

# A flood episode in Northern Italy: multi-model and single-model mesoscale meteorological ensembles for hydrological predictions

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## Abstract

Numerical weather prediction models can be coupled with hydrological models to generate streamflow forecasts. Several ensemble approaches have been recently developed in order to take into account the different sources of errors and provide probabilistic forecasts feeding a flood forecasting system. Within this framework, the present study aims at comparing two high-resolution limited-area meteorological ensembles, covering short and medium range, obtained via different methodologies, but implemented with similar number of members, horizontal resolution (about 7 km), and driving global ensemble prediction system. The former is a multi-model ensemble, based on three mesoscale models (BOLAM, COSMO, and WRF), while the latter, following a single-model approach, is the operational ensemble forecasting system developed within the COSMO consortium, COSMO-LEPS (Limited-area Ensemble Prediction System).

The meteorological models are coupled with a distributed rainfall-runoff model (TOPKAPI) to simulate the discharge of the Reno river (Northern Italy), for a recent severe weather episode affecting northern Apennines. The evaluation of the ensemble systems is performed both from a meteorological perspective over the entire Northern Italy and in terms of discharge prediction over the Reno river basin during two periods of heavy precipitation

1 between 29 November and 2 December 2008. For each period, ensemble performance has  
2 been compared at two different forecast ranges.

3 It is found that both mesoscale model ensembles remarkably outperform the global ensemble  
4 for application at basin scale as the horizontal resolution plays a relevant role in modulating  
5 the precipitation distribution. Moreover, the multi-model ensemble provides a better  
6 indication concerning the occurrence, intensity and timing of the two observed discharge  
7 peaks, with respect to COSMO-LEPS. A thorough analysis of the multi-model results shows  
8 that this behaviour is ascribable to the different characteristics of the involved meteorological  
9 models and represents the added value of the multi-model approach.

10 Finally, a different behaviour comes out at different forecast ranges. For short ranges, the  
11 impact of boundary conditions is weaker and the spread can be mainly attributed to the  
12 different characteristics of the models. At longer forecast ranges, the similar behaviour of the  
13 multi-model members forced by the same large scale conditions, indicates that the systems are  
14 governed mainly by the boundary conditions, although the different LAMs characteristics  
15 may still have a not-negligible impact.

16

## 17 **1 Introduction**

18 Coupling Numerical Weather Prediction (NWP) and hydrological models is an essential  
19 practise in order to generate short- to medium-range hydrological forecasts. Moreover, it is  
20 certainly a necessary step for implementing an early warning system suitable for a medium-  
21 sized catchment (1000-10000 km<sup>2</sup>), characterized by complex orography and short response  
22 times. A timely prediction of the hydrological response of these river basins, suitable for  
23 emergency planning, cannot rely on observed precipitation, but needs an alternative forcing  
24 function available at earlier times (Melone et al., 2005), that is meteorological forecast fields.

25 The provision of accurate streamflow forecasts, especially in case of flood events, represents a  
26 major research and operational challenge (Rotach et al., 2012). In such an effort, early  
27 warning systems have been developed, based on coupled state-of-the-art meteorological and  
28 hydrological models. When data from different model simulations are combined, such  
29 systems provide different scenarios and valuable probabilistic information that acknowledges  
30 the different sources of errors affecting the meteo-hydrological forecasting chains.

1 Although each component of the system is affected by its source of error, the available  
2 literature (Krzysztofowicz, 1999, Hapuarachchi et al., 2011, Zappa et al., 2011) seems  
3 inclined to indicate that the uncertainty affecting Quantitative Precipitation Forecasting (QPF)  
4 is dominant. Recently, the hydrological model uncertainty was estimated to be ten times less  
5 pronounced than the uncertainty from rainfall forecasts (Zappa et al., 2011). Errors in QPF  
6 arise from uncertainties in the initial (and boundary) conditions and in the models  
7 formulation, growing during the forecasting process and propagating from atmospheric  
8 (rainfall) to hydrological (runoff) predictions (Zappa et al., 2010).

9 Considering such problems, the main efforts for the improvement of discharge prediction  
10 have been devoted to: (i) development of NWP models, i.e. increasing their resolution and  
11 improving the representation of the relevant physical processes in order to attain better  
12 rainfall forecast skill (Weusthoff et al., 2010; Bauer et al., 2011), especially at the small scales  
13 that are particularly relevant for hydrological applications; (ii) development of meteorological  
14 ensemble prediction systems, which represent a suitable way to cope and deal with  
15 uncertainties, as they provide probabilistic forecasts that represent an attractive product to be  
16 used for flood predictions. Cuo et al. (2011) provide an overarching review of this topic and  
17 an up-to-date description of the main open issues related to integrated meteo-hydrological  
18 forecasting systems.

19 Ensemble prediction is a well-established practise for global meteorological models, initiated  
20 in the 90's, since it proved to provide greater forecast skill than any single deterministic  
21 prediction (Buizza, 2008). Perturbed initial conditions, generated using either singular vectors  
22 (Palmer et al., 1997), bred vectors (Toth and Kalnay, 1997), perturbed observations in  
23 multiple data assimilation cycles (Houtekamer et al., 1996), or Ensemble Transform Kalman  
24 Filter (Wei et al., 2006), were employed to initialize a number of different forecasts, which  
25 form all together an ensemble prediction system (EPS). More recently, multi-analysis and  
26 multi-model procedures, obtained by combining different ensemble systems, each based on a  
27 different NWP model, proved to be even more skilful (Mylne et al., 2002; Bowler et al.,  
28 2008), thus leading to the implementation of super-ensembles (Krishnamurti et al., 1999; Park  
29 et al., 2008) and to specific international initiatives, such as TIGGE (THORPEX Interactive  
30 Grand Global Ensemble; Bougeault et al., 2010) programme.

31 EPS forecasts have been used as an input for hydrological models (Gouweleeuw et al., 2005;  
32 Hamil et al., 2005; Hou et al., 2007; Thielen et al., 2009; Rotach et al., 2012), thus

1 propagating the meteorological uncertainty along the flood forecasting system (Pappenberger  
2 et al., 2005) in order to provide a probabilistic and more informative hydrological prediction.  
3 Recently, there is a general agreement on the benefit of using ensemble forecasting for early  
4 flood warning applications. However, although representing a progress with respect to a  
5 deterministic approach, EPSs based on global models suffer from their coarse spatial  
6 resolution and often turned out to be not accurate enough for basin-scale applications,  
7 especially in areas characterized by complex orography. In response to such a limitation,  
8 during the last decade different ensemble approaches based on limited area models (LAMs)  
9 have been developed (Marsigli, 2009; Garcia-Moya et al., 2011; Iversen et al., 2011; Montani  
10 et al., 2011) sometimes involving convection-permitting models (Davolio et al., 2008;  
11 Gebhardt et al., 2011, Vié et al., 2012). This kind of limited-area ensemble prediction systems  
12 (LEPSs), that have recently become operational in several centres, basically perform a  
13 dynamical downscaling of global EPSs and represent the state-of-the-art for meteo-  
14 hydrological forecasting applications (Cloke and Pappenberger, 2009; Adams and Ostrowsky,  
15 2010; Addor et al., 2011), suitable especially for risk-related events. During MAP-DPHASE  
16 (Rotach et al., 2009), the forecasters appreciated the availability of ensemble information  
17 much more than being provided with a plethora of different models. Apparently, the usual  
18 probabilistic output (probability maps, etc.), as provided by ensemble modelling systems,  
19 meets their needs (Rotach et al., 2012).

20 However, the accurate description of analysis and model uncertainties at the mesoscale is still  
21 an open issue and the research is still far from assessing an optimal way for providing  
22 perturbed initial and boundary conditions to LAM ensembles (Marsigli et al., 2013). New  
23 methods of combining different LEPSs in a multi-model system are being developed; in  
24 particular, multi-analysis multi-model approaches seem able to provide a suitable way to  
25 describe the uncertainties affecting the forecasting system.

26 Within this framework, a meteorological ensemble system COSMO-LEPS coupled with a  
27 hydrological model (TOPKAPI) has been running operationally at ARPA-SIMC for several  
28 years, in order to provide discharge predictions for civil protection purposes. Previous studies  
29 (Marsigli et al., 2008; Diomede et al., 2008, 2009) suggested the possibility of improving the  
30 performance of this ensemble system. At the same time, collaborative research activities  
31 involving ARPA-SIMC and CNR-ISAC (Davolio et al., 2008; Diomede et al., 2008) have  
32 been carried out, exploiting different state-of-the-art limited area models, developed or

1 implemented in the two Centres, for a multi-model approach to discharge forecasting. These  
2 activities highlighted the promising capability of the multi-model meteorological system,  
3 coupled with the hydrological model, in providing probabilistic discharge peak predictions.

4 Thus, it appears necessary to investigate systematically whether it is possible to improve the  
5 performance of a single-model ensemble (the same implemented in Addor et al., 2011), in  
6 terms of hydrological prediction, using the information that can be conveyed by an available  
7 multi-model system. Within this framework, the aim of the present paper is a comparison  
8 between the two ensemble systems for a single severe event, looking not only at the short-  
9 range (as in Adams and Ostrowsky, 2010), but also at longer lead times. A case study  
10 approach clearly does not complete the investigation task, but represents just the starting point  
11 of a long and complex study.

12 Therefore, in the present study, two different ensemble approaches, both focused on the short-  
13 to-medium range, are compared: a multi-model ensemble, based on three LAMs developed  
14 independently, and a single-model ensemble. Both ensembles receive initial and boundary  
15 conditions from a limited number of members selected among the whole European Centre for  
16 Medium-range Weather Forecasts (ECMWF) global EPS through a clustering analysis. In  
17 order to allow a fair comparison, the two ensembles were implemented with a similar set up.  
18 The ensemble implementation is described in detail in Sect. 2, together with models and  
19 clustering procedure description. Both the ensembles have been used to generate probabilistic  
20 precipitation maps, analysed in Sect. 3, and to provide the input fields to the same  
21 hydrological model. The results, in terms of discharge predictions, are presented in Sect. 4  
22 and allow to evaluate the ensembles performance in a recent severe weather episode affecting  
23 the Reno river basin, located in Northern Italy (Fig. 1) in the Apennines. The multi-model  
24 ensemble is further analysed in Sect. 5, while Sect. 6 is devoted to concluding remarks.

25

## 26 **2 Numerical models and ensembles generation**

27 The multi-model ensemble implemented here is based on three mesoscale models, BOLAM,  
28 COSMO and WRF, briefly described in the following, while the single-model approach is  
29 based on the COSMO model only (COSMO-LEPS ensemble). The two ensembles have  
30 almost the same characteristics, such as the number of members, the model horizontal  
31 resolution (about 7-8 km), the driving global EPS (Table 1). Also, the integration domains

1 (Fig. 1) are very similar, although the grid points are not exactly coincident. In the present  
2 section, a short description of the numerical models and of the ensembles is provided.

### 3 **2.1 BOLAM**

4 BOLAM (BOlogna Limited Area Model; Davolio et al., 2008) is a hydrostatic, primitive  
5 equation meteorological model with prognostic variables distributed on a non-uniformly  
6 spaced Lorenz grid. The horizontal discretization uses geographical coordinates, with  
7 latitudinal rotation on the Arakawa C-grid. BOLAM uses a hybrid vertical coordinate system,  
8 in which the terrain-following sigma coordinate gradually tends to a pressure coordinate with  
9 increasing height above the ground, and with the relaxing factor prescribed as a function of  
10 the maximum orographic height present in the domain. The model implements a Weighted  
11 Average Flux scheme for the three dimensional advection. The temporal integration scheme is  
12 split-explicit, forward-backward for the gravity modes. The lateral boundary conditions are  
13 imposed using a relaxation scheme that minimises wave energy reflection. The water cycle  
14 for stratiform precipitation is described by means of five additional prognostic variables:  
15 cloud ice, cloud water, rain, snow, graupel. Deep convection is parameterized using the Kain–  
16 Fritsch (Kain, 2004) convective scheme. The surface and boundary layer parameterization is  
17 based on the E-1 approximation, in which turbulent kinetic energy is predicted explicitly  
18 (Zampieri et al., 2005). A four-layer soil scheme is implemented for the computation of  
19 surface balances, heat and water vertical transfer, vegetation effects at the surface and in the  
20 soil, taking into account different soil types and physical parameters. The radiation is  
21 computed with a combined application of the Geleyn's scheme (Ritter and Geleyn, 1992) and  
22 the ECMWF scheme.

### 23 **2.2 COSMO**

24 COSMO model (<http://www.cosmo-model.org/>; Steppeler et al., 2003) is the non-hydrostatic  
25 limited-area model of the COSMO Consortium, designed for both operational NWP and  
26 various scientific applications on the meso- $\beta$  and meso- $\gamma$  scale. COSMO is based on the  
27 primitive thermo-hydrodynamical equations describing compressible flow in a moist  
28 atmosphere without any scale approximation. The basic equations are written in advection  
29 form and the continuity equation is replaced by a prognostic equation for the perturbation  
30 pressure. The model equations are solved numerically using the traditional finite difference  
31 method. A basic state, represented by a time-independent dry atmosphere at rest, is subtracted

1 from the equations to reduce numerical errors associated with the calculation of the pressure  
2 gradient force in case of sloping coordinate surfaces. The model equations are formulated in  
3 rotated geographical coordinates and a generalized terrain following height coordinate.

4 The parameterization schemes used operationally are:  $\delta$ -two stream radiation scheme of Ritter  
5 and Geleyn (1992) for short- and long-wave fluxes, with full cloud-radiation feedback;  
6 Tiedtke (1989) mass-flux convection scheme with equilibrium closure based on moisture  
7 convergence; precipitation formation with a bulk microphysics parameterization including  
8 water vapour, cloud water, cloud ice, rain and snow with 3D transport for the precipitating  
9 phases; prognostic turbulent kinetic energy closure at level 2.5; multi-layer version of the  
10 Jacobsen and Heise soil model.

### 11 **2.3 WRF**

12 The Weather Research and Forecasting (WRF) model (see <http://www.wrf-model.org>;  
13 Skamarock et al., 2008) is a numerical weather prediction system that solves the fully  
14 compressible, non-hydrostatic Euler equations. The model uses the terrain-following,  
15 hydrostatic-pressure vertical coordinate with vertical grid stretching. The prognostic equations  
16 are cast in conservative (flux-) form for conserved variables, while non-conserved variables  
17 like pressure and temperature are diagnosed from prognostic conserved variables. The  
18 horizontal grid is Arakawa-C.

19 WRF offers multiple options for physics parameterization schemes that can be selected based  
20 on the specific problem that is investigated. In the present model configuration (version  
21 ARW-3.1), the following schemes have been chosen: Thompson et al. (2004) microphysics,  
22 which includes six classes of moisture species plus number concentration for ice as prognostic  
23 variables; Kain (2004) cumulus parameterization; Rapid Radiative Transfer Model for long-  
24 wave radiation and Dudhia (1989) scheme for short-wave radiation; a turbulent kinetic energy  
25 closure, the Mellor-Yamada-Janjic scheme, for the boundary layer; the Noah land-surface  
26 model (Niu et al., 2011).

### 27 **2.4 Ensemble systems: COSMO-LEPS and Multi-model**

28 COSMO-LEPS is the mesoscale limited-area ensemble developed and implemented by  
29 ARPA-SIMC in the framework of the COSMO Consortium and running operationally at  
30 ECMWF since November 2002 (Montani et al., 2011). The ensemble is based on 16 runs of

1 the COSMO model and was designed for high-resolution probabilistic forecasts up to day  
2 five. The ensemble is generated from the global ECMWF EPS and combines the forecast  
3 potential of a high-resolution non-hydrostatic limited-area model with the probabilistic  
4 information of the ensemble approach. Due to the constraints on the computational resources,  
5 the methodology on which COSMO-LEPS is based reduces the number of global-ensemble  
6 elements driving the limited-area runs, but still keeps a large fraction of the driving-ensemble  
7 information. Specifically, an ensemble-size reduction is performed on 102 members of two  
8 successive ECMWF EPS runs (00 and 12 UTC of day  $d$ ), since each EPS consists of one  
9 control run plus 50 perturbed members. EPS members are grouped into 16 clusters, following  
10 a cluster analysis (see Montani et al., (2011) for details) performed over the area shown in  
11 Fig. 1. From each cluster, a representative member (RM) is selected, which provides initial  
12 and boundary conditions to each COSMO model run. Moreover, for each COSMO-LEPS run  
13 the procedure chooses randomly either Kain-Fritsch or Tiedtke convection scheme, and  
14 perturbs turbulence and other physics parameterization schemes randomly.

15 The same clustering procedure described above is applied again for selecting 5 RMs in order  
16 to drive the multi-model forecasting system. Since the results of the cluster analysis are  
17 different from that for COSMO-LEPS, different initial/boundary conditions may force the two  
18 ensembles. For each initialization time, the multi-model is therefore based on 5 forecasts  
19 issued by each implemented LAM, producing 15 forecasts overall.

20 Summarizing, the main difference between the two ensembles resides in the relative  
21 importance attributed to the representation of the boundary condition error with respect to that  
22 of the LAM error. For the single-model ensemble, the same LAM has been run 16 times  
23 receiving initial and boundary conditions from 16 selected members of the ECMWF EPS,  
24 while for the multi-model ensemble, only 5 EPS members have been selected out of the EPS,  
25 but 3 different LAMs have been run on each EPS member. Both ensemble systems are  
26 integrated in time for 132 hours, and three initialization times 24 hour apart have been  
27 selected: 12 UTC of three consecutive days, 26, 27 and 28 November 2008. Hourly rainfall  
28 fields produced by the two ensemble systems are provided to the same hydrological model  
29 TOPKAPI in order to produce ensemble discharge forecasts.



## 1 **2.5 Hydrological model: TOPKAPI**

2 The streamflow predictions are provided by TOPKAPI (TOPographic Kinematic  
3 APproximation and Integration) (Todini and Ciarapica, 2002), a distributed rainfall-runoff  
4 model. TOPKAPI couples the kinematic approach with the topography of the catchment and  
5 transfers the rainfall-runoff processes into three “structurally-similar” zero-dimensional non-  
6 linear reservoir equations. Three equations, which derive from the integration in space of the  
7 non-linear kinematic wave model, describe the drainage in the soil, the overland flow on  
8 saturated or impervious soils, and the channel flow, respectively. The parameters of the model  
9 are shown to be scale independent and obtainable from digital elevation maps (DEM), soil  
10 maps and vegetation or land-use maps in terms of slopes, soil permeabilities, topology and  
11 surface roughness. Land cover, soil properties and channel characteristics are assigned to each  
12 grid cell that represents a computational node for the mass and the momentum balances. The  
13 flow paths and slopes are defined starting from the DEM, according to a neighbourhood  
14 relationship based on the principle of minimum energy. The evapo-transpiration is taken into  
15 account as water loss, subtracted from the soil water balance. This loss can be a known  
16 quantity, if available, or it can be calculated using temperature data and other topographic,  
17 geographic and climatic information. The snow accumulation and melting component is  
18 driven by a radiation estimate based upon air temperature measurements. A detailed  
19 description can be found in Liu and Todini (2002).

20 The calibration and validation procedures of TOPKAPI over the Reno river basin are based  
21 on an hourly meteo-hydrological dataset available from 1990 to 2000. TOPKAPI is currently  
22 used for the real-time flood forecasting system operational at ARPA-SIMC.

23

## 24 **3 Meteorological analysis**

### 25 **3.1 Case study**

26 The severe weather period between 29 November and 2 December 2008 was characterized by  
27 the presence of a deep cold trough over the western Mediterranean Sea (Fig. 2) in the middle  
28 troposphere. This synoptic configuration was associated with a cyclonic circulation affecting  
29 all western and northern Europe, driving several frontal systems towards the Italian peninsula.  
30 The presence of a blocking anticyclone located over Eastern Europe, together with the  
31 meridional flow along the western side of the trough, maintained the synoptic situation nearly

1 unchanged for several days. Intense warm and moist south-westerly flow on the eastern side  
2 of the trough, impinging on the northern Apennines, was responsible for severe weather and  
3 heavy precipitation in the area. In particular, two periods of intense precipitation (Fig. 3),  
4 during the nights of 29 November and in a 24 hour period between 30 November and 1  
5 December produced two relevant discharge peaks of the Reno river, a medium-sized  
6 catchment (total dimension about 5000 km<sup>2</sup>), whose upstream portion (about 1000 km<sup>2</sup>)  
7 belongs to the north-eastern slopes of the Northern Apennines. The Reno river basin has been  
8 studied in the past (Davolio et al., 2008; Diomede et al., 2008) and was the subject of  
9 investigation in several European research projects in relation to the application of real time  
10 flood forecasting systems. In both periods of heavy rainfall analysed in the present study, the  
11 warning threshold was exceeded at the closure section of the mountain portion of the Reno  
12 catchment, Casalecchio Chiusa, characterized by a concentration time of about 10–12 hours.  
13 In the operational practice, a flood event at such river section is defined when the water level,  
14 recorded by the gauge station, reaches or overcomes the value of 1.6 m (corresponding to a  
15 discharge value of about 630 m<sup>3</sup>/s). This value represents the warning threshold, while the  
16 alarm level is set to 2.5 m (corresponding to a discharge value of about 1480 m<sup>3</sup>/s).

### 17 **3.2 Ensemble results: probability of precipitation**

18 The evaluation of the ensemble systems is firstly performed from a meteorological  
19 perspective over an area larger than the single catchment (e.g. entire Northern Italy). The  
20 attention is focused on the two periods of intense precipitation: 6 hours between 29  
21 November, 18 UTC and 30 November, 00 UTC, and 24 hours between 30 November, 12  
22 UTC and 1 December, 12 UTC. Moreover, for sake of brevity, only the simulations starting  
23 on 26 and 28 November are thoroughly analysed and discussed: thus, for each period, the  
24 ensemble performance will be compared at two different forecast ranges. For reference,  
25 global EPS results are also shown. They refer to the operational ECMWF ensemble,  
26 composed of 51 members, run at a horizontal spectral resolution T<sub>L</sub>399 (about 50 km).

27 During the 29<sup>th</sup> of November, intense precipitation in excess of 20 mm/6h (Fig. 3) affected the  
28 whole northern Apennines (with peaks close to 100 mm/6h, locally) and also some Alpine  
29 areas. Results of the two LEPSs and the global EPS, in terms of probability maps of  
30 occurrence of precipitation exceeding 20mm/6h, are shown in Fig. 4, for two different  
31 forecast lead times. At longer range (78–84 h; initialization time 12:00 UTC, 26 November),  
32 the global EPS does not provide any indication of intense precipitation over the Reno basin,

1 but only over western Apennines (probability up to 60 %). On the other hand, both LEPSs  
2 forecast some probability of rainfall (up to 60% for the multi-model, 30% for COSMO-LEPS)  
3 over the Reno river basin. Moreover, only the multi-model provides a signal also over the  
4 central Alps, where precipitation did occur. Similarly, for shorter forecast range (30-36 h;  
5 initialization time 12 UTC, 28 November), only the two LEPSs are able to forecast the  
6 possible occurrence of intense precipitation (up to 90%) over the target basin. Very high  
7 probability is assigned to intense rainfall over western Apennines and the Alpine chain by all  
8 the prediction systems, with a progressively increasing probability with shorter lead times,  
9 thus improving the confidence in the prediction as the event approaches. It is worth noting  
10 that, in the multi-model forecasts, broader areas are indicated as possibly affected by heavy  
11 precipitation, showing more uncertainty in the forecast.

12 Similar results have been obtained for the second period of intense precipitation. However, in  
13 this case, a longer interval of time has been considered, 24 hours instead of 6 hours. This was  
14 chosen since the observed rainfall lasts for a longer period, and for accounting some timing  
15 errors that were evident in the precipitation forecasts, due to the much longer forecast ranges.  
16 The threshold has been increased accordingly from 20 mm/6h to 50 mm/24h. Rainfall  
17 exceeding this threshold (Fig. 3) affected both the Apennines and the Alps. A nonzero  
18 probability of intense precipitation is forecast by both the ensembles, five days in advance  
19 (Fig. 5). However, only the multi-model and, partially, COSMO-LEPS are able to provide a  
20 warning for possible intense precipitation over the Reno river basin. Approaching the event,  
21 the pattern of rainfall probability does not change significantly and still the multi-model  
22 forecasts intense rainfall over the Reno basin, with a probability ranging between 30 and 60%.

23 While the multi-model identifies the Reno river basin as likely to be affected by intense  
24 precipitation more than three days in advance, the global EPS probability maps provide no  
25 evidence of heavy rainfall there, even at short forecast range. This result confirms that  
26 structural global model deficiencies, i.e. the low resolution and consequently the coarse  
27 representation of the orography, pose a limit to this kind of ensemble approach at such scales.  
28 Higher resolution models are needed at basin scale for medium-sized watershed, thus  
29 explaining the remarkable added value of LAM ensembles with respect to global ensembles  
30 for hydrological applications.

31

## 1 4 Hydrological predictions

2 The two intense precipitation events generated two relevant and distinct discharge peaks in  
3 the Reno basin (Fig. 6 top), both exceeding the warning threshold, but not reaching the alarm  
4 level. The river discharge started to increase rapidly during the night of 29 November,  
5 reaching a maximum of almost 900 m<sup>3</sup>/s at 06 UTC, 30 November. A second peak, of the  
6 same magnitude, but characterized by a less steep increase of water level, occurred in the  
7 morning of 1 December. The discharge computed using raingauges data, spatially distributed  
8 using the Thiessen Polygons method, is in good agreement with the observation at the basin  
9 closure, thus indicating that the error ascribable to the hydrological model is reasonably  
10 limited. In the following analysis, in addition to the ensemble mean, the 90-percentile is  
11 chosen as an indicator of the ensemble performance. This choice is based on previous  
12 statistical investigations (Diomede et al., 2008, 2009) showing that, at least for COSMO-  
13 LEPS coupled with TOPKAPI, the highest quintiles (75-90 %) provide the most informative  
14 support to the forecasters in case of high-discharge events in the Reno watershed.

15 The ensemble discharge forecasts are strongly related to the results shown in the maps of  
16 probability of precipitation. Indeed, at longer forecast range (forecasts initialized on 26  
17 November), discharge predictions driven by the global EPS fail to generate any relevant peak,  
18 while those driven by both LEPSs are remarkably better (Fig. 6, top panels). Although  
19 underestimated in magnitude, the possible occurrence of high discharge peaks is forecast  
20 respectively four and five days ahead by both LEPSs. In particular, at these long forecast  
21 ranges, some members of the multi-model correctly exceed the warning threshold.  
22 Furthermore, a reasonable reproduction of the two peaks, observed 24-h apart, is provided by  
23 the 90-percentile of the multi-model. COSMO-LEPS displays some relevant peaks, although  
24 below the warning level, and the 90-percentile does not represent the occurrence of two  
25 separate peaks.

26 Even at shorter forecast ranges (initialization date 28 November), up to respectively two and  
27 three days in advance, LEPSs remarkably outperform the global EPS (Fig. 6, bottom panels).  
28 Among the ensemble systems, the discharges obtained with the multi-model display a larger  
29 spread among the members and the 90-percentile provides a more accurate prediction,  
30 especially concerning the second peak. Also, at this range, the 90-percentile of the  
31 hydrological ensemble driven by COSMO LEPS provides some hints of the occurrence of  
32 two peaks, although underestimating their magnitude. On the other hand, the flood event is

1 still missed using the global EPS. Although improving the hydrological forecasts with respect  
2 to the system driven by the global ensemble, in general both LEPSs underestimate the  
3 discharge peaks, even considering the 90-percentile (Fig. 6, green line).

4 By analysing each curve of the multi-model ensemble forecasts at long range (Fig. 7), it is  
5 possible to recognize that the highest peaks are associated with mesoscale forecasts driven by  
6 the same global ensemble representative members (namely, members 3, 35 and 36 of the  
7 EPS). Moreover, all the meteorological forecasts driven by member 35 produce the two  
8 separate peaks in the discharge prediction, although the intensity of the peaks is significantly  
9 different among the models. It means that for longer lead times (more than 3 days) the  
10 behaviour of the different members of the multi-model is dominated by the boundary  
11 condition forcing, although the characteristics of each single LAM still have an impact at least  
12 in modulating the peak intensity. This is not true for shorter forecast ranges (not shown),  
13 where it is not possible to identify the same clear correspondence between discharge forecasts  
14 and driving representative members. In this case, the impact of the boundary conditions is  
15 weaker and the difference among the members is reasonably ascribable to the characteristics  
16 of the single models of the ensemble.

17

## 18 **5 Further considerations on multi-model performance**

19 In order to provide some support to these conclusions and to investigate in more detail the  
20 behaviour of the multi-model ensemble, a further meteorological analysis is performed. In the  
21 following, the attention is thus focused on the multi-model results, and the precipitation fields  
22 forecast by its single members are shown for different lead times. Only the first period of  
23 intense precipitation (night of 29 November, Fig. 3) is considered, since it allows to analyse  
24 the forecasts behaviour at both short- (+36 h) and long-range (+84 h).

25 At longer forecast range (simulations initialized at 12 UTC, 26 November), the variability of  
26 the rainfall fields (Fig. 8) among the five forecasts issued by the same LAM is larger than the  
27 variability among the forecasts issued by the three LAMs driven by the same representative  
28 member. In the latter case, although the same boundary conditions provided by the  
29 representative member tend to force the three LAMs towards a similar prediction, the  
30 different model characteristics seem able to preserve still remarkable differences in the  
31 forecasts. Therefore, in a qualitative way, it is quite simple to identify the worst forecast for  
32 each of the three LAMs as the one driven by the same global representative member (m12)

1 (Fig. 8, second panel of each row). The three mesoscale predictions that use the initial and  
2 boundary conditions provided by this representative member are affected by a remarkable  
3 underestimation of the precipitation all over the displayed domain, both over the Apennines  
4 and over the Alps, missing completely the heavy precipitation over northern Italy and the  
5 Reno basin.

6 A straightforward explanation of the LAM forecast failure may be found comparing the large  
7 scale fields of the m12 forecast (that drives the LAM predictions) with the ECMWF analysis,  
8 both at 18 UTC, 29 November 2008, corresponding to the beginning of the heavy rainfall  
9 period (Fig. 9). Indeed, the geopotential field at 500 hPa of the m12 simulation presents a  
10 remarkable and evident error, displaying a westerly and slightly anti-cyclonic mid-  
11 tropospheric flow over Northern Italy and in particular over the Apennines, instead of the  
12 observed south-westerly flow, typically harbinger of heavy precipitation in the target area.  
13 Also the forecast temperature field in the lower layer does not agree with the analysis. Being  
14 driven by a forecast characterized by such a large error, at long forecast range (more than  
15 three days in advance) all the corresponding LAM forecasts are consequently affected by a  
16 similar and remarkable error too. It is worth noting that an error of the same magnitude is not  
17 present in the forecasts provided by any other representative members. Moreover, it is  
18 possible to assess that mesoscale forecasts driven by representative member m36 display a  
19 pretty good forecast.

20 Therefore it seems reasonable to conclude that at long forecast range (day 3-5) the forcing  
21 provided by the boundary conditions is evident in the behaviour of the multi-model ensemble.  
22 However, LAMs characteristics may remarkably impact the forecast, although often at a less  
23 extent, and this represents the main expected added value of the multi-model approach.  
24 Indeed, BOLAM generally forecasts more intense precipitation with respect to the other two  
25 models of the ensemble. Also, small qualitative differences among the model precipitation  
26 fields are amplified in terms of hydrological response, so that pretty similar rainfall patterns,  
27 produced by the three LAMs forced by the same representative member (Fig. 8), generate  
28 significantly different discharge predictions (Fig. 7). This sensitivity of the hydrological  
29 response to small-scale rainfall pattern is a clear indication that coupled atmospheric-  
30 hydrological simulations may serve as an effective validation tool for atmospheric models at  
31 regional (or sub-regional) scale (Jasper and Kaufmann, 2003).

1 Repeating the analysis of the multi-model results for shorter forecast range (36 hours) during  
2 the same period of heavy rainfall (Fig. 10), the five forecasts issued by the same mesoscale  
3 model present much less variability than that observed before for long forecast range. In this  
4 case, the different forecast “trajectories”, due to different initial conditions, have not fully  
5 diverged yet, since the initial perturbations have not grown enough during such a short  
6 forecast range. This is partially due to the properties of the global EPS whose initial  
7 perturbations are optimized for the medium range, as the clustering window is between +96  
8 and +120 hours. Also, the large scale fields driving the multi-model (not shown) as boundary  
9 conditions are quite close to each other and in good agreement with the global analysis, and  
10 have not fully entered the integration domain from the boundaries. At short forecast ranges,  
11 the strong similarities between the LAM forecasts driven by the same representative member  
12 (as seen for long lead times) are not present any longer and it is not easy anymore to  
13 recognize if a specific representative member of the global EPS drives the worst or the best  
14 forecast for all the LAMs. However, moving from one model to the other, large differences  
15 among the precipitation fields are evident. Therefore it is reasonable to speculate that the  
16 variability among the LAM forecasts is dominated by the model characteristics. This is one of  
17 the positive aspects of the multi-model, which allows a quite large spread among the forecasts  
18 also at short ranges. Similar considerations can be drawn from the second period of intense  
19 precipitation.

20

## 21 **6 Conclusions and future plans**

22 In the present study, two different meteorological limited-area ensemble approaches to  
23 quantitative precipitation forecasting have been implemented in order to provide a range of  
24 possible meteorological scenarios to the same hydrological rainfall-runoff model: a multi-  
25 model ensemble based on three mesoscale models, BOLAM, COSMO and WRF, and a  
26 single-model approach, the COSMO-LEPS ensemble. In order to allow a fair comparison, the  
27 two ensembles have been implemented with almost the same characteristics; also, both  
28 ensembles are driven by a limited number of members taken from the same large scale EPS,  
29 to which the two limited-area ensembles have also been compared. The implementation of the  
30 proposed systems is presented for a case study characterized by two periods of intense  
31 precipitation over Northern Apennines, whose ground effects are evaluated over the Reno  
32 river basin, a medium-sized catchment in Northern Italy.

1 Although limited to a single event, the comparison among EPSs highlights important aspects,  
2 which deserve further investigations. In particular, it highlights the added value of mesoscale  
3 models for ensemble forecasting with respect to the global ensemble. At variance with LEPS,  
4 the global EPS forecasts do not provide evidence of any relevant probability of intense  
5 precipitation over the Reno river basin, even at short forecast ranges. This points out that  
6 structural large scale model deficiencies (i.e. low resolution, coarse representation of the  
7 orography) negatively affect the rainfall prediction at the scales typical of hydrological  
8 applications. Instead, higher resolution models are needed: both LEPSs remarkably improve  
9 the forecast quality with respect to the “driving” global model ensemble for this case study, in  
10 terms of both probability of precipitation over the area affected by intense rainfall and  
11 discharge prediction over the Reno river basin.

12 Looking in more detail at the multi-model results, the system seems able to identify the Reno  
13 river basin as likely to be affected by intense precipitation almost four days in advance, with a  
14 progressively increasing probability at shorter lead times, thus improving the confidence in  
15 the prediction as the event approaches. The multi-model ensemble provides better results with  
16 respect to COSMO-LEPS. In particular, it allows to properly address the potential threat  
17 associated with the specific event discussed, correctly indicating the occurrence, intensity and  
18 timing of the two discharge peaks 24-hour apart. The multi-model approach takes into  
19 account both the uncertainty associated with the model error and that related to the initial and  
20 boundary conditions. The latter is accounted for by COSMO-LEPS too, but the former,  
21 namely the model error, is addressed only via perturbations of few parameters of the model  
22 physical scheme, this approach being far from a comprehensive representation of the model  
23 error. The mesoscale model diversity implemented in the multi-model approach permits to  
24 account for a larger fraction of the model error. In the multi-model forecasts, the areas with  
25 high probability of heavy precipitation are generally broader, and the differences in the  
26 forecast members are larger. The 90-percentile curve of the discharge forecasts, issued using  
27 the multi-model system coupled with TOPKAPI, is able to correctly reproduce, especially at  
28 longer range, the occurrence of two separate intense peaks. Based on the local forecasters  
29 experience, as well as on previous statistical analysis, this would have been a valuable  
30 information for the actual forecast of the flood. The possible flood occurrence would have  
31 been predicted with a sufficient lead time, and the magnitude of the event could have been  
32 properly estimated by the decision makers.



1 Still focusing on the multi-model ensemble, a different behaviour can be identified  
2 considering short and long forecast ranges. For short forecast ranges, the large scale  
3 conditions are similar and have not affected the integration domain yet, thus the impact of  
4 boundary conditions is weaker and the spread can be mainly attributed to the different  
5 characteristics of the models. At longer forecast ranges, the similar behaviour of the  
6 corresponding multi-model members indicates that they are governed mainly by the large  
7 scale boundary conditions. Nonetheless, the different LAMs characteristics still have a  
8 significant impact on the forecasts even at these long ranges.

9 However, it is worth stressing again that the considerations of the present research are  
10 confined to just one case study. Further events, associated with different synoptic conditions,  
11 need to be analysed in order to support these conclusions. Also, the present paper is limited to  
12 ensembles based on convection-parameterized models. The horizontal resolution adopted here  
13 (7-8 km) is close to the “no man's land” (Weisman et al., 2008) separating classical  
14 convective parameterization schemes from explicitly convection-resolving models. As a  
15 result, the ability of mesoscale models to accurately reproduce atmospheric phenomena on  
16 such fine spatial scales can be questionable. Further simulations using short-range ensembles  
17 employing convection-resolving models at higher resolution, which should be able to better  
18 represent the small scales and to better simulate convective rainfall, will be analysed in a  
19 future study.

20

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25

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- 16
- 17

1 Table 1. Model set up: horizontal and vertical resolution, grid characteristic and  
2 initial/boundary conditions.

3

---

Model	Horizontal Resolution	Number of Grid Points	Number of Vertical Levels	Initial/boundary conditions
BOLAM	8 km	426 x 354	50	EPS (5 members)
COSMO	7 km	511 x 415	40	EPS (5 members)
WRF	7.5 km	460 x 380	40	EPS (5 members)
COSMO-LEPS	7 km	511 x 415	40	EPS (16 members)

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4

5



## 1 **FIGURE CAPTIONS**

2 Figure 1: (a) Localisation of the Reno river basin in the Emilia-Romagna Region, Northern  
3 Italy. The upper basin closure at Casalecchio Chiusa river section is indicated. (b) Model  
4 integration domains (blue area), and domain employed for the cluster analysis (red line).

5

6 Figure 2: ECMWF analysis at 00 UTC, 30 November 2008. Geopotential height at 500 hPa  
7 (gpm, colour shading) and mean sea level pressure (hPa, contour).

8

9 Figure 3: Observed precipitation (mm) for the two period of most intense rainfall: (a) 6-h  
10 accumulated rainfall at 00 UTC, 30 Nov. 2008; (b) 24-h accumulated rainfall at 12 UTC, 01  
11 Dec. 2008.

12

13 Figure 4: Maps of probability of precipitation exceeding 20 mm in 6h obtained at long (+84 h,  
14 top panels) and short (+36 h, bottom panels) forecast ranges: multi-model (left), COSMO-  
15 LEPS (middle) and ECMWF global EPS (right) forecasts valid at 00 UTC, 30 Nov. 2008.  
16 Reno river basin is also indicated by the black rectangle.

17

18 Figure 5: Maps of probability of precipitation exceeding 50 mm in 24h obtained at +120 h  
19 (top panels) and +72 h (bottom panels) forecast range: multi-model (left), COSMO-LEPS  
20 (middle) and ECMWF global EPS (right) forecasts at 12 UTC, 1 Dec. 2008.

21

22 Figure 6: Discharge forecasts ( $\text{m}^3/\text{s}$ ) as a function of the forecast range (h). The different  
23 (grey) curves have been obtained by feeding the TOPKAPI hydrological model with the  
24 precipitation forecast by the ensemble members: multi-model (left), COSMO-LEPS (middle)  
25 and ECWWMF global EPS (right). The raingauge-driven (thick blue line) and the observed  
26 (blue dashed line) discharges are also plotted for reference. The pink line represents the  
27 ensemble mean, while the two green lines represent the 10th and the 90th percentile curves.  
28 Top panels refer to forecasts initialized at 12 UTC, 26 Nov. 2008 (short-range in the text);

1 bottom panels to those initialized at 12 UTC, 28 Nov. 2008 (long-range in the text). Orange  
2 (red) horizontal line indicates warning (alarm) level.

3

4 Figure 7: Discharge forecasts ( $\text{m}^3/\text{s}$ ) as a function of the forecast range (h) obtained by  
5 feeding the TOPKAPI with the rainfall predicted by the five members of each model of the  
6 multi-model ensemble system and for the five representative members of the ECMWF global  
7 EPS. Forecasts are initialized at 12 UTC, 26 Nov. 2008 (long-range, see text). The raingauge-  
8 driven (thick blue line) and the observed (blue dashed line) discharges are also plotted for  
9 reference. The forecasts driven by a particular representative member of the global ensemble  
10 are indicated with arrows and with the member number. Orange (red) horizontal line indicates  
11 warning (alarm) level.

12

13 Figure 8: 6h accumulated precipitation (mm) at 00 UTC, 30 Nov. 2008 forecast by the  
14 different members of the multi-model ensemble at long-range (+84 h, see text). Five forecasts  
15 for each model: COSMO (top), BOLAM (middle) and WRF (bottom). Models are initialized  
16 at 12 UTC, 26 Nov. 2008. The driving global representative member (m) is indicated below  
17 each column of panels.

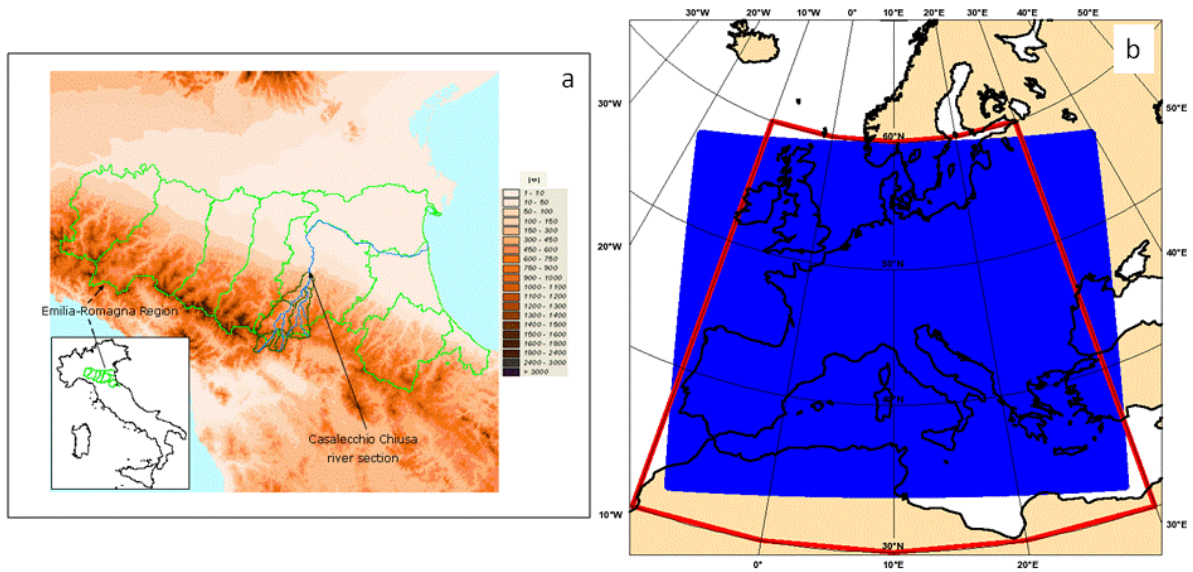
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19 Figure 9: Geopotential height at 500 hPa (gpm, contour lines) and temperature at 850 hPa  
20 (colour shading) at 18 UTC, 29 Nov. 2008. (a) ECMWF analysis. (b) Forecast fields issued  
21 by the ECMWF representative member number 12 (m12).

22

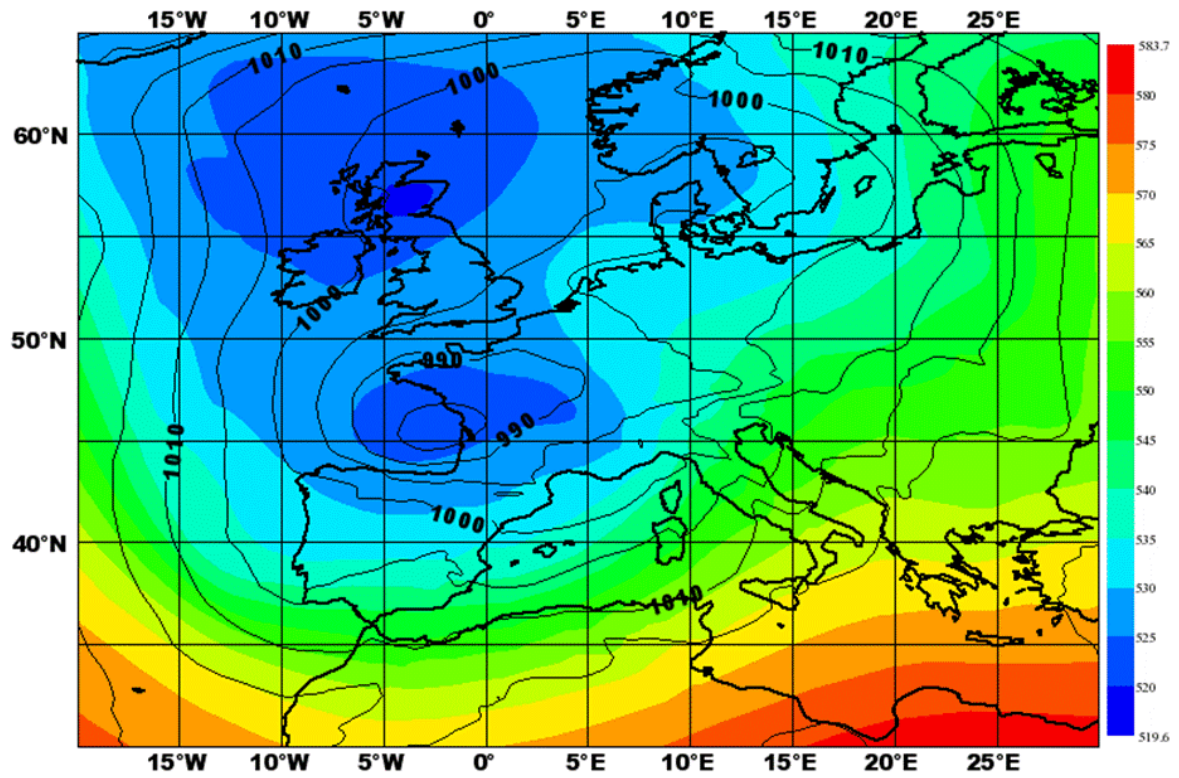
23 Figure 10: as in Fig. 8, but for the forecasts initialized at 12 UTC, 28 Nov. 2008 (short-range,  
24 +36 h, see text)

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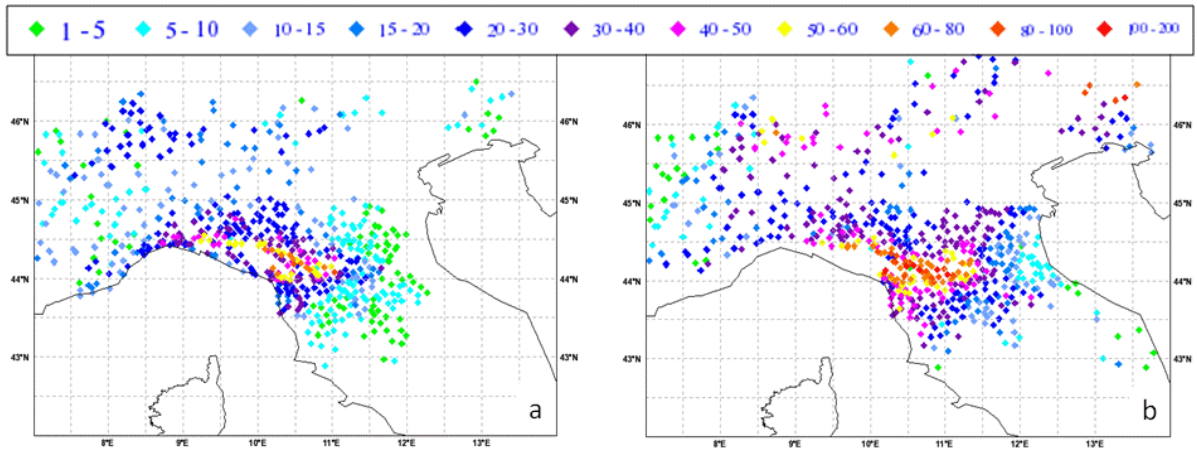
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Figure 1: (a) Localisation of the Reno river basin in the Emilia-Romagna Region, Northern Italy. The upper basin closure at Casalecchio Chiusa river section is indicated. (b) Model integration domains (blue area), and domain employed for the cluster analysis (red line).



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 2 Figure 2: ECMWF analysis at 00 UTC, 30 November 2008. Geopotential height at 500 hPa  
 3 (gpm, colour shading) and mean sea level pressure (hPa, contour).  
 4

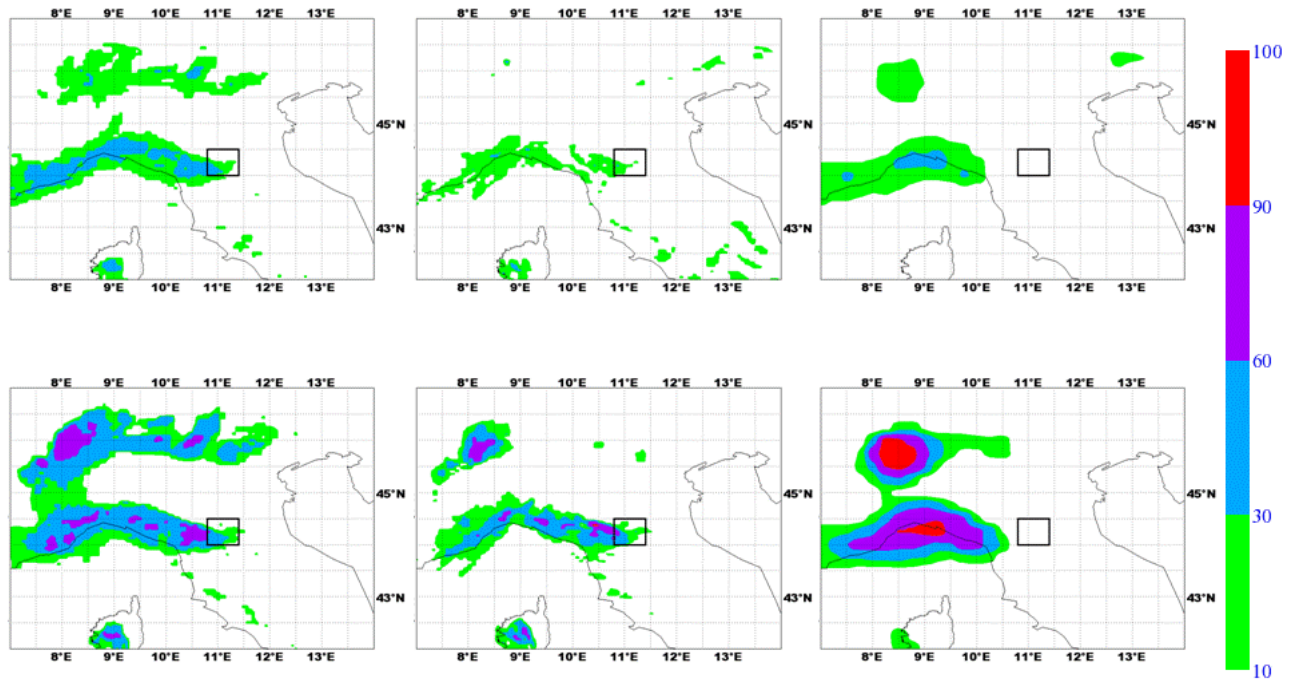
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3 Figure 3: Observed precipitation (mm) for the two period of most intense rainfall: (a) 6-h  
4 accumulated rainfall at 00 UTC, 30 Nov. 2008; (b) 24-h accumulated rainfall at 12 UTC, 01  
5 Dec. 2008.

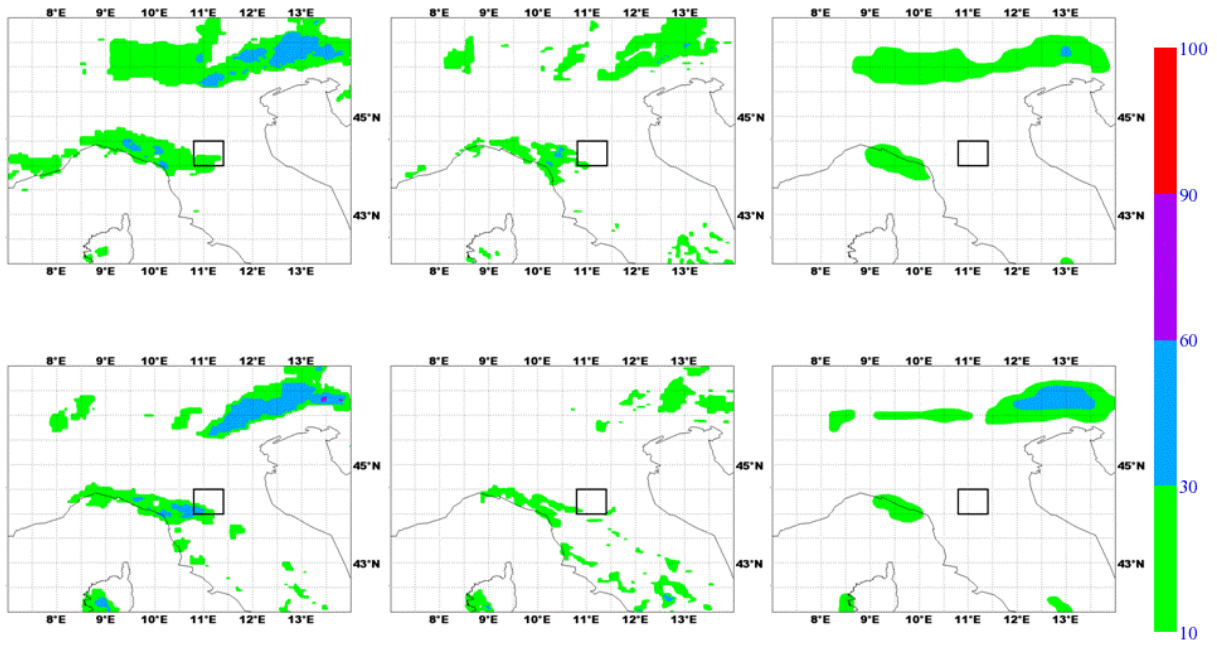
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2 Figure 4: Maps of probability of precipitation exceeding 20 mm in 6h obtained at long (+84 h,  
 3 top panels) and short (+36 h, bottom panels) forecast ranges: multi-model (left), COSMO-  
 4 LEPS (middle) and ECMWF global EPS (right) forecasts valid at 00 UTC, 30 Nov. 2008.  
 5 Reno river basin is also indicated by the black rectangle.

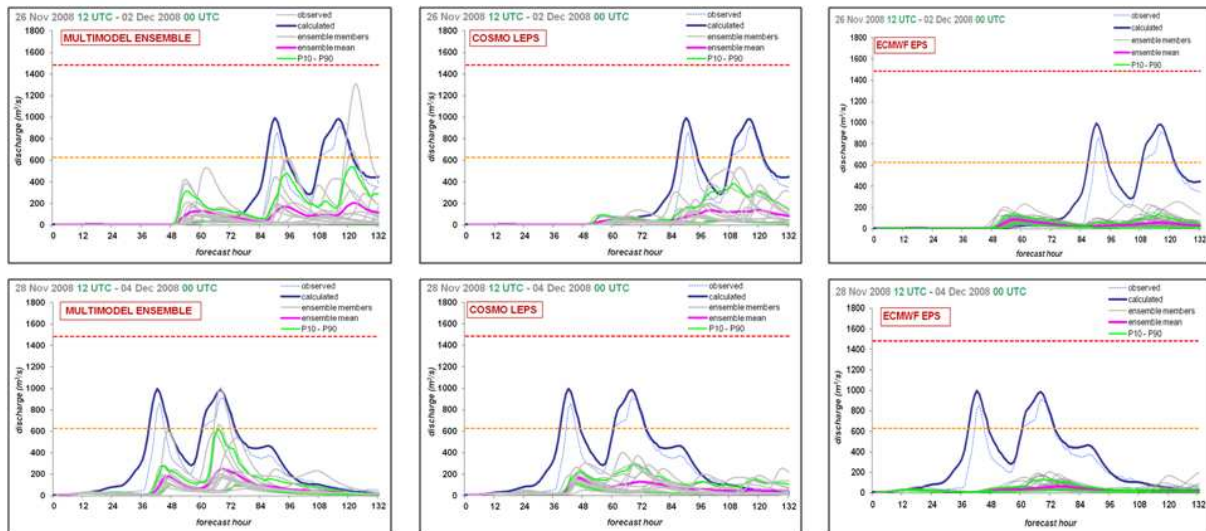
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2 Figure 5: Maps of probability of precipitation exceeding 50 mm in 24h obtained at +120 h  
 3 (top panels) and +72 h (bottom panels) forecast range: multi-model (left), COSMO-LEPS  
 4 (middle) and ECMWF global EPS (right) forecasts at 12 UTC, 1 Dec. 2008.

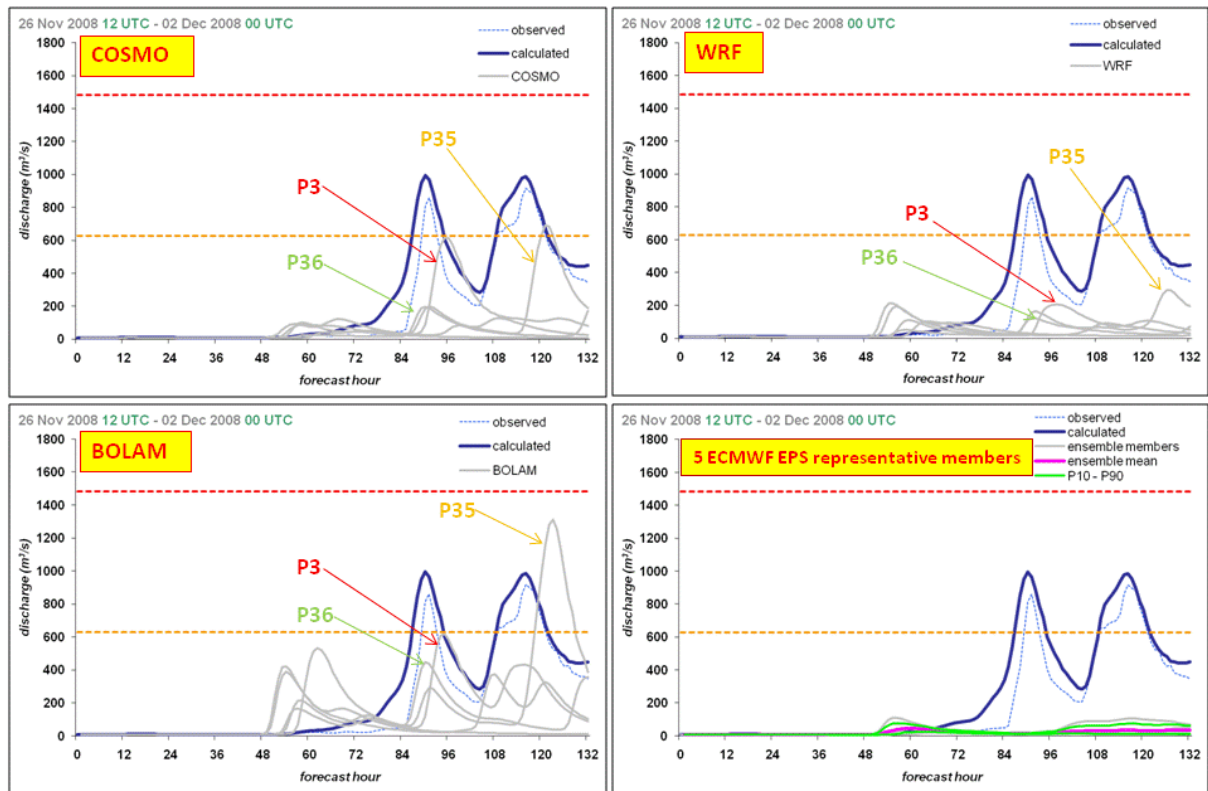
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 2 Figure 6: Discharge forecasts ( $\text{m}^3/\text{s}$ ) as a function of the forecast range (h). The different  
 3 (grey) curves have been obtained by feeding the TOPKAPI hydrological model with the  
 4 precipitation forecast by the ensemble members: multi-model (left), COSMO-LEPS (middle)  
 5 and ECWMF global EPS (right). The raingauge-driven (thick blue line) and the observed  
 6 (blue dashed line) discharges are also plotted for reference. The pink line represents the  
 7 ensemble mean, while the two green lines represent the 10th and the 90th percentile curves.  
 8 Top panels refer to forecasts initialized at 12 UTC, 26 Nov. 2008 (short-range in the text);  
 9 bottom panels to those initialized at 12 UTC, 28 Nov. 2008 (long-range in the text). Orange  
 10 (red) horizontal line indicates warning (alarm) level.

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 2 Figure 7: Discharge forecasts ( $\text{m}^3/\text{s}$ ) as a function of the forecast range (h) obtained by  
 3 feeding the TOPKAPI with the rainfall predicted by the five members of each model of the  
 4 multi-model ensemble system and for the five representative members of the ECMWF global  
 5 EPS. Forecasts are initialized at 12 UTC, 26 Nov. 2008 (long-range, see text). The rain gauge-  
 6 driven (thick blue line) and the observed (blue dashed line) discharges are also plotted for  
 7 reference. The forecasts driven by a particular representative member of the global ensemble  
 8 are indicated with arrows and with the member number. Orange (red) horizontal line indicates  
 9 warning (alarm) level.

10

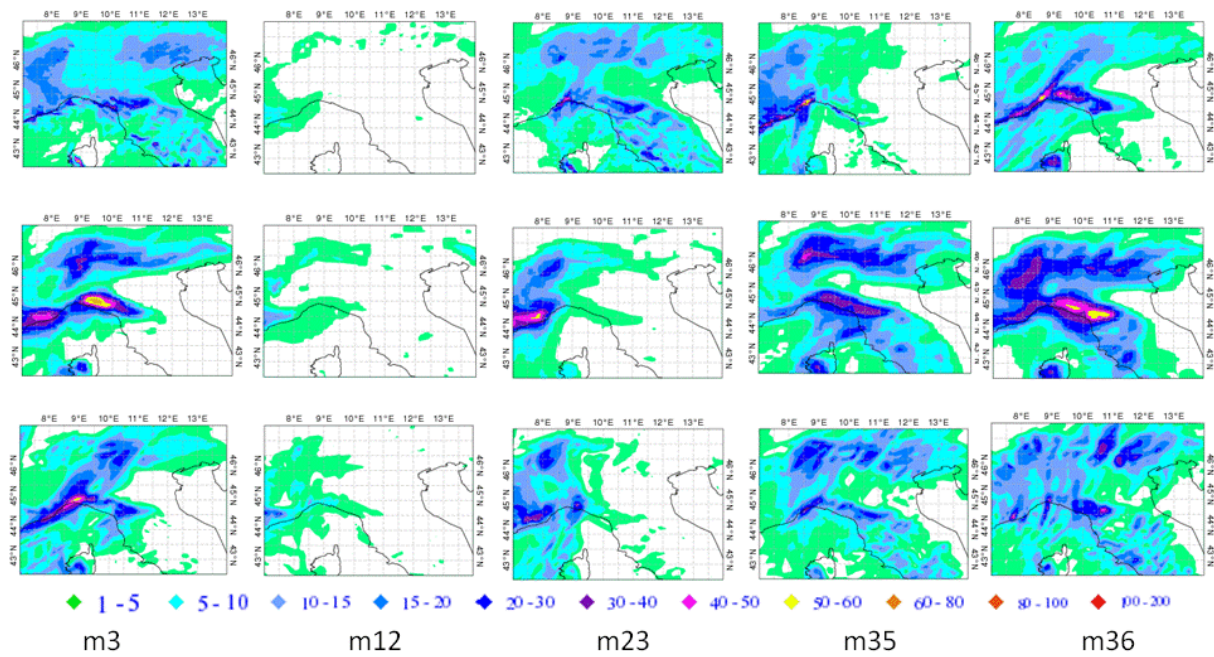
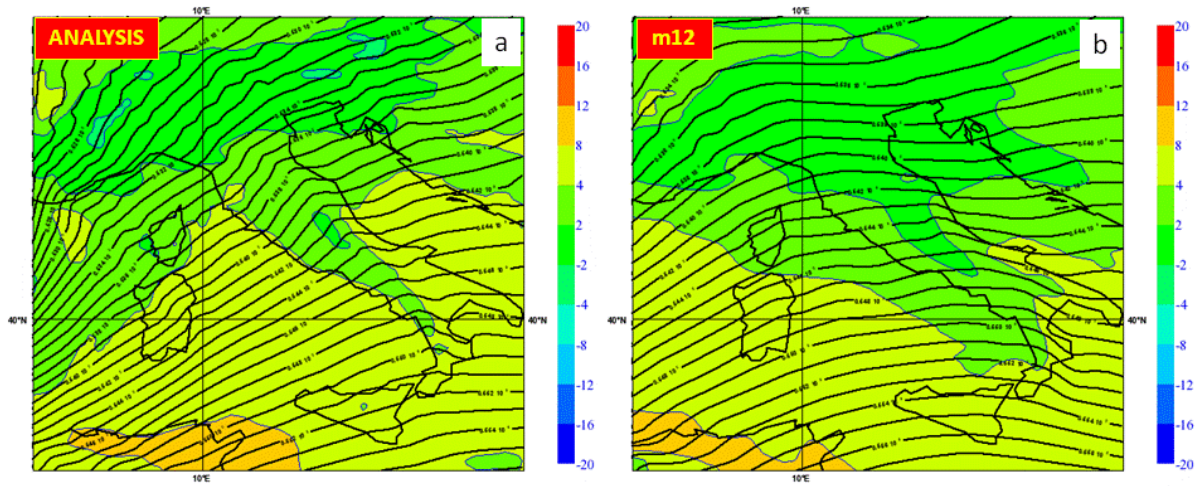


Figure 8: 6h accumulated precipitation (mm) at 00 UTC, 30 Nov. 2008 forecast by the different members of the multi-model ensemble at long-range (+84 h, see text). Five forecasts for each model: COSMO (top), BOLAM (middle) and WRF (bottom). Models are initialized at 12 UTC, 26 Nov. 2008. The driving global representative member (m) is indicated below each column of panels.



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2 Figure 9: Geopotential height at 500 hPa (gpm, contour lines) and temperature at 850 hPa  
 3 (colour shading) at 18 UTC, 29 Nov. 2008. (a) ECMWF analysis. (b) Forecast fields issued  
 4 by the ECMWF representative member number 12 (m12).

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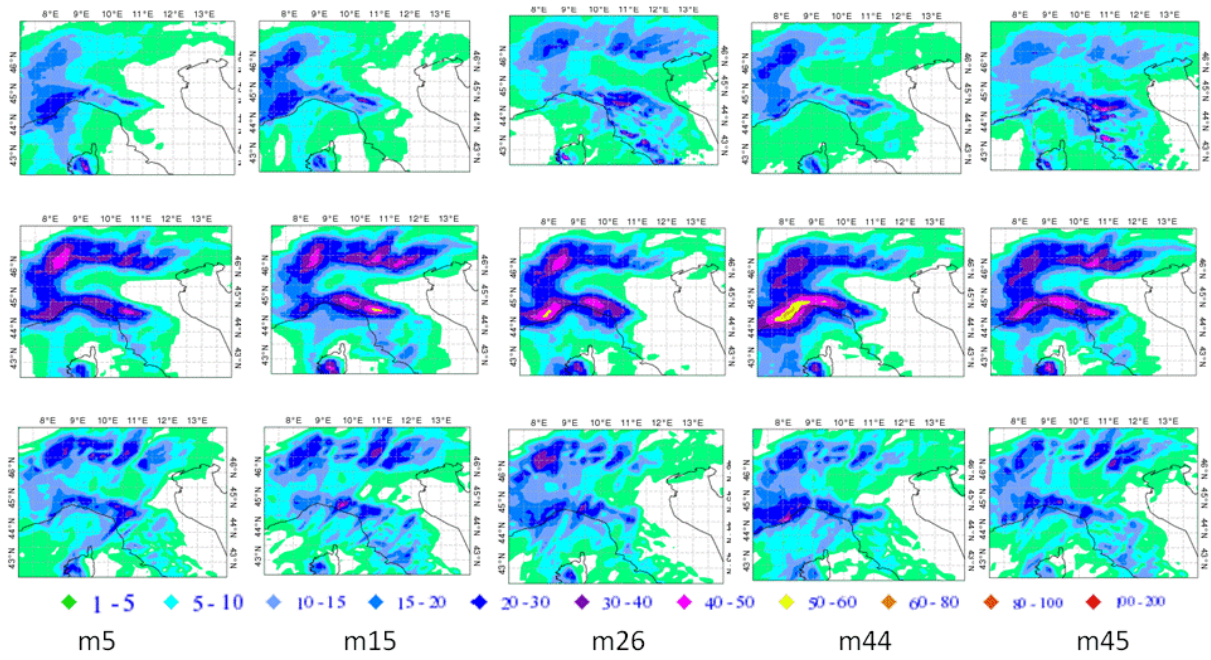


Figure 10: as in Fig. 8, but for the forecasts initialized at 12 UTC, 28 Nov. 2008 (short-range, +36 h, see text)