).

observations do (i.e. neglecting the errors in the motion field, if the simulated growth and decay of rainfall statistically reproduces observed growth and decay – see also discussion in Section 3).

We have, thus, compared Lagrangian extrapolation forecasts against SBMcast ensembles in terms of the correlation, CSI and CMAE as a function of the lead time (solid lines in Figs. 2–4). These

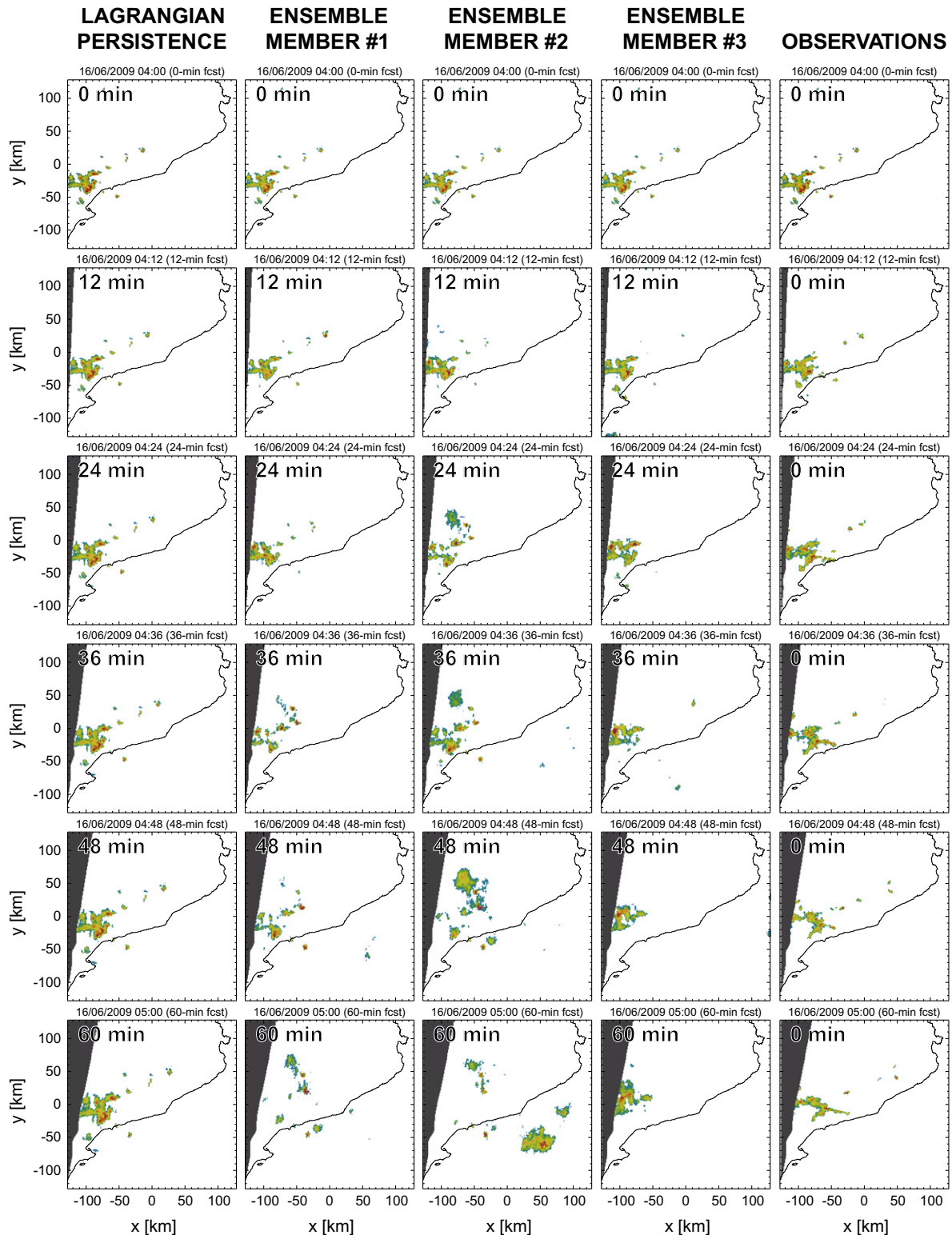


Fig. 8. Same as Fig. 7, but for the case of 16 June 2009 at 04:00 UTC.

scores are to be compared against those presented in Section 4.1, where Lagrangian extrapolation was evaluated against real observations (dashed lines in Figs. 2–4). We have computed the correlation and CMAE with ensemble forecasts according to Eqs. (1) and (5) in which the summations are done for all the members of the ensemble; and hits, misses and false alarms in Eqs. (2)–(4) are counted for all the ensemble members.

In Fig. 4, the CMAE obtained for the comparison between forecasts obtained by Lagrangian extrapolation and SBMcast simulations (solid lines) resembles the results obtained for the verification of Lagrangian extrapolation forecasts (dashed lines), i.e. compared to real observations. This implies that, in terms of the CMAE, the ensembles satisfactorily reproduce the errors in Lagrangian extrapolation forecasts, which reflects the skill of the

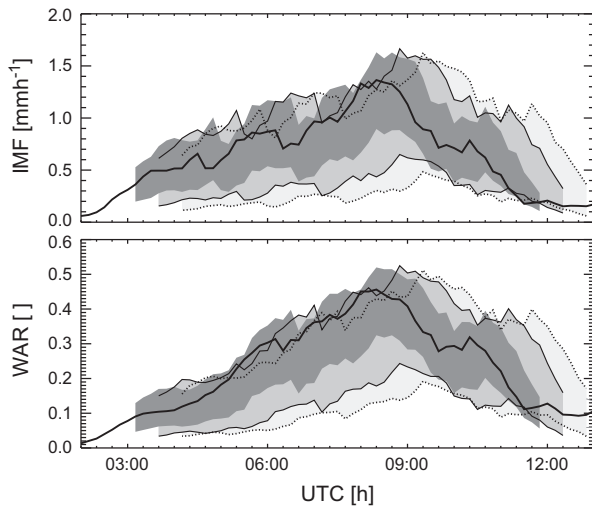


Fig. 9. Evolution of IMF and WAR (top and bottom panels, respectively) along the case of 19 July 2001. The solid line corresponds to the values computed from radar observations, and the shaded areas correspond to the 10%– and 90%-percentiles for the 30-, 60- and 90-min forecasts of IMF* and WAR* (dark grey, thin solid-contoured grey and dotted-contoured light grey areas, respectively) as obtained from an ensemble of 50 realizations.

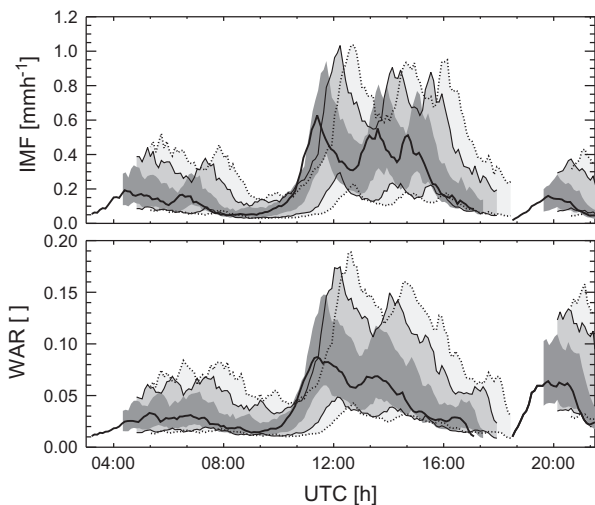


Fig. 10. Same as Fig. 9, but for the case of 16 June 2009.

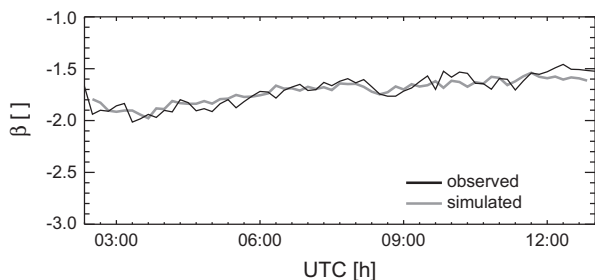


Fig. 11. Time series of the exponent fitted to the power spectrum of the Fourier spectrum of the reflectivity field in logarithmic units [see Eq. (7) and Appendix A] for the event of 19 July 2001. The black line corresponds to the observations and the grey line, to the simulated series of reflectivity fields.

probabilistic nowcasting technique in reproducing the errors in the areas where rainfall was both observed and predicted with either of the nowcasting systems. In contrast, the probabilistic

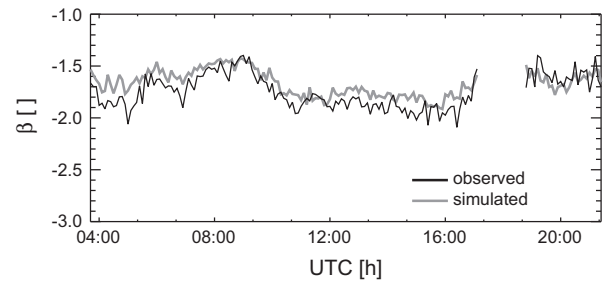


Fig. 12. Same as Fig. 9, but for the case of 16 June 2009.

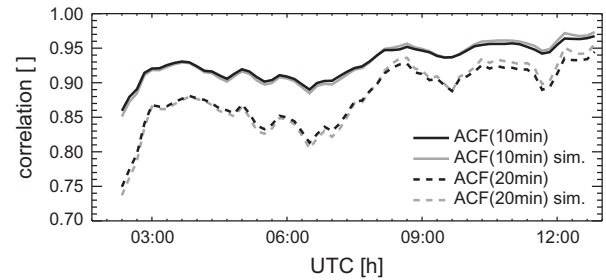


Fig. 13. Time series of the lag-1 (solid lines) and lag-2 (dashed lines) time auto-correlations of the reflectivity field for the event of 19 July 2001. The black lines correspond to the observations and the grey lines to the simulated series of reflectivity fields.

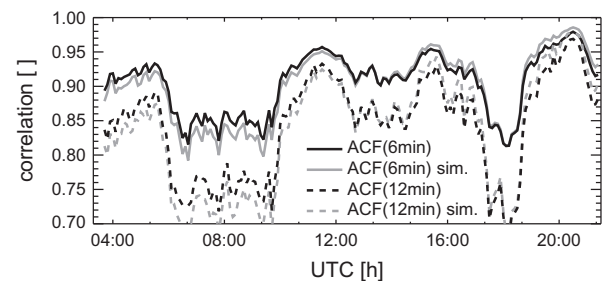


Fig. 14. Same as Fig. 13, but for the event of 16 June 2009.

nowcasting technique overestimates both the correlation and the CSI obtained for the comparison between Lagrangian extrapolation forecasts and real observations (Figs. 2 and 3, respectively). Given that SBMcast produces unbiased simulations of rainfall coverage, WAR (as it can be observed in Figs. 9 and 10), it can be interpreted that the probabilistic nowcasting technique underestimates the errors in Lagrangian extrapolation forecasts. Such differences are especially significant for the long-lasting, widespread rainfall events (i.e. the cases of 14 January 2001, 19 July 2001 and 15 November 2001). At least partially, we explain the higher values of correlation and CSI between Lagrangian extrapolation forecasts and the simulations of our ensemble technique by the fact that the errors associated with the motion field (i.e. the errors in rainfall tracking and due to the non-stationarity of the motion field) are, so far, neglected in SBMcast.

In summary, the higher degree of matching between deterministic and probabilistic forecasts (that results in higher correlation and CSI values) can be explained by the fact that we are using the same constant motion field to advect rainfall fields in both the deterministic Lagrangian extrapolation algorithm and SBMcast. However, in the areas where rainfall is present both in observa-

tions and forecasts, the probabilistic nowcasting technique shows certain skill in reproducing the observed errors.

4.2.3. The performance of the nowcasting ensembles

The stochastic nature of the forecasts generated with SBMcast implies that we cannot expect the ensemble to be consistently better than the deterministic forecasts obtained by Lagrangian extrapolation in terms of the departures between rainfall observations and forecasts. As an example, Appendix B shows that we should expect the mean squared error (MSE) of the ensemble to be about twice that of the deterministic forecast by Lagrangian extrapolation.

Alternatively, we have analyzed the performance of SBMcast in terms of the Brier score [see Eq. (6)], which was originally defined for the evaluation of ensemble systems. The Brier scores averaged over each of the six events of the analysis are presented in Fig. 15, which shows how the score increases with lead time. For comparison, Fig. 15 also shows the results obtained for the deterministic Lagrangian extrapolation forecasts [in (6), the number of members is set to $n_m = 1$].

The scores obtained for the deterministic Lagrangian extrapolation forecasts are significantly higher than those for the ensembles generated with SBMcast, showing the benefit of working with the probabilistic ensemble. It could be speculated that the stochastic algorithm has been able to create/dissipate rainfall near the boundaries of rainfall systems (where the deterministic version of the

algorithm frequently suffers from misses and false alarms) thanks to the role of the pair $\begin{bmatrix} WAR(t) \\ IMF(t) \end{bmatrix}$. However, further evidence is required to make this statement more solid.

Also, it has to be noted that the analysis of the Brier score particularly penalizes errors in yes/no forecasts as those obtained with the Lagrangian extrapolation algorithm. Therefore, it has to be considered that the lower Brier scores obtained for SBMcast ensembles specially show the extra information depicted by the ensembles, and do not imply that individual SBMcast members show better performances than forecasts obtained by Lagrangian extrapolation. In fact, on average, slightly higher Brier scores are obtained for individual members when treated as deterministic forecasts (not shown).

5. Summary and conclusions

The study demonstrates the performance of SBMcast, a version of the String of Beads model (Pegram and Clothier, 2001a, 2001b) adapted to produce an ensemble of nowcasts compatible with radar observations. The final aim of such a technique is to describe the uncertainty in deterministic rainfall nowcasting by Lagrangian extrapolation while preserving the space and time structure of the simulated scenarios of rainfall (the latter is crucial since the final goal of the technique is to be used to study how errors in rainfall nowcasts propagate through rainfall–runoff models).

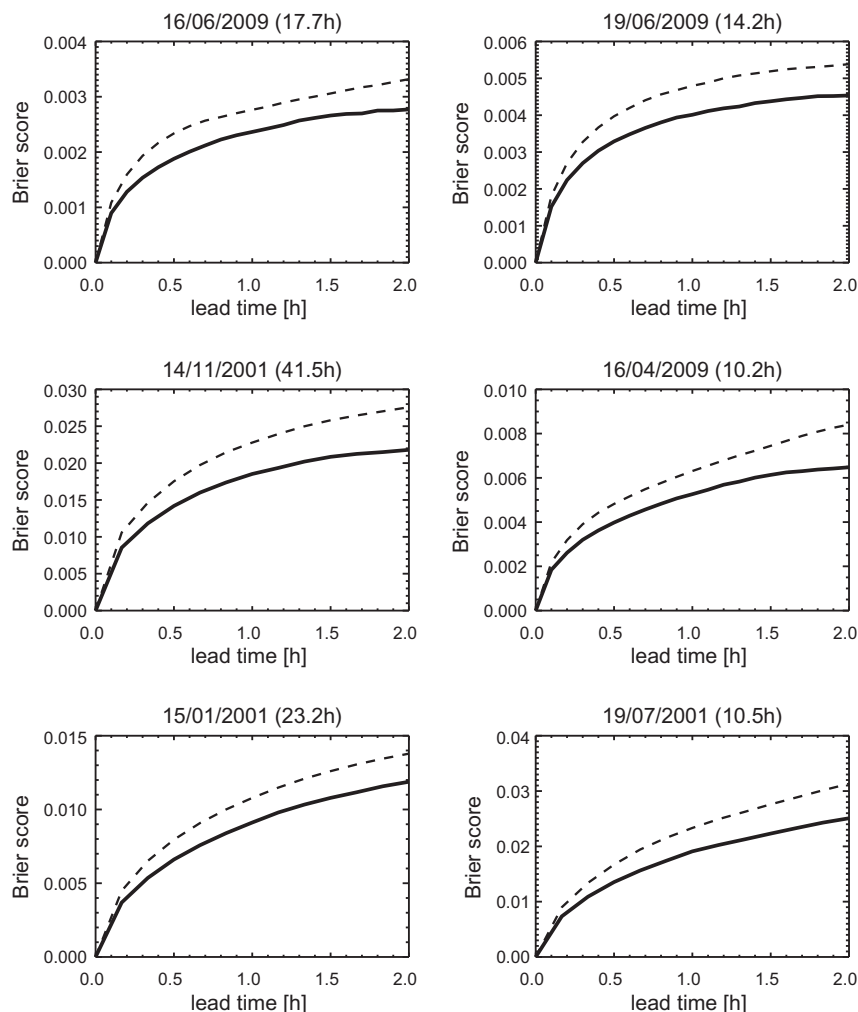


Fig. 15. Dependence of the Brier score between observations and the forecasts obtained by (1) Lagrangian extrapolation (dashed line), and (2) the probabilistic nowcasting technique (solid line).

The results show that this objective is fulfilled in part: while SBMcast shows significant skill in describing the errors in rainfall nowcasts obtained by Lagrangian extrapolation conditioned to the areas where rainfall was both observed and forecasted, the general (non-conditional) errors are significantly underestimated. These results can be (at least in part) explained by the fact that a constant motion field was used in the production of the forecasts and was identical for both the deterministic Lagrangian extrapolation algorithm and SBMcast, neglecting in the latter the errors related to the motion field. These are due to (i) the estimation of the motion field, and (ii) due to the evolution of the motion field, which is kept stationary in time along the produced forecasts.

On the other hand, probabilistic forecasts seem to have slightly more skill than the deterministic version of the Lagrangian extrapolation technique in forecasting the location of rainfall occurrence. Given that the motion fields used to generate both sets of forecasts are the same, the only feasible explanation that we can find for this result is that the bivariate AR(5) model used to forecast the evolution of IMF and WAR does not merely add a stochastic component in such forecasts but has some skill in forecasting their evolution. However, it does not seem trivial to find a way to verify this hypothesis and further evidence would be necessary to make it conclusive.

There are some similarities between SBMcast and STEPS, the ensemble nowcasting system proposed by Bowler et al. (2006). STEPS has the capability of blending radar-based rainfall nowcasts with NWP model rainfall forecasts, but conceptually it can also work with radar-based nowcasts alone (see, e.g. Seed and Bowler 2003), similarly as SBMcast. Both techniques assume the ensemble approach to describe the uncertainty in rainfall nowcasting by Lagrangian extrapolation by conditioning a model for the space and time variability of the rainfall field on recent observations. STEPS considers the uncertainty in the motion field (further research on this topic is planned to be included in SBMcast). Other than this, the most fundamental differences between the two approaches lie in the differences between these models (SBMcast is based on the String of Beads model – Pegram and Clothier, 2001a,b, and STEPS on the model used by S-PROG – Seed, 2003). These result in that:

- (1) STEPS models the evolution of the rainfall field after decomposing it into a number of independent band-pass filtered fields in the Fourier domain (the so-called multiplicative cascade), addressing the differences in the predictability of the different scales separately, whereas SBMcast treats the rainfall field as a whole [see (A3)]. Implicitly, both methodologies assume that the spatial power spectrum of the fields $X(t)$ [defined in (A2)] stays constant along the ensemble nowcasts, the main difference between the two systems being that the coefficients $\phi_1(t)$ and $\phi_2(t)$ in (A3) depend (are independent) on the spatial scale for STEPS (SBMcast) simulations. The result is that for SBMcast, the spatial power spectrum of ζ [the random component of the simulations in (A3)] is proportional to that of $X(t)$, whereas for STEPS it depends on the predictability of the different scales of $X(t)$.
- (2) The reconstruction of the simulated rainfall fields is done differently for the two models. Whereas STEPS uses constant values of $\mu(t)$ and $\sigma(t)$ [see (A2)], SBMcast uses the simulations of the couple $\begin{bmatrix} \text{WAR}(t) \\ \text{IMF}(t) \end{bmatrix}$, which has a fundamental role in depicting the spread of the nowcasting ensembles. In this way, SBMcast can generate simulations that are not purely second-order stationary, allowing the general enhancement and decay of the rainfall field.

It is worth mentioning that improving the deterministic component of nowcasts obtained by Lagrangian extrapolation was not the

principal aim of the developed technique, but rather quantifying their inherent uncertainty. However, there is room for improving the description of such errors. For instance by identifying the locations where growth and decay are more likely to occur, instead of assuming them to be uniform and nearly stationary processes (as it is implicit to the proposed method – see equations of Appendix A.3).

Similarly, the deterministic component of the ensembles could be improved by identifying the locations and times of the day more prone to systematic errors caused by systematic sources of rainfall growth and decay such as the diurnal cycle of solar heating (e.g. Carbone and Tuttle, 2008; Surcel et al., 2010) or the mechanisms that contribute to the orographic enhancement of precipitation (see Panziera and Germann, 2010 and references therein). The natural variability of such phenomena makes the ensemble approach appropriate to include their effects.

Discussion is also needed on the fact that the generated ensembles only consider the uncertainty associated with the evolution of rainfall intensities along the forecasts and, thus, the uncertainty in radar estimation of rainfall is neglected in the ensembles. The description of the structure of errors affecting radar QPE for the generation of QPE ensembles is a topic that has recently risen certain interest (see the works of Ciach et al., 2007; Lee et al., 2007; Berenguer and Zawadzki, 2008, 2009; Llort et al., 2008; Germann et al., 2009; Villarini et al. 2009), which seems to suggest coupling the two ensemble techniques as the most direct approach to describe the overall uncertainty in radar-based rainfall forecasts.

Acknowledgements

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Appendix A. Generation of ensembles of rainfall nowcasts obtained by Lagrangian extrapolation

A.1. Generation of a single reflectivity map based on the hypotheses of the String of Beads model

Clothier and Pegram (2001) and Pegram and Clothier (2001a) described the methodology to generate a random realistic reflectivity field with parameters $[\text{IMF}(t), \text{WAR}(t)$ and $\beta(t)]$ with the “String of Beads” model, which is the basis of the presented nowcasting technique. The method can be summarized with the following steps (further details may be found in Section 3 of Pegram and Clothier, 2001a):

- (1) Convoluting a Gaussian white noise field with a $\beta(t)/2$ -exponent power-law filter to generate a spatially correlated field, Y , with mean 0 and variance 1.
- (2) Finding a , such that the proportion of the domain where the field $\mathbf{R} = R_{th} \exp(Y + a)$ exceeds R_{th} matches $\text{WAR}(t)$. $\mathbf{R}$ is truncated setting the values below $R_{th} = 1 \text{ mm/h}$ to 0 mm/h.
- (3) Finding $\lambda(t)$ that results in a rainfall field $\mathbf{R} = R_{th} \left(\frac{1}{R_{th}} \mathbf{R} \right)^{\lambda(t)}$ with an average value over the domain equal to the required $\text{IMF}(t)$. $\lambda(t)$ is obtained using Newton's method.

The field of rain rate, R , generated in this manner will respect the values of the parameters prescribed above.

A.2. A model for the evolution of WAR and IMF in time

The evolution of WAR and IMF has been modeled according to a bivariate model (as can be seen, for example in Figs. 9 and 10, these two variables show significant dependence and, thus, need to be modeled jointly).

Additionally, Clothier and Pegram (2001) showed how these two variables are far from being Gaussian, and suggested to apply a normal score transform (e.g. Goovaerts, 1997), to convert the non-Gaussian WAR(t), IMF(t) into the Gaussian distributed WAR'(t), IMF'(t).

The evolution of the latter pair has been modeled according to a bivariate AR(5) model (as justified in Pegram and Clothier, 2001b). The values of $\begin{bmatrix} \text{WAR}'_t(t+n \cdot \Delta t) \\ \text{IMF}'_t(t+n \cdot \Delta t) \end{bmatrix}$ forecasted at t for a lead time $n \cdot \Delta t$, have thus been simulated according to:

$$\begin{bmatrix} \text{WAR}'_t(t+n \cdot \Delta t) \\ \text{IMF}'_t(t+n \cdot \Delta t) \end{bmatrix} = \sum_{i=1}^5 \Phi_i \begin{bmatrix} \text{WAR}'_t[t-(n-i) \cdot \Delta t] \\ \text{IMF}'_t[t+(n-i) \cdot \Delta t] \end{bmatrix} + Z(t+n \cdot \Delta t) \quad (\text{A1})$$

The asterisk indicates that those correspond to forecasts of the variables; ϕ_i are the model coefficients estimated with the Yule–Walker equations from the covariance matrices of $\begin{bmatrix} \text{WAR}'(t) \\ \text{IMF}'(t) \end{bmatrix}$, and $Z(t+n \cdot \Delta t)$ is a bivariate white-noise process with covariances ensuring that the simulations of $\begin{bmatrix} \text{WAR}'(t) \\ \text{IMF}'(t) \end{bmatrix}$ are second-order stationary. For consistency, $\begin{bmatrix} \text{WAR}'_t(t-k \cdot \Delta t) \\ \text{IMF}'_t(t-k \cdot \Delta t) \end{bmatrix} = \begin{bmatrix} \text{WAR}'(t-k \cdot \Delta t) \\ \text{IMF}'(t-k \cdot \Delta t) \end{bmatrix}$ for $k \in \{0, \dots, 4\}$ (i.e. the values as computed from radar observations).

Finally, forecasted $\begin{bmatrix} \text{WAR}'_t(t+n \cdot \Delta t) \\ \text{IMF}'_t(t+n \cdot \Delta t) \end{bmatrix}$ are obtained by applying the inverse of the normal score transform mentioned above to $\begin{bmatrix} \text{WAR}'_t(t+n \cdot \Delta t) \\ \text{IMF}'_t(t+n \cdot \Delta t) \end{bmatrix}$.

A.3. Generation of a complete forecast with SBMcast

In this section we describe the procedure to generate a realization of possible future rainfall scenarios in Lagrangian coordinates given recently observed reflectivity fields and the values forecasted for $\begin{bmatrix} \text{WAR}'_t(t+n \cdot \Delta t) \\ \text{IMF}'_t(t+n \cdot \Delta t) \end{bmatrix}$.

The evolution of the reflectivity field, dBZ(t) is modeled in terms of the standardized variable:

$$\mathbf{X}(t) = \frac{\text{dBZ}(t) - \mu(t)}{\sigma(t)} \quad (\text{A2})$$

where $\mu(t)$ and $\sigma(t)$ are the mean and the standard deviation of a non-truncated Gaussian distribution that are univocally related to IMF(t) and WAR(t) as discussed in Clothier and Pegram (2001).

For simplicity and because Pegram and Clothier (2001a) found that the exponent of the power spectrum of reflectivity fields, $\beta(t)$, does not significantly change with time, we have assumed that the exponent of the spectra of $X(t)$, $X(t - \Delta t)$ and $X(t - 2\Delta t)$ are the same.

Under this assumption, at each time step, t , we have simulated time series of fields $\mathbf{X}'_t(t+n \cdot \Delta t)$ according to an AR(2) model (similarly as done to impose the temporal correlation to the time series of simulated fields by Germann et al., 2009). That is:

$$\begin{aligned} \mathbf{X}'_t(t+n \cdot \Delta t) &= \phi_1(t) \cdot \mathbf{X}'_t[t+(n-1) \cdot \Delta t] \\ &+ \phi_2(t) \cdot \mathbf{X}'_t[t+(n-2) \cdot \Delta t] + \zeta(t+n \cdot \Delta t) \end{aligned} \quad (\text{A3})$$

where $\phi_1(t)$ and $\phi_2(t)$ are the coefficients estimated at t with the Yule–Walker equations, $\zeta(t+n \cdot \Delta t)$ is a 0-mean, $v^2(t)$ -variance white noise process in time, correlated in space according to a power-law Fourier spectrum with exponent $\beta(t)$, with $v^2(t) = \frac{[1+\phi_2(t)][1+\phi_1(t)-\phi_2(t)][1-\phi_1(t)-\phi_2(t)]}{1-\phi_2(t)}$. A realization of $\zeta(t+n \cdot \Delta t)$ can be generated as indicated in step 1) of Appendix A.1 of this Appendix. Fields $\mathbf{X}'_t(t+n \cdot \Delta t)$ generated according to equation (A3) are second order stationary and respect the correlation model in time and space (as justified in Chapter 3 of Priestley, 1981).

For consistency, we have imposed $\mathbf{X}'_t(t) = \mathbf{X}(t)$ and $\mathbf{X}'_t(t-\Delta t) = \mathbf{X}(t-\Delta t)$. This guarantees the forecasts to be consistent with the two most recently observed reflectivity fields.

Forecasted rain fields in Lagrangian coordinates are obtained by imposing the forecasted values of $\text{WAR}'_t(t+n \cdot \Delta t)$ and $\text{IMF}'_t(t+n \cdot \Delta t)$ according to steps (2) and (3) of Appendix A.1 of this Appendix; finally, the fields are advected as described in Section 2.2 to simulate the evolution of the rainfall field in Eulerian coordinates.

Appendix B. Expected departures between observations and forecasts

This Appendix derives expressions for the expected values of the Mean Square Error of the forecasts for the two systems (deterministic and probabilistic nowcasting techniques) in terms of the observed and simulated fields of growth and decay.

The field of growth and decay between initial time, t , and time $t + \tau$ in Lagrangian coordinates can be obtained from observations as:

$$\delta(t, t + \tau) = \mathbf{X}_{\text{obs}}(t + \tau) - \mathbf{X}'_{\text{obs}}(t) \quad (\text{B1})$$

where ' indicates that the field is advected to the common reference system at time $t + \tau$ (i.e. the difference is computed in moving coordinates).

On the other hand, the errors in Lagrangian extrapolation forecasts initialized at t for a lead time τ can be expressed as:

$$\varepsilon_{LP}(t, t + \tau) = \mathbf{X}'_{LP}(t, t + \tau) - \mathbf{X}_{\text{obs}}(t + \tau) \quad (\text{B2})$$

and noting that, in moving coordinates, Lagrangian extrapolation forecasts stay by construction constant [e.g. $\mathbf{X}'_{LP}(t, t) = \mathbf{X}'_{LP}(t, t + \tau)$], and that at initial time t the forecasts coincide with observations, $\mathbf{X}'_{LP}(t, t) = \mathbf{X}_{\text{obs}}(t)$, it results that $\delta(t, t + \tau)$ relates to the errors in Lagrangian extrapolation forecasts as:

$$\begin{aligned} \varepsilon_{LP}(t, t + \tau) &= \mathbf{X}'_{LP}(t, t + \tau) - \mathbf{X}_{\text{obs}}(t + \tau) \\ &= \mathbf{X}_{\text{obs}}(t) - \mathbf{X}_{\text{obs}}(t + \tau) = -\delta(t, t + \tau) \end{aligned} \quad (\text{B3})$$

Analogously, the simulated departures from initial time and the errors in the forecasts for the k th member of the probabilistic ensemble at $t + \tau$ can be expressed, respectively, as:

$$\begin{aligned} \delta_{\text{ens},k}(t, t + \tau) &= \mathbf{X}'_{\text{ens},k}(t, t + \tau) - \mathbf{X}'_{\text{obs}}(t) \\ &= \mathbf{X}'_{\text{ens},k}(t, t + \tau) - \mathbf{X}'_{LP}(t, t + \tau), \quad \text{and} \\ &\times \varepsilon_{\text{ens},k}(t, t + \tau) = \mathbf{X}'_{\text{ens},k}(t, t + \tau) - \mathbf{X}_{\text{obs}}(t + \tau) \\ &= \mathbf{X}'_{\text{ens},k}(t, t + \tau) - [\mathbf{X}'_{LP}(t, t + \tau) + \delta(t, t + \tau)] \\ &= \delta_{\text{ens},k}(t, t + \tau) - \delta(t, t + \tau) \end{aligned} \quad (\text{B4})$$

From the equations above, the mean squared error of forecasts obtained by Lagrangian extrapolation for a lead time τ can be expressed as:

$$\text{MSE}_{LP}(\tau) = \langle [\varepsilon_{LP}(t, t + \tau)]^2 \rangle = \langle [\delta(t, t + \tau)]^2 \rangle \quad (\text{B5})$$

where $\langle \rangle$ is the expected value operator within the analysis domain and along the event. Similarly, for the forecasts obtained with the stochastic technique, the mean squared error is:

$$\begin{aligned} MSE_{ens}(\tau) &= \langle [\varepsilon_{ens,k}(t, t + \tau)]^2 \rangle \\ &= \langle [\delta_{ens,k}(t, t + \tau) - \delta(t, t + \tau)]^2 \rangle \\ &= \langle [\delta_{ens,k}(t, t + \tau)]^2 \rangle + \langle [\delta(t, t + \tau)]^2 \rangle - 2\langle \delta_{ens,k}(t, t + \tau) \cdot \delta(t, t + \tau) \rangle \end{aligned} \quad (B6)$$

where the $\langle \rangle$ operator here also averages over all ensemble members. Given the strong random nature of $\delta_{ens,k}$, one can assume that δ and $\delta_{ens,k}$ are practically uncorrelated [it can be proven that such a hypothesis is reasonable for SBMcast simulations], which would imply that $\langle \delta_{ens,k}(t, t + \tau) \cdot \delta(t, t + \tau) \rangle \approx \langle \delta_{ens,k}(t, t + \tau) \rangle \cdot \langle \delta(t, t + \tau) \rangle$. Also, the values of $\langle \delta(t, t + \tau) \rangle$ and $\langle \delta_{ens,k}(t, t + \tau) \rangle$ are very close to 0 when averaged along an entire rainfall event. The last term in (B6) could, thus, be neglected, resulting in:

$$\begin{aligned} MSE_{ens}(\tau) &= \langle [\varepsilon_{ens,k}(t, t + \tau)]^2 \rangle \\ &= \langle [\delta_{ens,k}(t, t + \tau)]^2 \rangle + \langle [\delta(t, t + \tau)]^2 \rangle \end{aligned} \quad (B7)$$

This guarantees that by construction MSE_{ens} is larger than MSE_{LP} [both quantities on the right-hand term of (B7) are positive]. Furthermore, if the ensemble is correctly constructed it is desirable that it creates the simulated departures from initial conditions, $\delta_{ens,k}(t, t + \tau)$, statistically similar to those of observations, $\delta(t, t + \tau)$. According to (B5) and (B7), in such a case this would imply that $MSE_{ens}(\tau) \approx 2MSE_{LP}(\tau)$.

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